University of Southern Queensland

WATER-ENERGY-FOOD (WEF) NEXUS IN AGRICULTURAL SYSTEMS

A Thesis submitted by

Shan Gao

(B.Sc., M.Sc.)

For the award of

Doctor of Philosophy

2024

ABSTRACT

Water and energy are often the two limiting factors in agricultural production in Australia which has also incurred considerable greenhouse gas (GHG) emissions. From a Water-Energy-Food (WEF) nexus perspective, agricultural water, land and energy uses, and crop production are intertwined. As such, this study develops a WEF nexus model to optimize resource uses, economic and environmental performances in an irrigated agricultural system with multiple scenarios designed in contrast to basic situations in the study area. In a baseline scenario, the optimized irrigated areas of wheat (72%; 7,768 ha) are remarkably higher than those of cotton (28%; 3,003 ha) under cotton irrigation application rate of 7.74 ML/ha and wheat irrigation application rate of 2.02 ML/ha. The gross margins per ha irrigated area are AU$4,132/ha in cotton cultivation, being higher than AU$1,584/ha in wheat cultivation. GHG emission intensities are also higher in cotton (3.25 tCO2e/ha and 0.52 tCO2e/t) than those in wheat (2.69 t CO2e/ha and 0.45 tCO2e/t). In comparison, for different crop prices the highest profits (approximately AU$32 million) are generated in the specific scenario involving cotton lint price over AU$650/bale and wheat price below AU$400/t. For alternative energy sources in irrigation, solar-powered irrigation can generate higher profits, AU$25.61 million, and lower total GHG emissions (27 ktCO2e). For methods in disposing crop residues, the economic performances are the best in the combustion scenario (total profits AU$38.44 million). The best environmental performances are in a mulching scenario (28 ktCO2e). For other influential factors, rainfall and power feed-in tariffs show more complex influences than the other factors. Across all scenarios, the maximal total profits (AU$60.77 million) are in the scenario involving combustion with an assumed efficiency of power generation being high (70%). This study contributes to the sustainable management of water, energy, land resources, and also effective crop residue disposals. It can be adopted as a generic model, applicable to a farm scale and extended to incorporate climate change and residue management in other agricultural systems that require more cost-effective production and sustainability.

CERTIFICATION OF THESIS

I, Shan Gao, declare that the Thesis entitled *Water-Energy-Food (WEF) nexus in agricultural systems* is not more than 100,000 words in length including quotes but exclusive of tables, figures, appendices, bibliography, references, and footnotes. The thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is entirely my own work.

Date: 22/02/2024

Endorsed by:

Associate Professor Guangnan Chen
Principal Supervisor

Professor Tek Maraseni
Associate Supervisor

Student and supervisors' signatures of endorsement are held at the University.

ACKNOWLEDGEMENTS

Many people have assisted me with bringing this thesis to completion. I would like to express my gratitude to all those who have been in support in the past four years, named or unnamed in this section. Particularly, I am really grateful for the financial support from the following sources that have made the completion of my study possible:

- Graduate Research School (GRS) at the University of Southern Queensland (UniSQ), who has granted me the International Fee Scholarship that made it possible for me to strive through my whole PhD period. They have also been very professional and promptly responsive to my queries whenever I am in need of support on my thesis. In particular, the GRS supplied the financial assistance in a timely manner while I was stuck at home due to the COVID pandemic.
- Iconnect, a specialized student support team at UniSQ, helping me out with serious financial and mental hardship in the last year of my thesis after I was struggling through the three years' challenging time of pandemic.

To my principal supervisor, Guangnan Chen, for his patience and technical guidance and especially for encouraging me to keep learning by constantly communicating with peers and attending professional academic conferences pertinent to my thesis topic. To my co-supervisor, Tek Maraseni, who has been patient with provisions of very precious and professional feedback and suggestions on my research.

I would also like to thank all the others throughout my PhD years, particularly UniSQ staff, who have been showing tremendous respect, excellence and integrity and not bothered at all to lend a hand to me whatsoever. The UniSQ has wonderfully presented a good environment with multicultural inclusivity and diversity, making me feel at ease while doing my PhD.

Last but by no means least, to my parents back in my home country, who have been supporting me both financially and mentally even if they were trapped by the pandemic as well during the past few years, for their love and inspiration; to all the other relatives and friends in my home country, who have encouraged me to achieve this milestone.

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ABBREVIATIONS

ABARES	Australian Bureau of Agricultural and Resource Economics and Sciences
ABS	Australian Bureau of Statistics
ACCUs	Australian Carbon Credits Units
ALCAS	Australian Life Cycle Assessment Society
APSIM	Agricultural Production Systems Simulator
AusLCI	Australian Life Cycle Inventory
AWEFSM	Agricultural Water-Energy-Food Sustainable Management
BOM	Bureau of Meteorology
CCMs	Crop Coefficient Models
CETS	Carbon Emissions Trading Scheme
CLEWs	Climate-Land-Energy-Water systems
CRDC	Cotton Research and Development Corporation
CSIRO	Commonwealth Scientific and Industrial Research Organisation
CWPF	Crop Water Production Function
DAF	Department of Agriculture and Fisheries
DAFF	Department of Agriculture, Fisheries and Forestry
DAWE	Department of Agriculture Water and the Environment
DCCEEW	Department of Climate Change, Energy, the Environment and Water
DEA	Data Envelopment Analysis
DES	Department of Environment and Science
ECR	Clean Energy Regulator
EEAs	Empirical Estimation Approaches
EJ	Exajoule
ERF	Emissions Reduction Fund
ETS	Emissions Trading System
FAO	Food and Agriculture Organization
FRL	Federal Register of Legislation
GAF	Greenhouse Accounting Frameworks
GLOBIOM	Global Biosphere Management Model

GHG	Greenhouse Gas
GIS	Geographic Information System
GL	Giga Litre
GMs	Gross Margins
GRG	Generalized Reduced Gradient
GWPs	Global Warming Potentials
HHV	Higher Heating Value
HI	Harvest Index
IFLFP	Interval Fuzzy Linear Fractional Programming
IOA	Input-Output Analysis
IPCC	Intergovernmental Panel on Climate Change
LCA	Life Cycle Assessment
LF	Leaching Fraction
LHV	Lower Heating Value
LP	Linear Programming
LR	Leaching Requirement
MCDM	Multi-Criteria Decision-Making
MDBA	Murray Darling Basin Authority
MILP	Mixed-Integer Linear Programming
MMAs	Mathematical Modelling Approaches
MuSIASEM	Multi-Scale Integrated Analysis of Societal and Ecosystem Metabolism
NGER	National Greenhouse and Energy Reporting
NLP	Nonlinear Programming
NSW	New South Wales
PCGMs	Process-based Crop Growth Models
PJ	Petajoule
PV	Photovoltaic
QCA	Queensland Competition Authority
QFF	Queensland Farmers' Federation
RCPs	Representative Concentration Pathways
RI	Residue Index
SDGs	Sustainable Development Goals

SLSQP	Sequential Least Squares Programming
SQP	Sequential Quadratic Programming
TGMs	Total Gross Margins
TWh	Tera Watt Hour
UNEP	United Nations Environment Programme
USDA-SCS	United States Department of Agriculture Soil Conservation Service
WEAP	Water Evaluation and Planning
WEF	Water-Energy-Food
WEFCNI	Water-Energy-Food-Climate Nexus Index
WEF-L	Water-Energy-Food-Land
WEFNI	Water-Energy-Food Nexus Index
WEFO	Water, Energy and Food security nexus Optimization
WEF-W	Water-Energy-Food-Waste

CHAPTER 1: INTRODUCTION

1.1. Overview

During the past decades, global demands for water, energy and food have been rising rapidly due to population increase, urbanization, and climate change (Hajkowicz et al. 2012, 2014; Mehran et al. 2017; Shah et al. 2018). Between 2009 and 2050, the global demand, on average, is projected to grow by 20%-30% for water (Boretti et al. 2019), by over 50% for energy (Yoon et al. 2010; Kahan 2019) and by 60%-70% for food (Bruinsma 2009; FAO 2009; Alexandratos et al. 2012; Hunter et al. 2017). Meanwhile, global greenhouse gas (GHG) emissions have been rising at the rate of 1.5% per annum over the last decade, stabilizing only briefly between 2014 and 2016 (UNEP 2019). Agriculture directly contributes roughly 10-12% of global GHG emissions and 13-18% if indirect sources are included (Vermeulen et al. 2012; Tubiello et al. 2013; Maraseni et al. 2018; Maraseni et al. 2020).

Under the varying climatic conditions, Water-Energy-Food (WEF) nexus was proposed as a conceptual framework to explore the inextricable connections among these three important resources (Biggs et al. 2015; Abdul Salam et al. 2017; Venghaus et al. 2018). WEF nexus is a cognition of the overall systematic interlinkages, within which dynamics in one sector of resource (either water, energy, or food) can have impacts on the other one or two either directly or indirectly (Abdul Salam et al. 2017). As such, it would imply that any resolution to a problem relating to one of the three resources, such as water issue, must equally or equivalently consider the other two resources, or more internal and external factors, in this interconnected nexus system (Smedley 2013).

Coined during the 2011 Bonn Conference (Hoff 2011b) and further highlighted at the World Economic Forum (2011), the WEF nexus framework has been demonstrated to be capable of coordinating and managing competing resources with minimized trade-offs and maximized synergies. As a vital concept in natural resource management, it has been increasingly conceptualized on interlinkages between the three sectors across both temporal and geographical scales, and cumulatively operationalised for application since 2015 (Hamidov et al. 2020). It has also been enabled to serve purposes of facilitating sustainable development (Bhaduri et al. 2015; Leck et al. 2015) and further aligning with multiple Sustainable Development

Goals (SDGs) established by the United Nations Development Programme (UNDP 2021).

1.2. Problem statement

The Australian agriculture and irrigation sector is currently one of the largest users of fresh water. It accounted for over 92% (9700 GL) of the total national agricultural water use in 2017-18 (ABS 2019; Maraseni et al. 2021). As the sector relies significantly on energy consumption in water delivery, transportation, distribution, and so on, irrigated cropping areas are also major users of energy for pumps and other activities (DAWE 2019b). Operating irrigation networks that involve piping often requires high energy usage as opposed to other farming activities, which leads to massive GHG emissions due to the conventional use of diesel fuel (Maraseni et al. 2012; Mushtaq et al. 2013; Hafeez et al. 2014). Moreover, minor changes in water and energy availability can significantly influence food production (Karabulut et al. 2018), in particular crop production, under varying climatic situations (Elliott et al. 2014; Sridharan et al. 2019; Scardigno 2020).

Furthermore, global climate change has adversely affected agricultural cropping systems in many countries including Australia (Anwar et al. 2013; Challinor et al. 2014; Rodriguez et al. 2014) in various ways including increased surface air temperature (CSIRO et al. 2012) and carbon fertilisation, and reduced water availability (Stokes et al. 2010). In crop planting, water, energy, food and land are commonly intertwined, which are all affected by climate change.

The impacts of climate change and extreme weather events on energy systems can also be significant, such as peak electricity demand (Perera et al. 2020). Implications on cropping are changes of evapotranspiration, therefore impacting on crop water demand and crop production. The fluctuation of water demand directly resulting from climate change will require water and land resource allocation change or re-allocation. Climate change may also impose negative impacts on soil, such as accelerating soil erosion along with water loss, which will further degrade arability of land (Borrelli et al. 2020; Dosdogru et al. 2020; Guo et al. 2020; Hung et al. 2020; Santy et al. 2020).

In addition, food waste is a non-negligible problem in many countries. It is estimated that around 1.3 billion tonnes of food is wasted or lost worldwide annually, accounting for approximately one third of total food production (FAO 2014a). Food waste incurs water and energy waste, as producing, processing and consuming of food contribute to approximately 70% of global water withdrawal and 30% global energy consumption (Garcia et al. 2016). Considering waste in conjunction with the WEF nexus enhances comprehensiveness, broadens the horizons of sustainability, and provides valuable insights into the principles of the circular economy and bio-economy, and thereby promotes the widespread adoption of findings (Del Borghi et al. 2020; Udugama et al. 2020).

During agricultural activities, waste is generated in the forms of such as wastewater, food waste and loss, livestock manure and crop residues. It may incur impacts on the environment. For example, wastewater or sewage generated would influence water security (Falconer et al. 2020; Petrariu et al. 2021), while agricultural waste could also be taken as biofuel or biomass that might facilitate prospective renewable energy generation (Makarichi et al. 2018; Malav et al. 2020; Melikoglu et al. 2020). Crop residues could be recycled as potential animal feedstuff and animal manure could be reused for potential fertilizers in the field (Slorach et al. 2020; Petrariu et al. 2021; Santeramo et al. 2021). Notably, crop residues have commonly been utilised for bio-energy and bio-mass generation at an international level (Duque-Acevedo et al. 2020).

However, the WEF frameworks and models that have been developed in studies so far are complicated if applied on a relatively larger geographical scale. They are made of large numbers of components and require massive datasets. The other ones are insufficiently integrated or deficient to study agricultural systems on a relatively smaller geographical scale. In particular, there have been few studies targeted at a farm or local scale.

Also, sectors especially food waste are rarely linked with WEF nexus. Agricultural WEF nexus has mainly focused on value chains up till post-harvest and not been expanded to include crop residue disposal after post-harvesting process. The dominating method to manage crop residues in Australia is ploughing into soils, as one of conventional agricultural methods, without taking any further actions. It would be valuable to develop a WEF nexus model incorporating waste component and climatic factors. In these regards, the research goal and specific objectives are proposed in the following section.

1.3. Research objectives

It is presumed through this study that a cropping system can achieve optimal total profits under coordinated resource constraints. Accordingly, this study aims to develop a WEF nexus-based optimization model for an irrigated single crop rotation system (cotton grown in summer and wheat grown in winter), coupled with constrained water availability and land use. This is to achieve optimal conjunctive performances of resource use (land and water), economic benefits, and environment (GHG emissions).

As such, the specific objectives of this work are:

(1) To develop an integrated optimization model on an agronomic framework in the form of total profits of a cropping system, and quantify the inputs and outputs of the cropping system and explore potential inherent connections between crop yields, resource uses (water, land, energy), and waste (crop residues, GHG emissions);

(2) To find out optimal outcomes on performances of land and water uses, profitability and GHG emissions for the cropping system under a series of water and land constraints with locally common conditions as a baseline scenario (business-as-usual);

(3) To find out optimal outcomes on performances of land and water uses, profitability and GHG emissions for the cropping system with different crop prices or alternative energy sources in irrigation, relative to the baseline scenario;

(4) To find out optimal outcomes on performances of land and water uses, profitability and GHG emissions for the cropping system with alternative methods to process, dispose and/or utilize crop residues, relative to the baseline scenario;

(5) To explore and investigate effects of other potentially influential factors on the optimal outcomes on performances of land and water uses, profitability and GHG emissions for the cropping system, relative to the baseline scenario.

1.4. Outline of the Thesis

Throughout this work, eight chapters are mapped out with the following description:

Chapter 1. Introduction

The research background guiding this work is described in this chapter. It also presents objectives, and the general study outline.

Chapter 2. Literature review

To get insights into WEF nexus related topics, reviews on peer studies, reports, and policies are conducted. This covers possible WEF nexus related methods, which facilitates an integrated model development for this study. Also, the review covers facets like water use, energy use and types, and crop production, as well as climate change and carbon policy related topics that likely intervene with the nexus and its elements. This will help to design consistent and coherent scenarios associated with varied resource and energy uses, relevant carbon price policies, and crop residue management methods.

Furthermore, agricultural residues related topics are reviewed, in particular crop residue management and disposal solutions, for a design of crop residue disposal related scenarios in this study. This is one of the novelty parts in this study, as crop residues are rarely correlated with WEF nexus.

Chapter 3. Methodology

This chapter describes the selected study area, crops, and data collection methods and tools used. It also details model development (including crop yield, irrigation water and energy, variable costs and associated GHG emissions), model solving method, and sensitivity analysis. Scenario designs are made in this chapter as guidance for further scenario analysis in the later chapters. Two series of agri-environmental scenarios are designed, relative to a baseline scenario that contains common farming conditions within the study area. These two series of scenarios will be implemented in Chapter 5 and Chapter 6 by three models, respectively. The first one, the basic integrated model, is used for scenarios in Chapter 5, while the second and the third ones are two further developed (extended) models for scenarios in Chapter 6 regarding methods for processing, disposing and utilizing crop residues.

Chapter 4. Basic case study: business as usual

This chapter applies the basic model developed in Chapter 3 to the real local situations. This application of the basic model is also the baseline scenario (business-as-usual), adopting common farming practices in the selected study area. The two subsequent chapters for scenario design and analysis are conducted and compared with the baseline scenario.

Chapter 5. Scenario study 1 - impacts of crop prices, energy sources in irrigation and associated costs

This chapter further applies the basic model to designed scenarios involving different crop prices and alternative energy sources in irrigation (diesel fuel, on-grid electricity, solar photovoltaic (PV)) coupled with different energy costs, and compares key results with those in the baseline scenario and have discussions.

Chapter 6. Scenario study 2 - impacts of alternative crop residue disposal methods

This chapter applies two further developed models to scenarios with three dominant crop residue disposal methods (mulching, composting, combustion), and compares key results with those in the baseline scenario and have discussions.

Chapter 7. Further discussions

In this chapter, more potential factors, including rainfall, costs of processing and disposing crop residues, efficiency of power generation by combustion, will be explored to examine how they may influence the cropping system. Associated implications will be discussed. Subsequently, limitations will be discussed throughout the whole work.

Chapter 8. Conclusions and prospects

This chapter gives a summary of research gaps, key findings, study limitations, recommendations for stakeholders and future research, and major contributions of this work.

CHAPTER 2: LITERATURE REVIEW

For the purpose of having an overall picture on Water-Energy-Food (WEF) nexus in line with the research objectives, the literature review in this chapter covers important aspects associated with WEF nexus, mainly from publications during the past decade and other sources. First, it covers WEF nexus related studies and existing methods and tools to provide insights into model development, including:

- Background of WEF nexus;
- Peer WEF nexus studies;
- Models and tools for WEF nexus.

Subsequently, reviews are also conducted for the three core resources (water, energy and food), their potential correlations with each other, external factors, and their possible interactions with the nexus system:

- Crop production and its functional relationships with water application;
- Different energy sources in irrigation and associated greenhouse gas (GHG) emissions;
- Relevant carbon policies on climate change and GHG emissions;
- Agricultural crop residues and their prospective linkages with WEF nexus.

2.1. WEF nexus

2.1.1. A brief history of WEF nexus

The concept of "Nexus" emerged at the earliest in 1983 as in the human-environment realm (Scott et al. 2015; Endo et al. 2017; Liu et al. 2018). Prior to 1983, an even earlier associated implicit perspective could be traced backward to the 1970s when it was applied to areas, such as agricultural water and linkages between socialism and political traditions (Lele et al. 2013). This perspective highlighted the interconnectivities among the three-pronged WEF resources. Subsequently, the Food-Energy Nexus Programme of the United Nations University, which was launched in 1983 and finalized in 1987 (Sachs et al. 1990), has brought to the public an initial conception on the "food-energy" nexus.

Prior to 2011, the predominant status of nexus research was a focus on dual-sector interactions, such as, water-energy, water-food or food-energy (Endo et al. 2017; Purwanto et al. 2021). The concept of "WEF nexus" commonly known to the public was preliminarily coined in the Bonn (2011) conference, headed "The Water, Energy, and Food Security Nexus - Solutions for the Green Economy”. It was a remarkable milestone when the WEF nexus was imprinted (Hoff 2011a). Afterwards, a few studies began to transition from segmented analytical approaches to systematic insights into WEF nexus, laying the foundation for succeeding research (Zhang et al. 2019).

2.1.2. Status quo of WEF nexus

Since 2011, the number of nexus publications has grown exponentially. These publications include dual-sectoral nexus such as Water-Energy, Energy-Food, three-pronged nexus such as WEF, Water-Energy-Carbon, Water-Energy-Land, and multi-sectoral nexus such as WEF-Climate, WEF-Waste, WEF-Land-Climate, WEF-Land-Environment, WEF-Land-Ecology, WEF-Society-Economy. The majority of them were published after the 2011 Bonn Conference (Hoff 2011a, 2011b) with the dual-sectoral nexus, Water-Energy nexus, still being a popular topic in the major trend and notably popular in the agricultural industry. In the beginning, the WEF nexus studies concentrated on larger spatial scales, such as global, transboundary and national scales, and less on smaller scales, such as local, urban, farm, or household.

For an overview on the situation of WEF nexus research, publications in the Web of Science have been searched via a generic key words combination “water energy food nexus” (**Figure 2.1**). A total of 918 WEF nexus related publications have been located from all the databases. The overall trend of publications since 2010 has been growing, when it has turned at 2016/17 in a sharp rise. The trend may imply an incremental prevalence of WEF nexus research over the years.

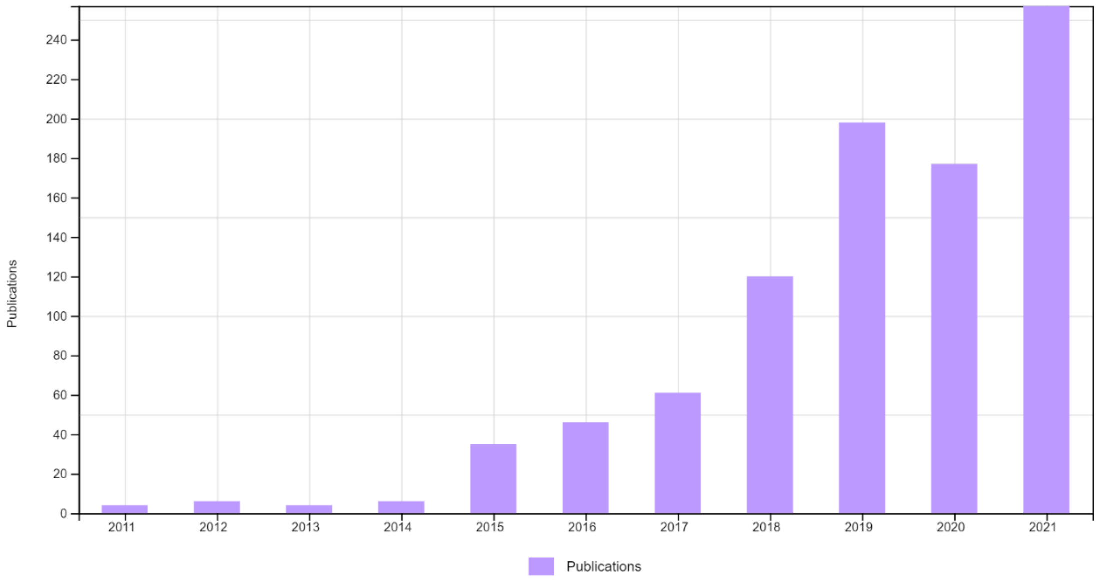


Figure 2.1. Number of publications for WEF nexus studies from 2011 to 2021.

By research areas, the top 10 WEF nexus studies have distributed in Environmental Sciences & Ecology, Engineering, Science Technology, Water Resources, Energy Fuels, Agriculture, Geology, Meteorology Atmospheric Science, Business Economics and Computer Sciences (**Figure 2.2**).

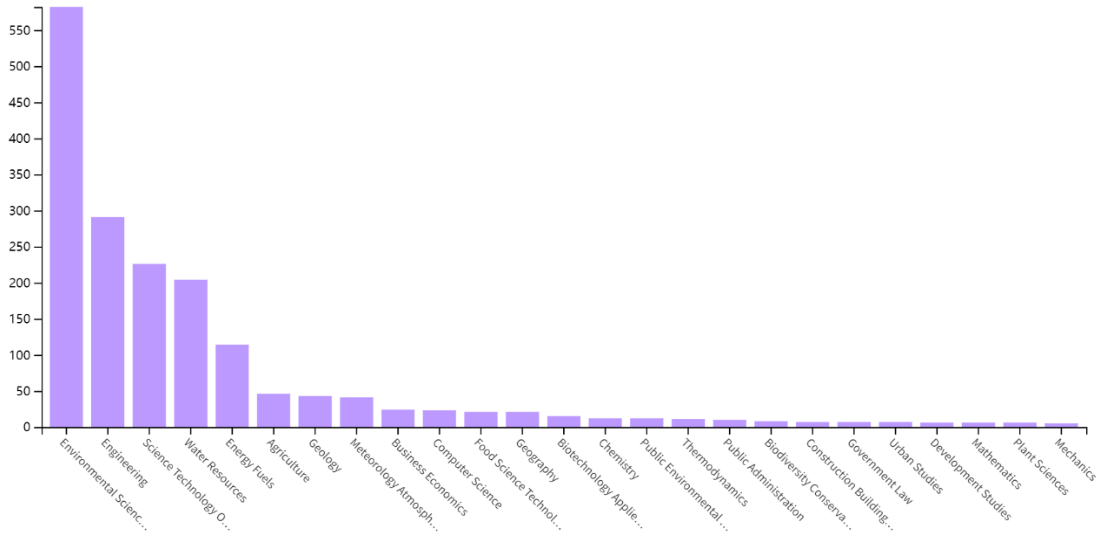


Figure 2.2. Number of publications for WEF nexus studies in various research areas. The top 10 areas in order are: (1) Environmental Sciences & Ecology, (2) Engineering, (3) Science Technology, (4) Water Resources, (5) Energy Fuels, (6) Agriculture, (7) Geology, (8) Meteorology Atmosphere, (9) Business Economics, (10) Computer Science.

The Environmental Sciences & Ecology has been the primary focus paired with an approximately 63% of the total, followed by Engineering 31%, Science Technology 24%, Water Resources 21%, Energy Fuels 12%, Agriculture 5%, respectively. Environmental resources have drawn the highest attention and among them water resources and energy fuels are two pivotal areas in the nexus research.

By locations for the publications, USA and China have contributed over half of the total (33% and 22% respectively), followed by England 14%, Germany 9.8%, Netherlands 6.7% and Italy 5.6%, respectively (**Figure 2.3**). Among the top 10, most are from European countries, while Australia is lagged behind, indicating that WEF nexus studies are far from being sufficiently conducted in Australia.

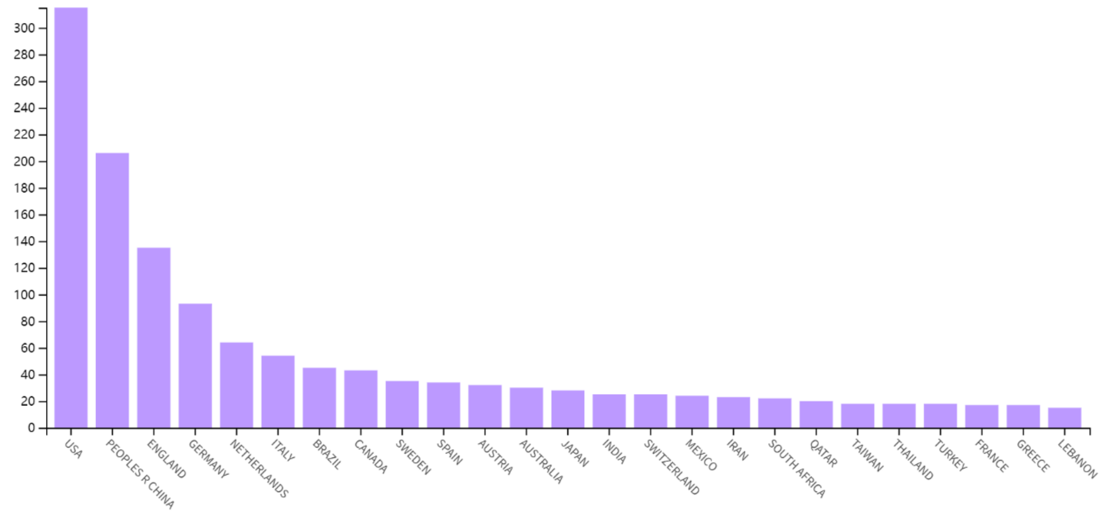


Figure 2.3. Number of publications for WEF nexus studies in different countries/regions. The top 10 nations/regions in order are (1) USA, (2) China, (3) England, (4) Germany, (5) Netherlands, (6) Italy, (7) Brazil, (8) Canada, (9) Sweden, (10) Spain.

Despite a considerable number of WEF nexus studies emerging in the past decade, this concept is still evolving and is still transitioning towards operationalization and implementation (Simpson et al. 2019a). The slow evolvement of nexus indicates a deficiency in adoption of national policies, execution of programs and establishment of institutions (FAO 2018), and an irrelevance between nexus governance and nexus resource availability and accessibility (Allouche et al. 2019). The intrinsic interlinkages have not yet technically been captured and tackled between the three pronged resources for discernible nexus governance and resource management outcomes (Albrecht et al. 2018; Galaitsi et al. 2018; Simpson et al. 2019a). Moreover, existing WEF nexus frameworks lack robust capabilities to sufficiently tackle other issues, such as insecurity of ecosystems and their services, low engagement of participatory stakeholders, under-represented perspectives of the local people, and a lack of context-specific and feasible policy implementation guidance on planning, analysis and evaluation (Purwanto et al. 2021).

Another frequent criticism of the WEF nexus is there being a lack of innovations in methods. Instead, it is methods developed earlier that have been restructured to serve for new ones (Simpson et al. 2019c). The applications of these methods have not sufficiently achieved expected outcomes, especially when they are “pieced together” by incompatible submodules. Bigger concerns have also been reflected for a serious lack of supportive available datasets particularly at appropriate geographical and temporal scales (McGrane et al. 2018; Lawford 2019). These data collections usually overlook the context of stakeholders, like the livelihoods, humanity and distributional justice as well as database harmonisation (Leese et al. 2015; Wichelns 2017). An additional number of remarkable gaps on the nexus approaches have simultaneously been identified by researchers as well, such as deficiency to address agricultural energy productivity and resource security amelioration (Purwanto et al. 2021; Zarei et al. 2021).

In responses to these deficiencies and gaps, a highly emphasized point concerning WEF nexus in peer reviewed studies over the past decade has been to develop an integrated quantitative method, which is urgently needed to address the complicated intrinsic nature of the nexus. This further needs successful collaborations between private and non-private sectors and translation into effective and implementable policies (van Gevelt 2020). In addition to policy adoptions, measures should be taken to potentially transform “conceptualisation” of the nexus into “implementation” , such as the operationalisation of nexus frameworks on natural resources at multiple spatial scales (global, national, regional, basin, transboundary, local and urban scales) (McGrane et al. 2018).

2.1.3. Peer WEF nexus studies

As abovementioned in 2.1.2, there has been exponential growth on the number of publications about WEF nexus during the past decade. For studies conducted as of 2016, researchers have spotlighted an identification of methods relating to nexus quantification, optimal management, and integrated or systematic approaches (Chang et al. 2016; Veldhuis et al. 2017; Wicaksono et al. 2017; Zhang et al. 2017; Mannan et al. 2018; Vakilifard et al. 2018; Torres et al. 2019; Endo et al. 2020; Al-Saidi et al. 2021). The subsequent three years have noteworthily seen above 80% of the studies highlighting nexus quantifications both on resources and on their underlying interactions (Naidoo et al. 2021; Peña-Torres et al. 2022).

Among the empirical studies, nearly 63% are classified as environmental management which are the biggest group. The approach applied most frequently is scenario analysis, followed by foot printing and Life Cycle Assessment (LCA) respectively. The second biggest group is pertaining to economic approaches, in which Input-Output Analysis (IOA) and Trade-off Analysis respectively are often applied (Albrecht et al. 2018; Roidt et al. 2019; Jacobson et al. 2022). Peer studies using these restructured methods are still limited in analysing and evaluating more nexus resources. It would take further endeavours for researchers to cross the hurdle for incorporating the methods compatibly with each other or with multi-dimensional indices in a quantitative, integrated and systemic manner.

Other studies such as those by Endo et al. (2015) and Zhang et al. (2018) have listed and compared currently available modelling approaches for WEF nexus, such as Ecological Network Analysis (Ulanowicz 2004), LCA (Klöpffer 2006), System Dynamics Modelling (Coyle 1997), Agent-Based Modelling (Janssen 2005; Crooks et al. 2011). Given contextual scenarios, these approaches should be further tailored and be fitted together to achieve specific study objectives. In addition, some empirical WEF nexus studies by sectors and spatial scales have been sorted as below.

2.1.3.1. WEF nexus by sectors

The three core nodes of the “nexus” in this study are water, energy and food. To align with different research goals, more sectors can be linked and embedded, such as land cover, carbon emissions, ecosystem, waste management. The literature review mainly highlights the nexuses with the three core resources (namely WEF)at a minimum. Those with only two-pronged resources (such as Water-Energy, Water-Food) have been excluded. By filtering and narrowing down to the most relevant WEF nexus studies and being rigorously subject to “WEF(-X) nexus” selection criteria, four major types have been categorised: (1) WEF nexus, (2) WEF-Land (WEF-L) nexus, (3) WEF-Waste (WEF-W) nexus and (4) WEF-X nexuses. The “X” in the fourth group represents all the other possible sectors, such as “Environment”, “Ecology”, “Carbon”, “Climate Change”, “GHG emissions”.

This categorization stresses the importance of the resources and sectors involved within the nexus and their intrinsic linkages with one another, as well as potential extrinsic connections with other components outside the nexus framework. Using the Web of Science databases, 145 core studies are selected with the highest number of over 80% studies in “WEF nexus” by the category of “Sector” (**Figure 2.4**). It reveals the WEF nexus publications have predominantly contributed to the three core resources. While sectors, such as waste, land, ecology, are commonly studied in a separate mode, their interactions with the WEF nexus are less constantly identified, linked to the nexus concept, or integrated to establish and develop a systematic nexus system.

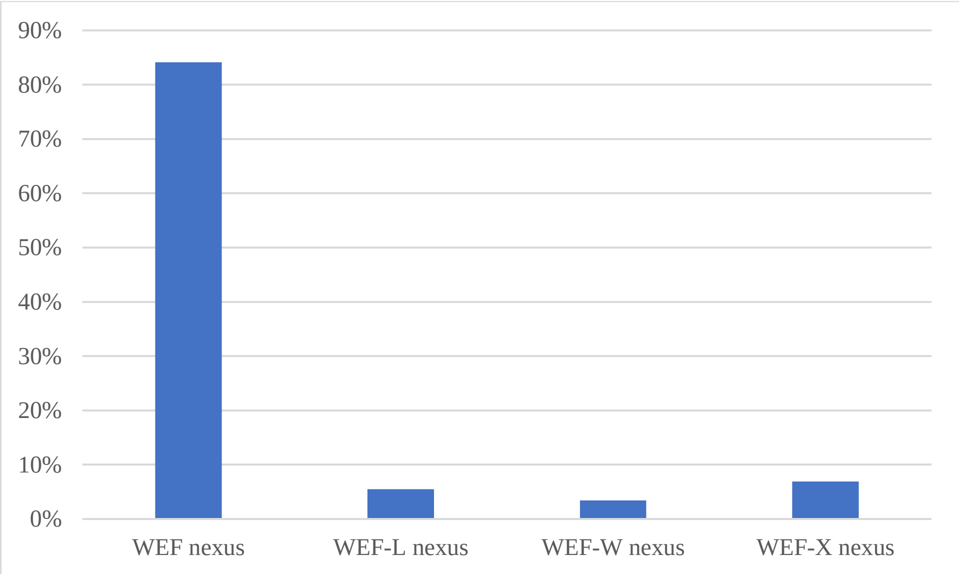


Figure 2.4. WEF nexus by sectors, categorized into (1) WEF nexus, (2) WEF-Land (WEF-L) nexus, (3) WEF-Waste (WEF-W) nexus, and (4) WEF-X nexuses. The “X” in the fourth group symbolizes all the other possible sectors, such as “Environment”, “Ecology”, “Carbon”, “Climate Change”, “GHG emissions”, and so on

(1) WEF nexus

Over the first few early years (2011-2015) and since the initial conception of WEF nexus in 2011, academic studies have placed their foci on a preliminary stage, such as conceptualisation, general governance and policy oriented, and qualitative thinking and approaches for nexus evaluation. For instance, Bazilian et al. (2011) put forward a generic framework exploring underlying interactions among the resources at a relatively high level of aggregation. They gave attention to socio-economic spheres probably connectively affecting the WEF nexus, and finally advocated for development of an integrated modelling approach. Likewise, Ringler et al. (2013)

brought broader contexts into the nexus, such as human wellness, environmental quality and social equity, and saw how these facets could interlink with the three core component of WEF nexus for the sake of improvement on resource utilization efficiency.

In the meantime, some studies have centred on one of the core WEF resources as an entry point or focus, taking the nexus as an auxiliary approach. For instance, Lawford et al. (2013) targeted at water issues, explored international water policies and regulations, and made a summary on primary factors impacting on the water policies along with a simple WEF nexus concept. Similarly, de Vito et al. (2017) addressed irrigation water in agriculture and Belinskij (2015) studied water-related laws, slightly touching on WEF concepts. In studying energy use, Flammini et al. (2014) and Cameron et al. (2019) aimed at energy sources as the entry point to explore the WEF nexus in the context of Sustainable Development Goals (SDGs), like López-Díaz et al. (2018) who also primarily examined energy sustainability and renewables research. Studies making food sectors as the centric point in the nexus involved food supply chain or production (Al-Ansari et al. 2015a; Al-Ansari et al. 2017; Laso et al. 2018), crop production (El Gafy et al. 2017; Lee et al. 2020), a whole agricultural system (Al-Ansari et al. 2015b), and households' food consumption (Jeswani et al. 2015; Batlle-Bayer et al. 2020). In particular, food supply chains that may relate to food loss and waste constantly applied footprint approaches to investigate trade-offs and synergies between the resources, among which LCA (Klöpffer 2006) has been a popular tool.

At this stage, WEF nexus studies mainly concentrated on the three core sectors without inclusion of extra sectors. They tended to focus on broader contextual facets such as society, economy, environment, humanity. Subsequently, achieving relevant SDGs in developing countries by means of WEF nexus framework emerge as an alternative direction in some research (Guta et al. 2017). This was naturally paired with external components such as climate, waste, land, which were internalized into nexus frameworks. These WEF nexus systems highlighted external connectivity and interactions with those extrinsic elements/components with the core three resources (Bazilian et al. 2011; Bhaduri et al. 2015).

On the other hand, studies such as Rasul et al. (2016) and Khacheba et al. (2018) were dedicated to examining dual interactions within WEF nexus, namely

Water-Energy, Energy-Food, Food-Water, and to simultaneously considering impacts of climate change on the whole nexus system in accordance with “Climate Action” goals. Yillia (2016) and Stephan et al. (2018), instead, were committed to making general guidance and directions for an overall nexus evolvement in line with multiple SDGs in developing regions. While attempting to conceptualize nexus frameworks, Ferroukhi et al. (2015) further detailed outlooks and prospects of nexus frameworks from the lens of renewable energy advancement consistent with “Clean Energy” goals. This focus was similar to the work by Flammini et al. (2014), who also explored the WEF nexus for alternative energy sources as the entry point to achieve potential clean energy outcomes.

With an outlook for development of integrated methods, some attention has been paid to fitting existing models together into integrated ones, such as Water Evaluation and Planning (WEAP) (Yates et al. 2005; Sieber 2006), Multi-Scale Integrated Analysis of Societal and Ecosystem Metabolism (MuSIASEM) (Giampietro et al. 2009), Climate-Land-Energy-Water systems (CLEWs) (Howells et al. 2013) and WEF Nexus Tool 2.0 (Daher et al. 2015). These studies often focused on decision-making levels in a qualitative pattern (Mohtar et al. 2016). Notwithstanding that integrated frameworks were evolving, the quantification methods were limited to dual relationships between resources (Mayor Rodríguez 2016) and evaluations on social phenomena, trends, and public policies (Martinez-Hernandez et al. 2017a). In this regard, optimal management methods began to emerge as a new focus in subsequent studies, which were paried with other existing models, such as LCA and Multi-Scale Modelling (Garcia et al. 2016; Belmonte et al. 2017).

Typical examples of the optimal management on WEF nexus were commonly in the form of mathematical programming, notably using constrained non-linear programming (Hang et al. 2016; Maraseni et al. 2021). Another mathematical programming method frequently applied was Multi-Objective Optimization Programming in conjunction with technical, policy and resource constraints, among which some studies worked to resolve water-energy related problems within the WEF nexus, such as hydropower (Dhaubanjar et al. 2017), reservoirs (Uen et al. 2018; Si et al. 2019). Others were conducted in series, which were significantly devoted to studying irrigated agricultural systems by means of various mathematical programming (Li et al. 2015; Li et al. 2016b; Li et al. 2016c; Li et al. 2017; Li et al. 2019b). These studies incorporated extra components such as land, waste and climate into the nexus and further explored complex interactions among different targeted systems. One of these innovative studies combined a forestry system with a cropping system (agri-forestry system) (Li et al. 2021).

(2) WEF-Land nexus

Other than WEF-X nexus (over 9%), “land use” is the most frequently affiliated sector to the WEF nexus frameworks (WEF-Land nexus) with approximately 5.5% out of the total associated publications reviewed. In the beginning stage of WEF nexus development, WEF nexus and “Land” sector did not make robust links. “Land” would often be disregarded among WEF nexus studies in the first few years since 2011. In the following years, “Land” was conceptualized in the nexus but merely restricted to generic “usable” land for any human activities exploiting it (Ringler et al. 2013). The WEF nexus then came to specify land use types including energy related activities occupying land use such as coal mining (Simpson et al. 2019b), ecological land use like ecosystem land cover (Karabulut et al. 2018), watershed (Wolde et al. 2021) and wetlands (Rai 2021), food manufacturing land cover (Laso et al. 2018).

In particular, It was common that researchers would contextualize the “Land” sector into “agricultural land” (Ibrahim et al. 2019). These WEF-Land nexus publications tended to associate land conceptions with occupations and applications for associated agroforestry activities such as cropping, irrigation and pumping, on-farm and pre-farm operations, livestock raising, forestry. These types were specifically divided into land use (Holt et al. 2017) for plasticulture (an intensive production system used for growing high-value crops), farmland with on-farm and in-field land cover (Siciliano et al. 2017), arable crop-pasture land (Ibrahim et al. 2019), crop-livestock agricultural land (Nie et al. 2019; Li et al. 2020), arable crop-forestry agricultural land (Li et al. 2021), agricultural land relating to photovoltaic technology utilization (Neupane Bhandari et al. 2021; Sargentis et al. 2021), irrigation land (Yue et al. 2021b).

(3) WEF-Waste nexus

WEF-Waste nexus related studies take up about 3.5% among the reviewed publications. Studies focusing on waste management alone are innumerable, while studies about “Waste” sectors linking to WEF nexus are few. WEF-Waste nexus is still in its infancy at the stage of conceptualization (Sarker et al. 2016) and relevant studies are mostly literature reviews (Kibler et al. 2018). Besides, “Waste” would be mostly conceptualized as food waste and food loss over the supply chain involving production, manufacture and processing. Waste in the agricultural industry, farming or cropping is rarely considered in conjunction with WEF nexus (Kibler et al. 2018; Slorach et al. 2020; Subramanian et al. 2021; Zhao et al. 2021; Skawińska et al. 2022).

Other waste types could include general agricultural and organic waste (Garcia et al. 2017), mixed agri-food waste (Del Borghi et al. 2020). Only a few studies such as Ji et al. (2020) delved into a certain type of agricultural waste like crop biomass to explore an optimal management pattern within WEF nexus frameworks. Ji et al. (2020) developed an Interval Fuzzy Linear Fractional Programming (IFLFP) model for planning regional food production with consideration of ecological protection, water resource conservation, biomass energy supply, and WEF nexus. The main advantages of this model are the capabilities to unveil uncertainties by setting up different characters as interval values and fuzzy sets and to provide efficiency measurement on the studied system by allocating ratios on conflicting objective functions. One of the few WEF-Waste nexus studies in Australia was by Feng et al. (2020), who presented a range of bio-mass processing technological options for waste-to-energy scenarios. It built up an array of economic and environmental indicators to optimize these scenarios based on an WEF-Waste nexus.

(4) WEF-X nexus

Compared to the previous three types of nexus, WEF-X nexus has emerged in a later stage, inclusive of WEF-Environment nexus (Geressu et al. 2020; Nasrollahi et al. 2021; Yue et al. 2021a), WEF-Ecosystem nexus (Europe 2018; Karabulut et al. 2018), WEF-Climate Change nexus (Laso et al. 2018; Laspidou et al. 2019; Li et al. 2021; Yue et al. 2021b), WEF-Carbon or WEF-GHG emissions nexus (Al-Ansari et al. 2017; Maraseni et al. 2021; Zhang et al. 2021a), and so on.

WEF-Carbon nexus and WEF-GHG emissions nexus are often used by researchers interchangeably. These studies primarily focused on GHG emissions and potential linkages with WEF frameworks. Targeted entities in a WEF-Environment nexus or a WEF-Ecosystem nexus could be standalone environmental/ecological systems containing a diversity of variables. For instance, Cristiano et al. (2021) took “green roofs” for the “Ecosystem” concept, which contained a range of ecosystem indices, similar to De Roo et al. (2021) involving multiple climatic indicators. These four nexuses have much overlap with the WEF-Climate Change nexus, which involves variables like precipitation, temperature, radiation, wind speed.

2.1.3.2. WEF nexus by different geographical scales

Different geographical scales in WEF nexus studies make differences in targeted systems including associated concepts and compositions. For instance, when it comes to a farm scale of WEF nexus, concepts (such as agroecology, irrigation, food security), nexus elements, and externally intervening factors have a disparity from those on an urban scale of WEF nexus. An urban WEF nexus involves additional pertinent concepts such as urbanisation, megapolitan land use, multiple types of wastes, societal stability. It contains its own particular compositions as opposed to a farm, such as urban consumable water versus agricultural water sources directly from nature, various energy sources in urban areas versus homogeneous energy sources on farms, manufactured food, food waste and loss in cities versus biomass waste from farming systems.

Figure 2.5 presents different spatial scales of the WEF nexus studies from small scales, such as household, farm and local, to large ones, such as national and global. Unlike the distribution pattern by sectors, the pattern by scales reflects less disparity among the geographical characteristics, except for remarkably high figures in national and global scales of nearly 23% and 19% respectively. Farm and local scales are the smallest foci, as well as household and urban scales. The national and sub-national scales are based on a geographical governance area categorization. They incorporate such factors into a systematic nexus framework as socio-economy, humanity, culture. Similar to an urban scale of WEF nexus, they can be even more sophisticated than large-scale nexuses such as transboundary basins, regional.

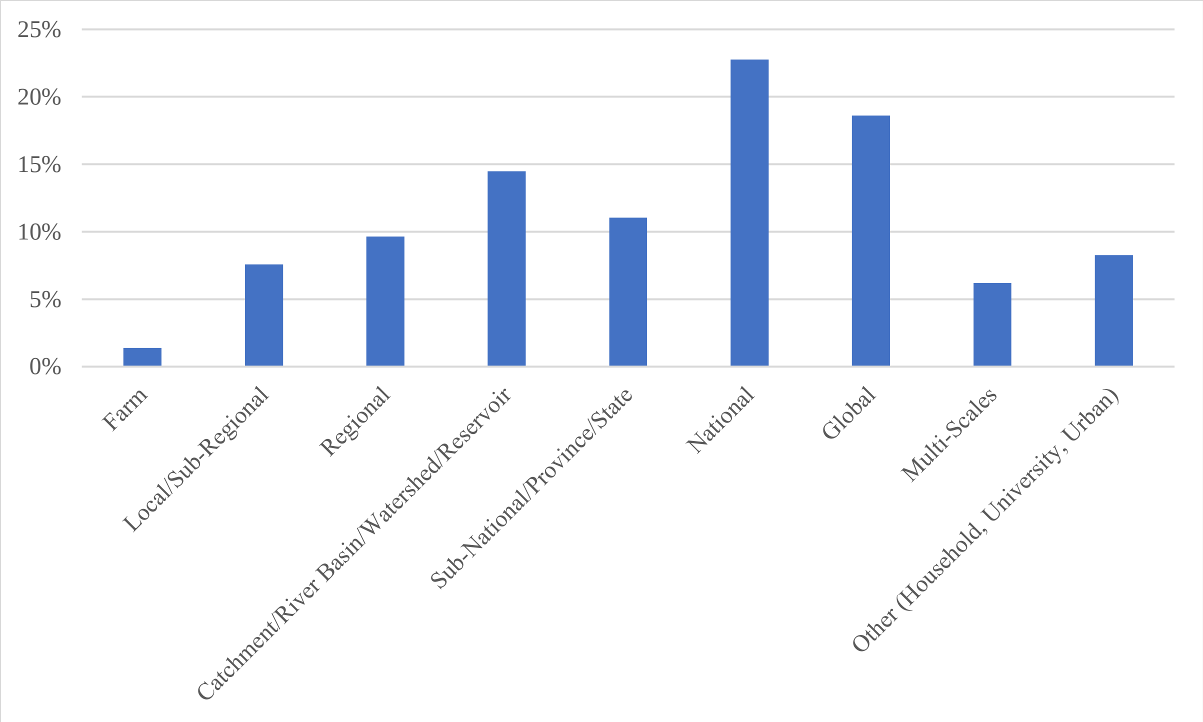


Figure 2.5. WEF nexus by spatial scales, from small scales, such as household, farm and local, to large ones, such as national and global.

A global, national, sub-national or multi-scale of WEF nexus features a sophisticated system with massive characteristics and components included, highly requiring extensive datasets, appropriate inter-linkages among a complexity of internal and external elements, efficient modelling approaches, and effective and compatible modules to be fitted in the whole framework. These large-scale WEF nexus studies could manage to align their objectives with global SDGs (Yillia 2016; Saladini et al. 2018; Stephan et al. 2018), or evaluate resource consumptions by multiple industries (Hang et al. 2016; Guta et al. 2017) or single industry (Mayor Rodríguez 2016; Belmonte et al. 2017) such as the agricultural sector in particular (Hamidov et al. 2020).

Among small-scaled studies, urban WEF nexus (Heard et al. 2017) emerged and worked to systematically simulate mechanisms of urban areas (Newell et al. 2019; Zhang et al. 2019). These studies discussed identification of comprehensive internal urban resource uses (Li et al. 2019a). While in the meantime, they also took on board essential affiliated sectors interacting with the nexus, for example urban environment quality and waste management, and determined urban system patterns in running, transforming and serving the public by resource distribution, allocation, and consumption (Walker et al. 2014; Gondhalekar et al. 2017; Li et al. 2019a). In addition, underlying interactions with exogenous intervening factors were established, such as climate change (Gondhalekar et al. 2017), rural agricultural communities (Sukhwani et al. 2019; Granero de Melo et al. 2020).

Furthermore, many current agricultural nexus studies on a farm scale focus on Water-Energy nexus only, in which the “food” sector and its correlations to the nexus are not explicitly considered. These studies contain methods that are comparatively simple in quantifying and simulating trade-offs within agricultural systems, which can be effective but not comprehensive or not user-friendly. Delving into higher resolutions of spatial scales, such as local or farm level, can further require WEF nexus framework to be contextualised, data-precise and applicable to real cases in targeted areas. It also requires extensive data availability and accessibility. These have added up to difficulties in researching WEF nexus particularly on a farm scale, which has led to the nexus being rarely studied on this scale.

In brief, a general trend of WEF nexus research on geographical scales has been directed from larger ones (global, national and sub-national in big countries) during the initial stage towards smaller ones (basin, regional, and sub-regional) during recent years. A bit more sectors and components have been added to WEF nexus for an integrated system and comprehensive approaches. The elements involved are becoming diversified and simulated by quantification methods developed. However, a long way is still lying ahead for the evolvement of WEF nexus on small scales, in particular for local, farm, communities and households. These should be contextualised on a case-by-case basis.

2.1.3.3. Agricultural WEF nexus in particular

By regions, agricultural WEF nexus studies have occupied nearly one third among all WEF nexus studies around the world. Australia’s agricultural WEF nexus studies take up about 1.4% among all WEF nexus studies. It implies Australian researcher’s insufficient attention apportioned to WEF nexus in agricultural industries as opposed to a total large number of publications in agriculture at an international level (**Figure 2.6**). By geographical scales, agricultural WEF nexus research has gradually been increasing in recent years on multiple spatial scales, such as regional (Li et al. 2019c; Hamidov et al. 2020), watershed (Smidt et al. 2016; Yang et al. 2016; Sadeghi et al. 2020), national (Nhamo et al. 2018), sub-national (Fabiani et al. 2020). Typical instances about integrated agricultural WEF nexus models in recent years include constrained single objective nonlinear programming model for optimization on profitability of an irrigated cropping system on a regional scale (Maraseni et al. 2020) and constrained multi-objective non-linear programming model, Agricultural Water-Energy-Food Sustainable Management (AWEFSM) model, developed by Li et al. (2019c) for optimization on total revenues and total GHG emissions, respectively, of an irrigated agricultural system on a regional scale.

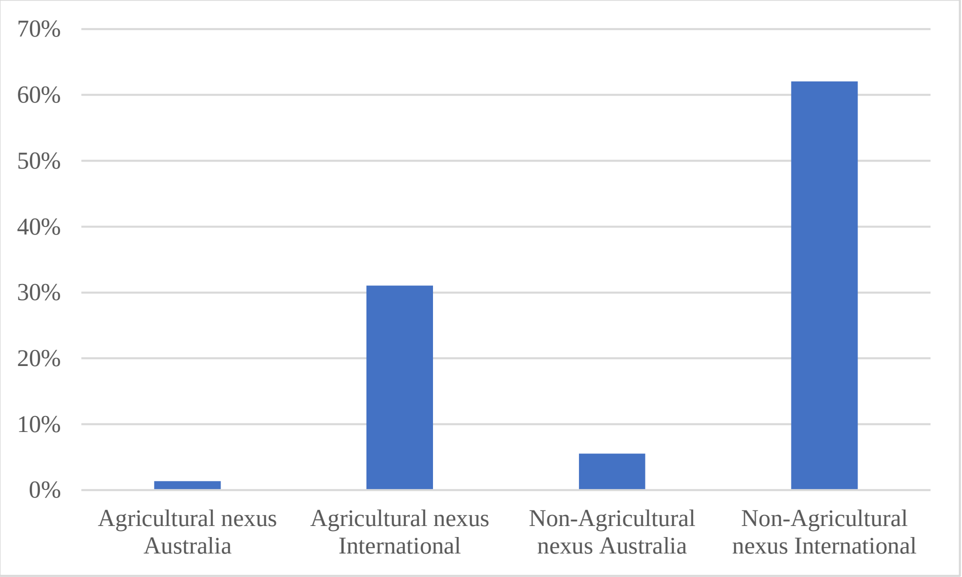


Figure 2.6. WEF nexus related studies targeting at (1) agricultural industry in Australia, (2) agricultural industry in nations/regions excluding Australia (international), (3) non-agricultural industries in Australia, and (4) non-agricultural industries in nations/regions excluding Australia (international).

As mentioned earlier, footprints can often be bound with index-based approaches to visualize an overall ranked performances on economic returns and environmental resource consumption. For instance, Bellezoni et al. (2018) developed the resource-environmental footprint quantification methods in conjunction with an economic-ecological Input-Output (IO) framework for analysis of ethanol production from sugarcane in Brazil. A hybrid extended IO-WEF nexus index framework was further designed for effective biofuel policy development, collectively addressing impacts on environmental, social and economic spheres. Analogously, El Gafy et al. (2017) and Ozturk (2017) took advantage of a binding framework with dynamic modelling and WEF nexus index-based footprint approaches to determine resources footprints and their dynamic behaviours and correlations in crop production and resource consumption at a national level. In addition, LCA was an applicable method not only alone (Al-Ansari et al. 2015b) but also coupling with other models and tools such as resource sustainability indicators (Irabien et al. 2016) and linear programming (Yuan et al. 2018).

2.1.4. A summary of research gaps in WEF nexus

Although the WEF nexus has been well conceptualized, more research is needed for further methodology development and implementation. On the one hand, WEF nexus research can be developed and navigated towards being more quantitative and being further incorporated onto a governance and policy-making level. On the other hand, there has generally been a lack of well-established nexus methodology. Many existing methods are overly complicated, with extensive data requirements, potential incompatibility between modules, and multitudes of uncertainties involved. They are partly remedied but remain unsuitable for a wide range of real cases and need to be reconstructed for specific contexts. Regarding development of models and tools, there has not been an “all-powerful” approach likely to unravel problems all in one effort. Delving into higher resolutions of spatial scales, such as local or farm level, can require WEF nexus framework to be contextualised, data-precise and applicable to real cases in targeted areas. It also indicates challenging data availability and accessibility.

Agricultural WEF nexus studies still account for a relatively small proportion out of the total WEF nexus studies. Most WEF nexus studies have major foci on environmental management areas. Among nations, the number of WEF nexus studies conducted in Australia is relatively low as opposed to that in USA and China, which have produced the most WEF nexus publications of all.

Furthermore, many current agricultural nexus studies focus on Water-Energy nexus, in which the “food” sector and its correlations to the nexus are not explicitly built up. These studies contain methods that are comparatively simple in quantifying and simulating trade-offs within agricultural systems, which can be effective but not comprehensive or not user-friendly.

Another notable issue is a severe shortage of agricultural WEF nexus research linking up “Waste” components. However, organic waste, such as crop residues and animal manure, is not ignorable in a farming system. Only a few studies pertaining to WEF-W nexus have been applied to regional waste disposal systems with all waste types mixed up (municipal waste, crop residue and animal manure, and other organic waste). The pre-farm or off-farm crop residues in Australia are commonly disposed by means of conservative agricultural ways, such as ploughing into soil, instead of methods such as compost, anaerobic digestion, co-fermentation, combustion, incineration, gasification.

2.2. Models and tools for WEF nexus

2.2.1. Overview

As mentioned above, approaches and methods in assessing WEF nexus are inclined to be conceptual and qualitative, merely limited to general policy description and governance in the preliminary stage of nexus development. Subsequently, quantification methods emerged in identifying WEF nexus resources and its intricacies. Some studies such as Albrecht et al. (2018), Kaddoura et al. (2017) and Dai et al. (2018) undertook a systematic comparative analysis on multiple existing methods, pointing out their common limitations and proposing prospective opportunities for future development of the nexus. These models and tools developed are highly complex, given their large geographical scales (such as global, transboundary, national), extensive data requirements, dataset availability and accessibility, compatibility of sub-models, calculation and quantification criteria, and multitudes of uncertainties (Bian et al. 2021; Purwanto et al. 2021).

However, as to types of models and methods, Zhang et al. (2019) has categorised nexus modelling methods and tools based on model functionality. Models and methods roughly fall into three groups: (1) resource-environmental footprint quantification methods, (2) assessment and systematic simulation methods, (3) optimal management methods. **Appendix A** compares some important existing models and tools.

2.2.2. Resource-Environmental Footprint Quantification

Roughly 75% of this group adopted quantitative approaches, 60% of which assessed WEF nexus by means of resource and environmental footprint management approaches, mostly using scenario analysis, followed by foot printing and LCA. The second biggest group used economic approaches, in which IOA and Trade-off Analysis were most frequently employed (Albrecht et al. 2018). Studies such as Endo et al. (2015) and Zhang et al. (2018) listed existing quantification tools, such as ecological network analysis, Data Envelopment Analysis (DEA), IOA, LCA, matter-element model, system dynamics modelling, agent-based modelling, integrated index. These methods could be used for generic quantification of nexus in economic or environmental performances. For specific cases, new models could be developed by combining these existing tools to deal with more complex cases, such as IOA-LCA (Sherwood et al. 2017) for ecological-economic indicators, extended matter-element model (Wang et al. 2018) for resource flow quantification on the nexus.

2.2.3. Assessment and Systematic Simulation

Simulation models like Q-Nexus, WEF Nexus Assessment 1.0 and 2.0 and NexSym were used to identify and simulate the sectors' interactions within the nexus (Daher et al. 2015; Martinez-Hernandez et al. 2017b; Daher et al. 2018; Karnib 2018). These models could also quantify sectoral dynamics to achieve synergies and reduce trade-offs. Other models, such as CLEWs and Global Biosphere Management Model (GLOBIOM), sought to identify land use in lieu of the food sector. For instance, the GLOBIOM system can possibly run optimal application and conversion from one certain type of land use to another, taking into account resource (namely, land and water) constraints and environmental management standards, greenhouse gas emission, and so on (Ermolieva et al. 2015). These methods were typically applied to relatively larger scales such as global and national levels. Likewise, models like Multi-Scale Integrated Analysis of Societal and Ecosystem Metabolism (MuSIASEM) (Giampietro et al. 2009) focused on social-economic aspects along with ecosystem perspectives in a broad point of view.

Assessment and systematic simulation methods evolved towards integrated approaches. One common approach may be an index-base type, evaluating multi-dimensional implications with the WEF nexus. Different indices have been proposed, considering a range of influential factors linked with research objectives. For instance, de Vito et al. (2017) designed three indicators (irrigation water footprint, energy footprint for irrigation, irrigation water cost footprint), to analyse the WEF nexus from these three indicators for water-energy efficiency and overall effect on farming economy. Other studies like Gaddam et al. (2022) developed dual interaction indicators between sectors within an overall Water-Energy-Land-Food nexus system, such Food-Water, Food-Energy, Land-Water, Water-Energy, to evaluate the efficiency of this multiscale system. Furthermore, Nhamo et al. (2019) utilised multitudes of indicators and implemented an integral evaluation on WEF nexuses by ranking and pairing various functionalities with the individual indicators in correspondence to different study objectives. Usually, index-based methods calculated and normalised the indices, ranked and rated the results for environmental performances of resources and the whole nexus system, such as a Water-Energy-Food Nexus Index (WEFNI) which has been more popular in the past few years (Segovia-Hernández et al. 2023). Typical studies such as El-Gafy (2017) and Karamian et al. (2021) applied this developed WEFNI to agricultural systems on a national and a provincial scale, respectively, and evaluated the overall efficiency of consumed agricultural inputs/resources, food and economic productivity to examine performances of farm management.

In a further step, index-oriented approaches may be integrated with other models to achieve more research objectives, like Nhamo et al. (2019) having applied a Multi-Criteria Decision Making (MCDM) model to multi-dimensional decision making. Another typical example was a set of indexes developed and applied for sustainability goals being integrated with LCA, such as Laso et al. (2018) who developed a weighted aggregated index based on calculation and normalisation for sustainability implications of food and food waste. In contrast, some other studies tended to centre on indexes alone without matching existing or developing models. Such methods were oriented towards qualitative research particularly in the early stages of nexus development. Along the way through nexus progression, such index-based methods and models were directed towards more closely linking sustainability goals with WEF nexus (Saladini et al. 2018).

2.2.4. Optimization

The third category is optimization methods, aimed at achieving the overall best outcomes for the nexus system under policy-oriented, economical, societal, technological, resource-environmental or ecological conditions. These methods are capable of considering synergies and trade-offs among conflicting nexus resources and sectors. One common approach used for an integrated optimal evaluation was modelling each sector one by one and their relationships respectively as well as other additional components interacting with the nexus system (Tian et al. 2018). This method may still appear insufficiently robust in setting up sectoral relationships. Workloads can be large, especially when it comes to a large volume of datasets in complicated cases. Results obtained would not likely provide adequately prompt feedback on improvement of the model.

In this regard, numerous integrated methods have evolved towards a form of optimal management, typically like Water, Energy and Food security nexus Optimization (WEFO) model (Zhang et al. 2017). These types of models are more capable of resolving issues in an “all-in-one-effort” manner. In nature, they attempt to determine nexus sectoral inputs and outputs by functional relationships and to explore optimal outcomes of conflicting objectives and trade-offs between resources by means of mathematical programming.

The simplest mathematical programming model is linear programming (LP). For example, WEFO utilised constrained LP to optimize the total costs caused by water applied, energy consumed, and food produced. Existing complex models such as CLEWs, GLOBIOM and WEFO serve as an optimization approach as well, but they may not suit specific study objectives as these models’ structures are relatively fixed up.

Fitting with other existing models could be another option to resolve specific problems. For instance, targeting at both optimization and environmental footprints, Yuan et al. (2018) developed an integrated framework combining LCA and LP to assess minimal environmental impacts on spatial distribution of crop bioenergy production under different climatic conditions.

Likewise, Laso et al. (2018) applied LCA and LP with a weighted aggregated index of Water-Energy-Food-Climate Nexus Index (WEFCNI) while in the meantime incorporating waste component into WEF nexus. An optimization practice was conducted to evaluate the best overall environmental performances on food waste-to-food strategies in a food and food waste/loss disposal system. It highlighted the interconnectivity of food and food waste/loss to explore how to reduce food loss and waste in accordance with the SDG target 12.3 “Halving Food Waste”, while boosting the development of the circular economy.

In contrast, López-Díaz et al. (2018) and Feng et al. (2020) employed a Mixed-Integer Linear Programming (MILP) model with various constraints to evaluate a regional Water-Energy-Food-Waste (WEFW) nexus system. This programming incorporated simplicity of model structures with multiple functional objectives and potentially refrained from model uncertainties by quantifying the parameter values into integers.

Single objective constrained non-linear programming has been developed and applied frequently (An-Vo et al. 2015; Maraseni et al. 2021). Compared with linear programming, non-linear programming can not only tackle relatively more complicated problems, as real cases are usually non-linear, but also avoid utilising overly complex model structures, which may benefit those who are targeting at developing easy-to-use and user-friendly models.

Slightly more complex non-linear programming models can include multiple objectives for conflicting problems to achieve compromised synergies and abate trade-offs, such as AWEFSM model (Li et al. 2019c). This study employed multi-objective non-linear programming with a series of constraints for optimization on the total revenues and total GHG emissions in irrigated agricultural systems on a regional spatial scale. This model could be the most integrated method for WEF nexus assessment so far, due to its strong capabilities to reveal the nature of conflictions among sectors and resources, to accommodate underlying relationships of different components, and to attain promising “multi-wins” outcomes for resource conflicts. Nonetheless, it would accordingly contain numerous uncertainties and require high calculation levels, extensive data inputs and adequate apprehension of advanced mathematical skills by researchers.

In response to in-built uncertainties in models, some mathematical programming methods integrated uncertainty analysis methods, such as stochastic theory (Karan et al. 2018; Liu et al. 2020; Cansino-Loeza et al. 2021) and fuzzy theory (Martinez et al. 2018; Li et al. 2019c). They essentially left the uncertain parameters as “vague” values being incorporated into the models and further reduced the uncertainties by assigning those parameters more definite or a numerical range of values during calculation. These theories, in particular “fuzzy theory”, have commonly been noted in Mo Li’s series of studies since 2015 (Li et al. 2015). Their studies would often apply multi-objective modeling for optimization on WEF nexus in irrigated agriculture under uncertainties of modelling parameters (Li et al. 2016b; Li et al. 2017; Li et al. 2019b; Li et al. 2020; Li et al. 2021).

In short, the advancement of optimal management methods has witnessed a prevalence in mathematical programming that may be generally grouped into constrained linear programming coupled with existing models (such as LCA, IOA, MCDM), constrained multi-objective mixed-integer linear Programming, and constrained single- or multi-objective non-linear programming.

2.2.5. Summary

In a short summary, prevalent models and tools to assess WEF nexus can fall into three major categories as noted above. While methods in early stages were on a qualitative and descriptive basis, models like these types have been transitioning towards a quantitative basis factoring more facets in.

Resource-environmental footprint quantification models are primarily targeted at resource use and environmental performances by tracking their footprints in studied systems. Typical instances are LCA and/or IOA. This type quantifies resource consumption and environmental impacts effectively and in an integrated way and may not be difficult to use. But it can also be restricted to merely environmental and ecosystem areas and not be sufficing for objectives in other areas such as agriculture that emphasizes economic parts or urban systems that simultaneously give attention to societal stability, public wellness and welfare and humanity.

Assessment and systematic simulation models may similarly design indicators to assist with quantification and an integrated evaluation on the nexus. This type can cover more areas and industries as opposed to the first type. However, they are more complicated themselves and may be a bit more difficult to understand. These models require researchers to consider a number of factors for targeted systems in conjunction with possible extensive data inputs and a high level of calculations.

Optimization models have become more prevalent as these models have advantages identical to the first two types while avoid some disadvantages. These models essentially have a simple rationale and structure and are easy for researchers to comprehend. Meanwhile, they can cover more factors and elements according to specific study objectives and provide insights into optimal balance of synergies and trade-offs among conflicting resource use and sectors in targeted systems. Unlike assessment and systematic simulation, this type of models may combine existing models without compatibility issues. The disadvantage is high requirement for researchers' mathematical knowledge and skills.

Based on the reviews on both WEF nexus studies and associated models and tools, the subsequent sections in this chapter provide further reviews on sub-modules and linkages of an agricultural WEF nexus for irrigated cropping systems in Australia. This is to gain knowledge in possibly filling up relevant research gaps as abovementioned and further to develop an appropriate modelling method in line with our research objectives.

2.3. Crop production and water inputs

2.3.1. Overview

Crop yield and productivity could be considered as a priority in agricultural WEF nexus, as in farming they are essential benchmarks for agricultural economic growth. Productivity unveils how efficiently inputs (labour, capital, land, materials, and services) are applied to produce outputs (crops, wool, and livestock) over time. Growth in the ratio of outputs produced to inputs used can be converted to enhanced profitability and competitiveness for farmers. Crop industries contribute significantly to the national economy and numbers of regional communities. For instance, in Australia cotton and sugar bring a gross value of production over $2 and $1 billion, respectively, while grains and oilseeds' annual gross value of production totals around $9-13 billion (DAFF 2022b).

In general, different amounts of resource inputs will bring different amounts of outputs. This can reflect in a functional relationship between water inputs and crop outputs in the form of mathematical equation with multi-variates. Thus, to explore potential relations between crop yields with other resource inputs, a crop water production function (CWPF) is an entry point to work on.

2.3.2. Crop Water Production Function (CWPF)

Some yield models involve various kinds of farm inputs as independent variables as multi-input production functions, such as water, fertilizers, and soil management (Nathan 1971; Foster et al. 2018). A typical example is the Cobb-Douglas production functional model (Praveen et al. 2019; Smirnov et al. 2019). However, irrigation is fundamental to agricultural productivity and is the most valuable resource for crop production (FAO et al. 2011). Therefore, a crop water production function is central among these crop yield models and pivotal to an irrigated cropping system (Foster et al. 2018).

A crop water production function refers to the functional relationship between the crop yields and the quantity of water resources consumed to produce the yields on the basis of consistent agricultural production level and techniques (Zhang 2009). It is a useful tool to develop proper irrigation strategies and determine potential crop yields in water deficiency situations (Kipkorir et al. 2002; Garcia-Tejero et al. 2013; Pushpalatha et al. 2020). Also, it is important to economically analyse water use in cropping, which depicts, in mathematical patterns, how crop yields are responsive to different levels of water inputs within a given set of climatic conditions and farm management practices (Steduto et al. 2012).

Thus, crop water production functions can be built in agronomic models for evaluation of farm performances (Foster et al. 2018). The following parts present two main categorized approaches to estimate crop water production functions (Choudhury et al. 2014; Dahikar et al. 2014; Ramesh et al. 2015; Foster et al. 2018; Khaki et al. 2019): (1) Empirical Estimation Approaches (EEAs) and (2) Mathematical Modelling Approaches (MMAs).

2.3.3. Empirical Estimation Approaches (EEAs)

EEAs for predicting crop yields use statistical methods to fit functional relationships between observational data for crop yields and different levels of applied irrigation water inputs. The observational data are usually derived from farm surveys or real in-field experiments. Those experiments are most commonly carried out throughout numerous years to capture variability in the crop water production function caused by inter-annual differences in weather conditions during the growing season, such as precipitation and temperature, which have impacts on water demands and lengths of growing seasons for crops (Foster et al. 2018).

Field experiments or farm surveys can be well designed, so models can possibly grasp reliable linkages of crop yields and irrigation water applications. However, EEAs are rigorously subject to critical limitations, in particular massive and lengthy experiments with reliable data, thus making it time consuming and costly to gain satisfying CWPFs. Hence, such approaches are not quite readily applicable to irrigated farming systems due to disparities among constraints of technology. In this regard, Mathematical Modelling Approaches (MMAs) can work as an alternative or supplement to empirical models when necessary.

2.3.4. Mathematical Modelling Approaches (MMAs)

MMAs can help to obtain two major groups of CWPFs: 1) Crop Coefficient Models (CCMs) and 2) Process-based Crop Growth Models (PCGMs) (Foster et al. 2018).

2.3.4.1. Crop Coefficient Models (CCMs)

In terms of crop growth period, this group of models can be subdivided into two types, respectively based on: (a) the whole crop growth period and (b) each individual crop growth stage. The former one is broadly applied to planning, design and macroeconomic analysis, though it is limited to reflecting accurate impacts of water deficit on different crop growth stages. The latter one can manifest the water amount used and implications on yields by water supply time at each crop growth stage, and yet it is comparatively complex (Zhang 2009).

- CCMs on the whole crop growth period with either “irrigation water application rate” or “crop evapotranspiration”

In the CCMs, there are two concepts which involve related water use, namely “applied irrigation water” (Wirri) and “evapotranspiration” (ETc) (Doorenbos et al. 1979; Igbadun et al. 2007; Geerts et al. 2009). Wirri refers to the amount of water delivered to crops in field by irrigation system (ML/ha) and ETc is the amount of water lost, retained and used by both evaporation in field and transpiration in crops (Allen et al. 1998a). The “crop evapotranspiration” and “crop water need/demand/requirement” are often used interchangeably (Rao et al. 1977; Al-Kaisi 2000; Al-Kaisi et al. 2009; Smilovic et al. 2016; Satpute et al. 2021).

- CCMs on the whole crop growth period with Wirri

These CWPFs are based on the whole crop growth period with irrigation water as the core independent variable. The forms of the functions are mainly quadratic/parabolic (Li et al. 2019c), cubic (An-Vo et al. 2015; Maraseni et al. 2021), and non-linear (Rajput et al. 1986). In general, the crop yield will increase as irrigation water application rate rises until a maximal yield point is reached with a full irrigation water quantity correspondingly. Afterwards, when the water amount continues to be growing, the yields will drop. The increasing and decreasing rates of yields are determined by the empirical coefficients. The models can reflect an overall relationship between the yield and irrigation water under ideal or set conditions. The coefficients are seriously dependent on climatic conditions, soil types, irrigation practices, crop types and species, so they will vary in different regions. These empirical coefficients must be determined by certain experimental methods.

- CCMs on the whole crop growth period with ETc

These CWPFs are based on the whole crop growth period with evapotranspiration or crop water need as the independent variable. The forms of the functions are mainly linear, quadratic/parabolic model (Peng et al. 2003; Zhang 2009), and Stewart model (Doorenbos et al. 1979). They are suitable for low-yield irrigated areas with insufficient irrigation water, low management level and insufficient agricultural production materials (Zhang 2009).

With the improvement of water resource management, crop yield and crop water need show a nonlinear relationship, in which the yield increases significantly in the beginning and subsequently rises slowly until it arrives at the maximum point. Thereafter, yield falls with the increase of water need. An ideal form of this overall pattern is a quadratic or parabolic model, which is appearing symmetrical by the maximal crop yield point. The cubic function is not rigorously symmetrical and can be closer to a real crop water production relationship.

- CCMs on each individual crop growth stage with "crop evapotranspiration"

CWPFs on each individual crop growth stage only take crop water need as the core independent variable. Crop yields are not only related to the overall crop water need, but also closely associated with the allocation of water supply on the whole growing period. This allows for water demand in every specific growing stage, that is, sowing to tillering, tillering to jointing, jointing to heading, heading to filling, and filling to harvest, respectively (Zhang 2009; Steduto et al. 2012). An additive model and a multiplicative model are two main ones in CCMs.

The additive model is suitable for grain yield estimation in semi-arid and sub-humid regions, and for biological yield estimation on forage and forage crops in arid regions. But it assumes that the influences of water deficit on yields at each growth stage are mutually independent. In fact, when a crop is in shortage of water at some growth stage, it will not only affect the growth of the current stage, but also the subsequent growth stages, and eventually result in the yield reduction. Crops can even die of water shortage at any stage, regardless of other stages, and result in no yield.

With this concern, the multiplicative model has been developed to compensate for this deficiency. Compared with the additive model with the form of all submodules adding up together, the multiplicative model is in the form of all submodules multiplying/timing together. Thus, the advantage of the multiplicative models lies in the interlinkages between every individual growth stage when water shortage occurs in a certain stage. This entails water shortage in each stage, which not only impacts the current stage, but also reflects the overall impacts of water deficit in multiple stages on the yield through this continuous multiplication. The multiplicative model features its high sensitivity to the total output given interacting implications between different stages. It is regarded that the multiplicative model is more sensitive and realistic than the additive model towards the target response of the constituent yield (Rajput et al. 1986; Wang et al. 2001).

2.3.4.2. Process-based Crop Growth Models (PCGMs)

Process-based crop growth models refer to mathematical models simulating the growth, development, and yields of a crop under certain environmental conditions, such as weather, soil type, and management practices, for example irrigation or fertilizer applications (Monteith 1996; Foster et al. 2018). Unlike crop coefficient models, which mainly take water as the key input variable and are highly determined by empirical coefficients, crop growth models integrate more environmental inputs. With the advancement of information technology, these models can be obtained by software with simulations on crop growth processes. In this way, CWPFs generated by robust computing power are more precise in predicting natural crop-water correlations on the whole and on each crop growth stage, compared with additive and multiplicative models. They can also bridge the deficiency of the crop coefficient models in a way, such as uncertainties and reliability of the coefficients, and at the same time averts the disadvantage of empirical estimation models about being too time consuming and troublesome.

In spite of being as a powerful tool to simulate crop growth and estimate crop yield, the process-based crop growth models may show up disadvantages like high demands for appropriate experimental/observation data to be calibrated and validated with parameter rectification. When it comes to CWPF simulations, the tool requires massive datasets to “train” the model (Monteith 1996; Foster et al. 2018). Subsequently, decisions by farmers on temporal precision, application rates of water, and irrigation plan may significantly impact the crop yield responses to total seasonal water demands and further accuracy of CWPF determination, as these practices cannot be incorporated and reflected in the modelling process engaged in software (Shani et al. 2009; Smilovic et al. 2016).

2.3.5. Summary

On the whole, a crop water production function (CWPF) serves as the foremost and one of the vital parts in an overall agricultural WEF nexus model for the potential relationship of crop yields and irrigation water application. Two dominant approaches for determining CWPFs are found and reviewed, namely empirical estimation approaches (EEAs) and mathematical modelling approaches (MMAs). While EEAs are relatively early developed CWPFs highly reliant on field experiments, MMAs are more accurate for the estimation and continue evolving by integrating information technology.

MMAs are divided into crop coefficient models (CCMs) and process-based crop growth models (PCGMs). CCMs are much less replying on empirical coefficients gained from field experiments and can be estimated using available experimental coefficients in peer studies. These coefficients can also be simulated in PCGMs. PCGMs are usually derived by using statistical data and simulating.

CCMs based on each crop growth stage consider the impacts of water inputs on each stage. CCMs on the whole crop growth period are commonly applied to macroeconomic analysis without deliberating these influences between each growth stage. CWPFs of this type are based on assumptions of decent irrigation schedule during the whole crop growth.

2.4. Agricultural energy use and GHG emissions

2.4.1. Overview

In the WEF nexus, energy is as important as water. Trade-offs between irrigation water use and corresponding energy consumption have commonly been studied in a dual Water-Energy nexus. Water application directly affects energy application and further determines GHG emissions incurred.

During the past over 40 years, both energy consumption and production have been growing steadily (DCCEEW 2022d, 2022c). In 2020-21, energy consumption for fossil fuels occupied up to 92% out of Australia’s primary energy mix, in which oil took up 36% in contrast to coal 29% and gas 27% while consumption for renewable energy sources accounted for 8% (DCCEEW 2022d).

The allocations of alternative fuel types among total energy production have mainly changed in natural gas and renewables (DCCEEW 2022d, 2022c). It has indicated a transition from conventional fuel types to more environmentally friendly types. The energy productivity has improved over the past ten years by 28%, contributing to a growth of Australian economy by 1.5% up to $2.0 trillion. This also entails a shift in the economy away from highly energy-intensive industries towards less energy-intensive ones as well as increased use of renewable energy for electricity generation instead of combustion-based generation sources (DCCEEW 2022b).

Energy use efficiency has been increasingly vital given incremental costs and insufficiency of energy sources and associated GHG emissions resulting in global warming (Chen et al. 2015a). Fossil fuels used to be inexpensively available, having enhanced agricultural productivity a lot. However, due to increasing fossil fuel prices over the last couple of years, agricultural production growth will be more severely constrained with arising environmental security issues (Go et al. 2019; Oakleaf et al. 2019). With projections for exponentially rising population up to 9.6 billion in 2050 (Hara 2020) and a "peak" fossil fuel availability by 2040 (Bardi 2019), a low-carbon energy transition ought to be necessitated from a net-energy perspective for the good of both global economy and environment (Delannoy et al. 2021).

2.4.2. Energy sources and types

There are many energy sources for agriculture production with renewables and non-renewables (**Table 2.1**).

Table 2.1 Classification of energy sources (Chen et al. 2015a).

Non-renewable (Limited)	Renewable (Unlimited)	Biological Renewables (Reproducible)
Oil	Solar	Wood
Coal	Wind	Energy crops
Natural gas	Hydropower	Biomass fermentation (ethanol)
Liquefied petroleum gas (LPG)	Tidal and wave energy	Biodiesel
Compressed Natural Gas (CNG), Coal Seam Gas (GSG), Liquefied Natural Gas (LNG)	Geothermal	Biogas (Anaerobic digestion)
Nuclear power (Uranium)		Animal and human power

Note: The energy sources are divided into three major groups, namely (1) non-renewable energy, such as oil, coal, natural gas, that is limited to extract, (2) renewable energy, such as solar, wind, hydropower, that is unlimited to utilize, and (3) biological renewable energy that can be converted and reproduced from sources such as wood, energy crops, biodiesel.

In particular, fossil fuel currently remains predominant over the other types of energy supply in the agricultural sector (Oakleaf et al. 2019). The common energy sources for agriculture involve diesel, petrol and electricity (Chen et al. 2015a).

2.4.2.1. Fossil energy

Fossil fuels or oils are commonly applied to on-farm machinery operation like tractors, or maintenance and repairs, as well as off-farm activities like logistics of nutrients, fertilizers, seeds and others. In fewer cases, gas may be utilised for multiple cases such as aviation for herbicides, heating, and drying (Chen et al. 2015a; Woods 2017).

2.4.2.2. Electricity

Electricity is commonly used as an energy source for agriculture. It features a premium power and being clean on-site, which is an edge over fossil fuels and gases. However, due to potential capital costs for distant locations of networks from farming areas, it would not be suitable for remote areas (Jamal et al. 2016). Grid electricity could be seen in use for two primary respects within agriculture: (1) water pumping for crop irrigation, cleaning and animal drinking, and (2) stationery operations, such as various machines and appliances of heating, cooling and ventilation (Chen et al. 2015a).

Whether on-grid electricity would contribute to a large volume of GHG emissions is mainly dependent on resources used to generate it. The Australian Government tracked the nation's GHG emissions through the National Greenhouse Gas Inventory in 2019 and found that, among all industries, energy production by burning fossil fuels to produce electricity was the largest contributor to Australia's carbon emissions at 33.6% followed by transport (17.6%), agriculture (14.6%), and industrial processes (6.2%) (CSIRO 2021). 2020-2021 has seen a peak total electricity generation in Australia throughout the past over 40 years, approximately steady at 266 TWh (956 PJ). In 2021, fossil fuels accounted for 71% of total electricity generation, including coal (51%), gas (18%) and oil (2%). The share of coal in the electricity mix has continued to decline, in contrast to the beginning of the century when coal's share was over 80% of electricity generation (DCCEEW 2022a).

2.4.2.3. Renewable energy

Renewable energy is a source of energy, naturally occurring and theoretically inexhaustible. It can fall into categories of those with the sun as the energy source (solar energy) and those with another source (non-solar energy) (Yusaf et al. 2011; Chen et al. 2015a). The solar energy involves solar power, wind energy, biomass and biofuels, while the non-solar energy includes tidal energy and geothermal energy (Chen et al. 2015a).

Renewables accounted for 29% of total electricity generation in 2021, with solar (12%), wind (10%) and hydro (6%) included. Around 17% of Australia's electricity was generated by business and households outside the electricity sector in 2020-21 (DCCEEW 2022a). As opposed to hydro which is mainly used in Tasmania and unchanged much over the decades, solar and wind source uses have increased significantly.

Renewable energy can be better fitted into rural and remote contexts and at times offer the lowest cost choices for energy access (Chen et al. 2015b). In various instances, it can contribute to getting energy access, diversifying farm revenues, refraining from waste disposal, lowering reliance on fossil fuels causing GHG emissions, and realizing SDGs. However, high upfront capital costs are still the main obstacle hindering renewable energy techniques from advancing (Chen et al. 2015a).

2.4.3. Energy use for farming

Energy uses for purposes of farming are divided generally into on-farm and off-farm uses (Saunders et al. 2006; Chen et al. 2010; Chen et al. 2015a). It may be further grouped into direct energy use, meaning fuels and electricity applied throughout agricultural production, and indirect energy use involved in and associated with the agricultural production, including all other inputs from machinery, equipment and agro-chemicals.

Australian farmers have opportunities to be assisted with reducing their energy expenses on the overall farm budget. These direct initiatives by the farmers to better manage the energy costs can be: (1) ameliorating systems and practices, (2) changing or modifying equipment, (3) swapping to alternate, less expensive and more environmental and renewable energy sources, and (4) purchasing energy more strategically or economizing on energy procurement (such as bulk energy purchasing) (DCCEEW 2021).

For instance, cotton cultivation has energy expenses as one part of the fastest rising costs for electricity and diesel, occupying up to 50% of the total cultivation input costs. This can provide significant opportunities for Australian farmers to reduce their energy expenditures and optimize profits. In this regard, the Cotton Research and Development Corporation (CRDC) has developed energy-efficiency information for cotton cultivation businesses to implement and reduce operating costs (DCCEEW 2021).

2.4.4. Associated GHG emissions from farming

Energy use, especially fossil fuel use, involves noteworthy environmental issues, for example the considerable amount of GHGs discharged over the processes. In Australia, it is recognized that agriculture is responsible for 14% of the national GHG emissions as the second largest emitter (Panchasara et al. 2021). It has been well established that GHG emissions from the energy consumption of many industries have incurred an ascending carbon dioxide (CO2) concentration in the atmosphere, which further leads to global warming (Yoro et al. 2020). The most direct influence caused by global warming will likely be a rise in surface temperature on the earth between 1℃ and 4℃ by 2100 (Alfonso et al. 2021), which further brings down on both short-term impacts, such as extreme weathers (Zhang et al. 2020a), and long-term consequences, such as damages on earth’s ecosystems and human survival (Sun et al. 2019).

In responses to these problems, the National Greenhouse and Energy Reporting (NGER) scheme has been mapped out and set up by the NGER Act 2007 (FRL 2007) as a national framework for reporting and disseminating business information about GHG emissions, energy production and consumption, and other information specified under NGER legislation (Australian Government 2022b). The GHGs reported under this scheme involve carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), sulphur hexafluoride (SF6) and specified kinds of hydro fluorocarbons and perfluorocarbons.

GHG emissions are gauged in kilotonnes of carbon dioxide equivalence (CO2e). It signifies that the amount of a GHG a business lets off is determined as an equivalent amount of CO_2 which has a global warming potential of "one". For instance, one tonne of CH_4 discharged into the atmosphere will cause the same amount of global warming as 25 tonnes of CO_2. So, the one-unit tonne of CH_4 is expressed as 25 tonnes of CO_2 equivalence, or 25 t CO_2e (Australian Government 2022a).

Global warming potentials (GWPs) are values that allow direct comparison on the impact of different GHGs in the atmosphere by comparing how much energy one tonne of a gas will absorb compared to one tonne of CO_2. The GWPs have been revised since 1 July 2020 to maintain the accuracy and comparability of Australia's national emissions estimates with the global community (Australian Government 2022c). The GHG emissions that should be reported under the NGER scheme include three major scopes:

- Scope 1 emissions (on-farm)

Scope 1 GHG emissions are those released to the atmosphere as a direct result of an activity, or series of activities at a facility level. Scope 1 emissions are sometimes referred to as direct emissions (Australian Government 2022a). Examples for the agricultural sector are CH_4 and N_2O from the diesel fuel combustion in machinery like trucks and production of electricity by burning coal and from enteric fermentation (by cows and sheep) and manure (Australian Government 2022a; Ekonomou et al. 2022a).

- Scope 2 emissions (off-farm)

Scope 2 GHG emissions are those released to the atmosphere from the indirect consumption of an energy commodity, such as those from the use of electricity produced by the burning of coal in another facility, such as a power plant. An example for the agricultural sector is the emissions from the electricity consumed by on-farm activities, such as irrigation, and yet generated by a separately located and owned power plant (Australian Government 2022a; Ekonomou et al. 2022a).

- Scope 3 emissions (pre-farm)

Scope 3 GHG emissions are those not reported under the NGER Scheme, but can be used under Australia's National Greenhouse Accounts (DCCEEW 2022e). Scope 3 emissions are indirect GHG emissions other than scope 2 emissions that are generated in the wider economy. They occur as a consequence of the activities of a facility but from sources not owned or controlled by that facility's business (Australian Government 2022a). Examples for farming are extraction, production and manufacture of purchased materials, such as urea, and transportation of purchased fuels, such as diesel and petrol (Australian Government 2022a; Ekonomou et al. 2022a).

2.4.5. Summary

Energy sources and types can be generally categorised into fossil fuels, on-grid electricity and renewable energy. In renewables, solar, wind and hydropower are increasingly used, while the biomass such as wood, energy crops, agricultural residues and biogas are limited but promising with considerable availability. Considering alternative energy sources, in particular renewables, for farming can be more economically viable, effectively help to reduce GHG emissions, and potentially achieve sustainable goals for agricultural industries. These emissions can fall into on-farm (Scope 1), off-farm (Scope 2) and pre-farm (Scope 3) emissions for better estimation under current GHG emission management framework and regulations.

2.5. Climate change and related carbon policies

2.5.1. Overview

Speaking of GHG emissions, climate change is highly associated. It is known that Australia features high variability of climatic conditions as there is usually lower average rainfall and higher rainfall variability than most other countries. Consequently, Australian agriculture is more susceptible to climate associated risks than nearly any other nations throughout the world. Notwithstanding Australian farmers are acclimated to this variability, climate change over the past decades caused by complex factors has still emerged along with new challenges. Climate modelling methods has predicted foreseeable future rainfall changes and more severe floods and droughts. Also, climate in Australia has seen slumps in average winter precipitation in southern Australia and overall spikes in temperature (DAFF 2022a).

2.5.2. Climate change impacts

There are two major types of climate change impacts: (1) direct impacts due to changes in climate itself triggered by anthropogenic factors, and (2) indirect impacts due to changes in policies, programs, and activities aimed at addressing issues relating to climate changes (Li et al. 2021).

Regarding climate changes incurred by anthropogenic factors, there is an array of new scenarios, Representative Concentration Pathways (RCPs) (Van Vuuren et al. 2011; Wayne 2013), devised by the Intergovernmental Panel on Climate Change (IPCC) and outlined in the fifth evaluation report (AR5) (Allen et al. 2014). RCPs offer continuing projections for emissions and concentrations of radioactive gases and particulates over time and a broad range of anthropogenic climatic forcings (Jubb et al. 2013).

In terms of policy-based implications, a number of countries across the world have carried out two primary mechanisms to curb carbon emissions, namely cap-and-trade mechanism and carbon tax mechanism (Song et al. 2017). The cap-and-trade regulation is market-based and commonly applied by numerous nations or areas such as New Zealand, California, and particularly the European Union (Goulder et al. 2013; Toptal et al. 2014; Du et al. 2020). This carbon trading framework allocates businesses with free available emission credits on a “cap” volume, based on which businesses can trade those credits (buy when in deficit and sell when in surplus) at their own discretion and convenience (Xu et al. 2021). The carbon tax regulation is price-based and also conducted in multiple countries including Sweden and Canada. In essence, the business owners will be allotted with a constant tax rate for charges on equivalent carbon emitted (Goulder et al. 2013; Xu et al. 2021).

2.5.3. Australia’s Emissions Reduction Fund (ERF) scheme

The ERF is the most commonly operated scheme, associated with carbon pricing, tariffs or costs based on a policy-market combined framework. The ERF scheme offers landholders, communities and businesses the opportunity to manage projects in Australia which refrain from discharging GHG emissions or eliminating and sequestering carbon from the atmosphere.

Under this scheme, eligible participants can earn Australian Carbon Credits Units (ACCUs). This ACCU Scheme has replaced the ERF Scheme. Each ACCU equates to one tonne of CO2e emissions averted or sequestered by the project. The units can be sold either to the Australian Government via a carbon abatement contract or to private businesses in the secondary market (CER 2022b).

Sources of demand for ACCUs include (1) ERF auctions, (2) safeguard mechanism, (3) voluntary markets, and (4) state and territory governments. The ERF auctions in particular have been the predominant one, where participants may bid for a contract to sell their ACCUs to the Clean Energy Regulator (CER). Contract holders may also purchase ACCUs from un-contracted projects to meet contractual obligations (CER 2022a). In terms of the safeguard mechanism, it requires facilities to keep net emissions no higher than the baseline set by the CER. Businesses with excess emissions over the limit will be able to surrender the ACCUs to offset these excess emissions (CER 2019).

2.5.4. Summary

There are two major types of climate change impacts identified: direct impacts triggered by anthropogenic factors and indirect impacts brought on by policy-oriented changes aimed at unravelling issues relating to climate changes. In response to the direct impacts, Representative Concentration Pathways (RCPs) are proposed for projecting future climatic scenarios with parameters such as CO2e concentrations, GHG emissions, temperatures in different industries. Policies regarding carbon pricing are carbon taxation and carbon credit related. The carbon credit policies in Australia are contained in the Emissions Reduction Fund Scheme. Overall it aims to better manage projects in Australia and avoid emitting GHG emissions or removing and sequestering carbon from the atmosphere.

2.6. Agricultural crop residues and WEF nexus

2.6.1. Overview

Biomass, as an alternative energy source, is attracting increasing attention compared to other clean energy sources because of its high availability, accessibility, and renewability as well as its friendliness to the natural environment. Biomass is a type of organic matters sourced from plants or animals, such as agricultural crop residues, forests, energy plants/crops, agro-industrial wastes (Akkoli et al. 2018).

Today, approximately 60 EJ of biomass is utilized for energy generation across the globe. Over 60% is applied for conventional heating and cooking, while the rest of them is converted into heat and fuels in transport and electricity based on modern techniques (Perea-Moreno et al. 2019). Agricultural crop residues, as an essential part of the biomass, have been subject to limited uses for energy generation, such as heat or combined heat-and-power production, liquid biofuel production, at various scales, but the residue quantity is substantial (Bentsen et al. 2018).

Among all the residues utilized to generate energy, a number of studies (Ji et al. 2018; Jiang et al. 2019; Masud et al. 2019; Samadi et al. 2020) have showcased the major types of biomass feedstocks in conversion-to-energy technological methods, including livestock wastes, crop residues, forestry residues, energy crops (arable/annual, perennial), and industrial domestic wastes (municipal, sewage sludge, fat and oil). Main conversion methods include biological synthesis, physio-chemical conversion (mechanic extraction or esterification), bio-chemical conversion (fermentation, anaerobic digestion), and thermo-chemical conversion (liquefaction, pyrolysis, gasification, charcoal). The end products potentially gained are primarily liquid fuel, gaseous fuel, and solid fuel. Most of them are in an early stage of commercial deployment such as torrefaction, pyrolysis, gasification, while a small number of methods are in a stage of commercial establishment including anaerobic digestion and biogas upgrading (Agency 2017).

2.6.2. Crop residues

US, China, and India and are the major countries producing the highest number of studies on crop residue treatment methods at present. When examining crop residue treatment/conversion methods, these studies typically explore respects pertinent to soil environment, climate, crop residue properties and traditional agricultural practices. The main focus of these studies is to make good use of agricultural residues stemming from cereal crops, mainly wheat and corn which are the biggest part producing the residues out of the cereals. Numerous researchers have been devoted to studying this topic, who are mainly from government and academic institutions. (Kumar et al. 1999; Cropping 2005; Kruidhof et al. 2009; Turmel et al. 2015; Searle et al. 2017; Hiel et al. 2018; Ken Flower et al. 2019; Flower et al. 2020).

2.6.2.1. Crop residues in Conservative Agriculture

In conservative agriculture, crop residues are a kind of useful resources that significantly benefits broad-acre farming systems. They potentially contribute to water and soil conservation and soil fertility. In this regard, crop residue retention has been adopted in both summer and winter crop cultivation areas coupled with developed techniques to manage the residues and minimize relevant disadvantages (Flower et al. 2020). With crop residue retention as one of the three key principles of conservative agriculture (FAO 2022), crop residue management commences from harvest stage and goes on until seeding stage.

Appropriate level of crop residues should be retained to prevent erosion, maintain, or improve soil organic carbon, maximize infiltration of water into the soil and promote crop yields and quality, especially under water stress conditions. Some studies suggest that 2-3 t/ha retained in field at harvest is adequate to reap those benefits (Kirkegaard et al. 2014; Giller et al. 2015). Some others have recommended a level of 70% ground cover for minimizing soil erosion (Scott et al. 2010; Scott et al. 2013). A large number of studies have been conducted for crop residue management, but many of them focus on agricultural processing and treatment methods and few determine optimal quantity of crop residues that are most beneficial to agricultural systems (Kitonyo et al. 2018).

Of all agricultural businesses managing crop residues, the main crop residue management practices undertaken can be to leave stubble intact, ploughing crop residue into the soil, and removal of crop residue by baling, burning or heavy grazing. For instance, in Queensland the most common crop residue management practice undertaken is to plough crop residue into the soil (55%) (ABS 2011; Ken Flower et al. 2019).

Table 2.2 compares three alternative crop residue management practices in a conventional agricultural mode in Australia. Now that Australian farmers burn fewer than 4% of crop residues (Umbers et al. 2017), ploughing the residues into ground to fertilize the soil has been the major crop residue management practice (Murray 2022). It entails a remarkable transition from the farming systems 30 years ago when little stubble was retained (Flower et al. 2020). In comparison with other conventional practices on crop residue management, such as surface retention and removal, incorporation (ploughing into soil) can be the most economically viable and environmentally friendly solution for farmers as an agricultural engineering method (Kaur et al. 2019; Fu et al. 2021). It can help to increase crop yields (7.8%), soil nutrient stratification/reserves (1.9%-15.2%) and water content (5.9%) and improve soil structure and ecosystem, and so on (Pratley et al. 2019; Singh et al. 2020; Zhao et al. 2020). Whereas it can simultaneously be challenged against increasing soil acidification, greenhouse gas (GHG) emissions (by 31.7%, 130.9%, and 12.2% for CO2, CH4, and N2O, respectively) (Zhao et al. 2020), labour intensity, fallow periods and nitrogen immobilization (Goswami et al. 2020) as well as soil erosion if excessive residues are retained (Pratley et al. 2019; Singh et al. 2020).

Table 2.2 Comparisons of different residue management strategies for advantages and disadvantages (Pratley et al. 2019; Singh et al. 2020).

Residue management	Advantages	Disadvantages
Surface retention	↓ erosion ↑ soil moisture ↑ soil organic matter and nutrient reserves ↑ soil physical and biological quality ↓ prevalence of some weed and disease species.	↓ ease of planting and crop establishment ↓ nutrient availability due to stratification and/or immobilization ↓ air temperatures (frost) ↑ in some weed and disease species ↓ effectiveness of pre-emergence herbicides
Incorporation	↑ ease of seeding operations ↑ speed of nutrient cycling and crop availability ↓ nutrient stratification ↓ prevalence of some weed and disease species. ↑ effectiveness of pre-emergence herbicides	↑ rates of organic matter decomposition ↓ soil physical and biological quality ↓ soil moisture ↑ erosion
Removal (baling, burning)	↑ ease of seeding operations ↓ prevalence of some disease species. ↑ effectiveness of pre-emergence herbicides	↑ nutrient loss ↓ soil physical and biological quality ↓ soil moisture ↑ erosion

Note: Three major conventional residue management methods in the Australia's agricultural sector are available, namely surface retention (leaving residues to the surface of land), incorporation (ploughing residues into soil), removal (primarily turning residues into bales or burning them). In the table, the symbols " ↑ " and " ↓ " signify increase and decrease respectively.

However, crop residues have noteworthily been one of prospect biomass and bioenergy sources and researched in many studies around the world on conversions to biofuels for purposes of environmental sustainability (Gregg et al. 2010; Scarlat et al. 2010; Jiang et al. 2012; Hiloidhari et al. 2014; Cherubin et al. 2018; Ali et al. 2019; Prasad et al. 2020; Koul et al. 2022). Environmental methods for converting crop residues to biomass or bioenergy is of high significance, as making full use of crop residues in environmental ways can be environmentally, socially and economically beneficial (Simon et al. 2010; Archer et al. 2012; Qiu et al. 2014; Chen 2016; Zhang et al. 2021b; Yong et al. 2022).

2.6.2.2. Crop residues for bioenergy and biomass

In terms of energy production, crop residues can be promising as potential biomass and bioenergy sources, in particular compared with traditional fossil fuels which are challenged for decreasing availability and environmental contamination (Akkoli et al. 2018). Crop residues are demonstrated as better energy sources because they are usually surplus, generated in billions of tonnes annually across the world (Chen et al. 2019; Scarlat et al. 2019a), and can be used for energy supplying especially in rural areas (Akkoli et al. 2018).

Residue availability and accessibility is a popular topic in studies about utilizing crop residues for bioenergy and biomass production, as there is disparity of crop residue availability and accessibility from region to region and from season to season (Bentsen et al. 2018; Jusakulvijit et al. 2021). Some studies have found out that transport infrastructure and logistic distance are important to the efficiency of conversion from crop residues to usable biomass or bioenergy. Facilities that process and disposing crop residues are necessary to be situated in the vicinity of the farming areas (Iye et al. 2013a; Iye et al. 2013b; Zhao et al. 2016; Maraveas 2020).

Crop residues can roughly be classified into primary and secondary residues. Primary crop residues refer to the plant materials available on the field after harvesting, such as straw, stalk, stubble and leaves, while secondary crop residues refer to processed residues, such as husks, hulls, bagasse, corncob, coffee pulp (Honorato-Salazar et al. 2020). The amount of primary residues are calculated by the Residue Index (RI) of each crop, which is defined as the ratio of the dry weight of the amount of residues generated to the total amount of primary crop harvested for a particular cultivar (Smeets et al. 2004; Rosillo-Calle et al. 2007; Honorato-Salazar et al. 2020). RI is generally obtained from the Harvest Index (HI), which is defined as the ratio of harvested product to total aboveground biomass of the crop at the time of harvesting (Smeets et al. 2004; Unkovich et al. 2010).

2.6.3. Potential linkages for WEF nexus and crop residues

Except uses for bioenergy and biomass, other uses of crop residues are not well known because of limited data collection on residue generation and application (Bentsen et al. 2018). Moreover, very limited numbers of studies have been conducted to examine connections between WEF nexus and wastes, in particular, crop residues.

Ji et al. (2020) has adopted an IFLFP model, developed for planning regional food production taking into account WEF nexus and its interlinkages with energy generation from crop residues, water conservation, and ecological protection. The linkage between crop residues and WEF nexus was quantified in a functional relationship between crop yields and crop residue yields. This study used multi-objective non-linear programming to achieve a synergistic status of both agronomic and environmental benefits.

Likewise, Pastori et al. (2021) have developed a multi-objective linear programming model, paired with constraints of local crop residue resources and environmental management on bioenergy systems, to evaluate bioenergy potentials and the intricacies of the residues with WEF nexus. The relationship between crop residues and WEF nexus is similarly quantified in a functional relationship between crop residues and crop yields by means of parameters such as residue-yield coefficient, residue heating value potentials, and efficiency conversion factors.

2.6.4. Summary

Prevailing crop residue management style in Australia is to incorporate the residues into the soil, as a conservative agricultural method, at the stages of in-harvest and post-harvest. However, these residues have significant potential for conversions to energy use. Despite a lack of studies about combining crop residues with WEF nexus, there have been a plethora of studies on conversion-to-bioenergy methods from crop residues as a biomass resource, which can provide an entry point for a model development that integrates crop residues into the WEF nexus framework.

2.7. Conclusion

As aforementioned, main research gaps in WEF nexus studies can be outlined as:

- Difficulties in implementation due to complex contexts and policy background;
- Lack of all-round robust models - overly complicated methods for large

scales while not integrated enough for small scales, such as local or farm;

- Limitations in nexus optimization;
- Lack of waste components.

Research about WEF nexus has been generally well conceptualized and more studies should be carried out for quantitative methods, implementation, and engagement with governance, policymaking and stakeholders. In methodology development, researchers will need to consider data requirements, potential compatibility between sub-modules and various uncertainties in order to promote integration and accuracy of models. There is a need to make studies dive into smaller spatial scales such as local or farm level, which are one of the major research gaps. This can facilitate WEF nexus framework to be more contextualised, data-precise, and applicable to real cases in targeted areas by potentially addressing challenging data availability and accessibility.

In terms of WEF nexus in agriculture, major research gaps may be specified as:

- relatively small proportions of WEF nexus studies contributing to agriculture, compared with the whole number of WEF nexus studies;
- many agricultural nexus studies have a local or farm scale focus on a dual Water-Energy nexus without an emphasis on “Food” (crop yield or production);
- there are limited components engaged in the nexus, particularly waste.

For specific models and tools, they can fall into three major categories by their functionalities:

- resource-environmental footprint quantification,
- assessment and systematic simulation,
- optimization.

Resource-environmental footprint quantification models primarily target at resource use and environmental performances by tracking their footprints in studied systems. Assessment and systematic simulation models may be more complex, as this type can cover more areas and industries as opposed to the first type. Optimization models have become more prevalent, as these models bear advantages identical to the first two types while avoiding some disadvantages by combining simplicity in structures and integration with more components. Most importantly, they can offer direct optimal results of studied systems and trade-offs in conflicting resource uses. But they may require researchers to have a high level of mathematical knowledge and skills.

With study goals and literature review mentioned all above, the next chapter will present study scope, model development, sensitivity test design and scenario design by aligning with the goals and considering major research gaps.

CHAPTER 3: METHODOLOGY

3.1. Introduction

This work primarily aims at optimizing the total profits of an irrigated single crop rotation system based on insights of Water-Energy-Food (WEF) nexus. The nexus is quantified as potential dual relationships between water application in irrigation practices, energy consumption in both irrigation activities and non-irrigation activities on farm, and responsive crop yields. Irrigated land use and greenhouse gas (GHG) emissions are considered as well. As such, this chapter will describe the study scope, methods of data collection, model development and scenario design to achieve Objective (1) depicted in Chapter 1.

3.2. Study scope

3.2.1. Study area

The site selected for this study is Toowoomba Region (**Figure 3.1**), one of the four sub-regions within the Darling Downs region of Southern Queensland.

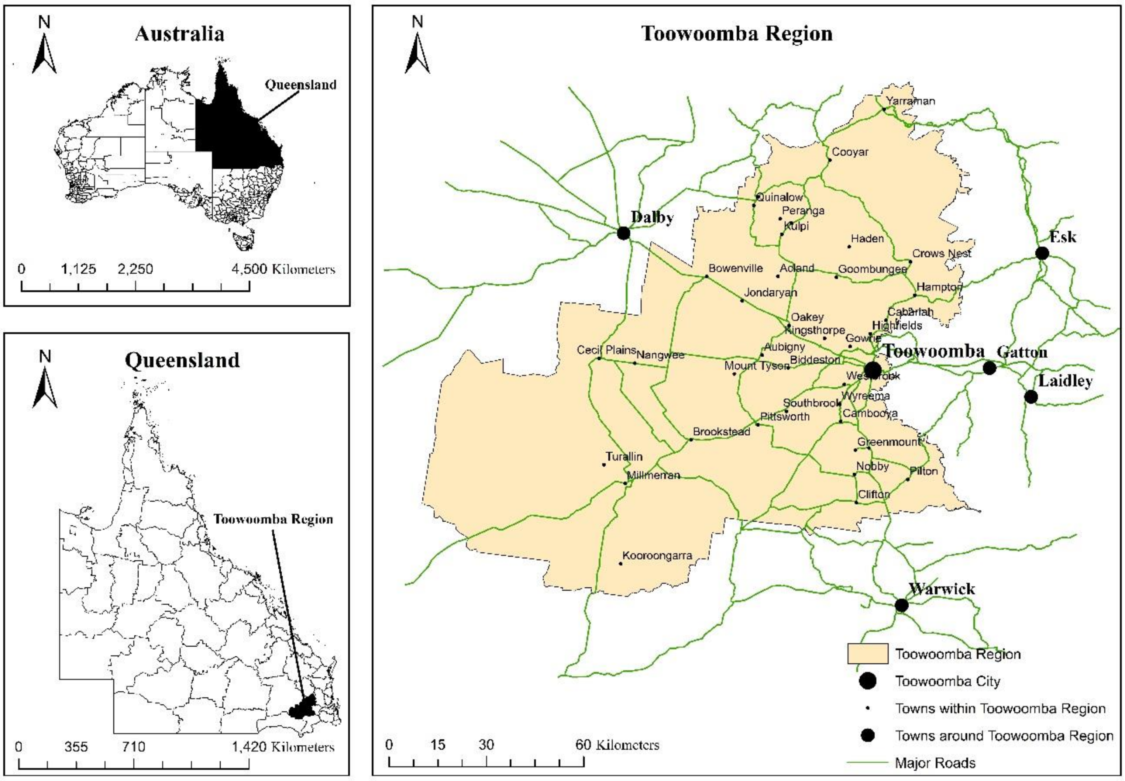


Figure 3.1. Study area, Toowoomba Region, made by ArcMap 10.8.1, data sourced from Queensland Spatial Catalogue (QSpatial) (ABS 2021).

The Toowoomba Region included an agriculture hub situated at the intersection of the New England Highway and Warrego Highway, interlinking industries in the regional areas and metropolitan areas. This region is a centre for agricultural activities in Southern Queensland.

As divided by type of industry, agriculture, forestry and fishing were the largest businesses operating within the Toowoomba Region from 2017 to 2021. The proportion for these agricultural businesses out of the total businesses has stayed steady throughout these years at over 20%, followed by the construction industry (over 15%). The gross value of crop production took up 34.33% of the gross value of agricultural production. The total land uses in 2021 were 1,295,721 ha, in which agricultural land uses were 899,871 ha (69.45%). The broadacre crops occupied most part of the agricultural uses, up to 30% (ABS 2022a). **Figure 3.2** shows all the types of land use within Toowoomba Region for the latest situations during 2019-20 (Queensland Government 2022c).

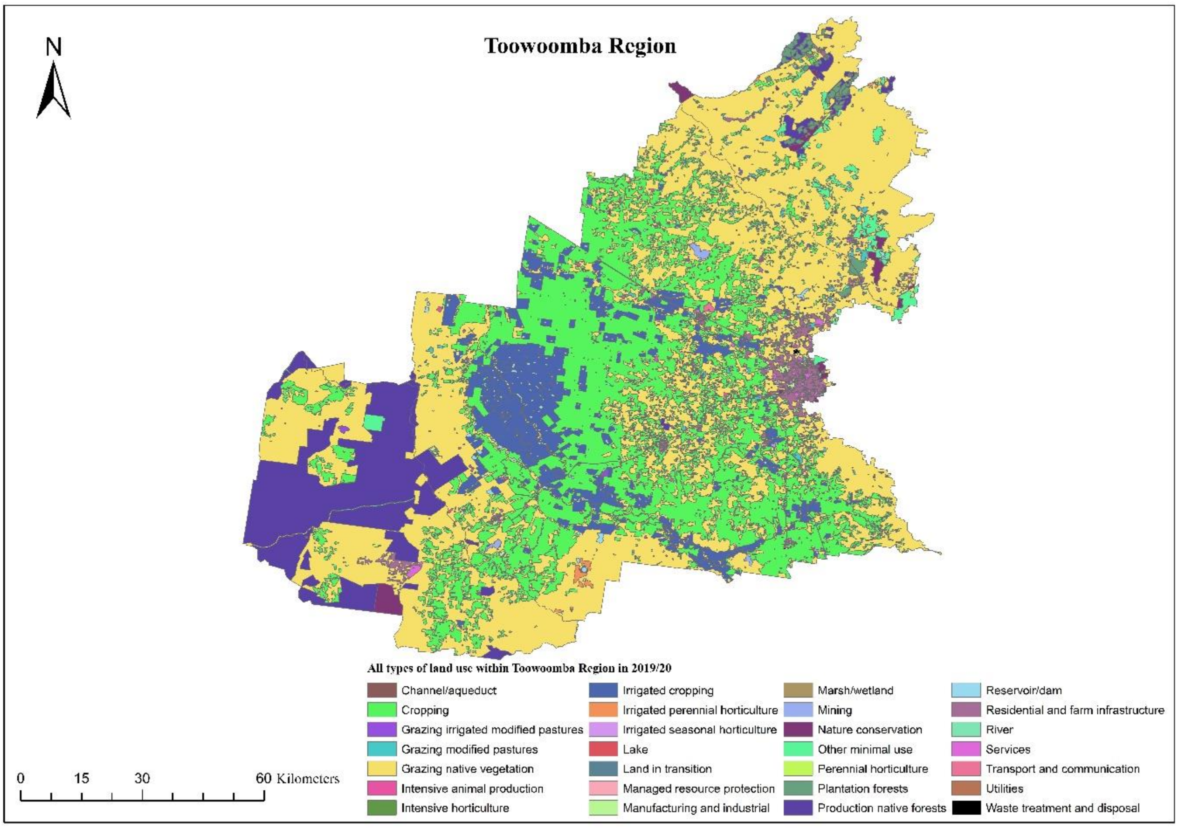


Figure 3.2. All types of land use in Toowoomba Region, made by ArcMap 10.8.1, data sourced from QSpatial (Queensland Government 2022c).

The map shows two types of land uses occupying the most part of the area: cropping areas (light green in the middle part); and grazing native vegetation areas (yellow in the north-eastern and south-western parts). The irrigated cropping areas are mainly distributed in the south-east and middle within the whole green cropping areas. These areas are in the proximity of main water resources and catchments within the region.

Most part of the Toowoomba Region is located within the Upper Condamine with a small area in the southwest crossing over to Border Rivers (Queensland Government 2022a). This has provided water supply for agricultural uses, especially for on-farm irrigation activities in this region. In **Figure 3.3**, the light blue areas are the main areas of un-supplemented surface water resources, while the dark blue areas represent the distribution of un-supplemented underground water resources. The supplemented and unallocated surface water resources are primarily derived from the Condamine River (Queensland Government 2022a), in which some irrigation water is provided from irrigation schemes by Sunwater (2019a).

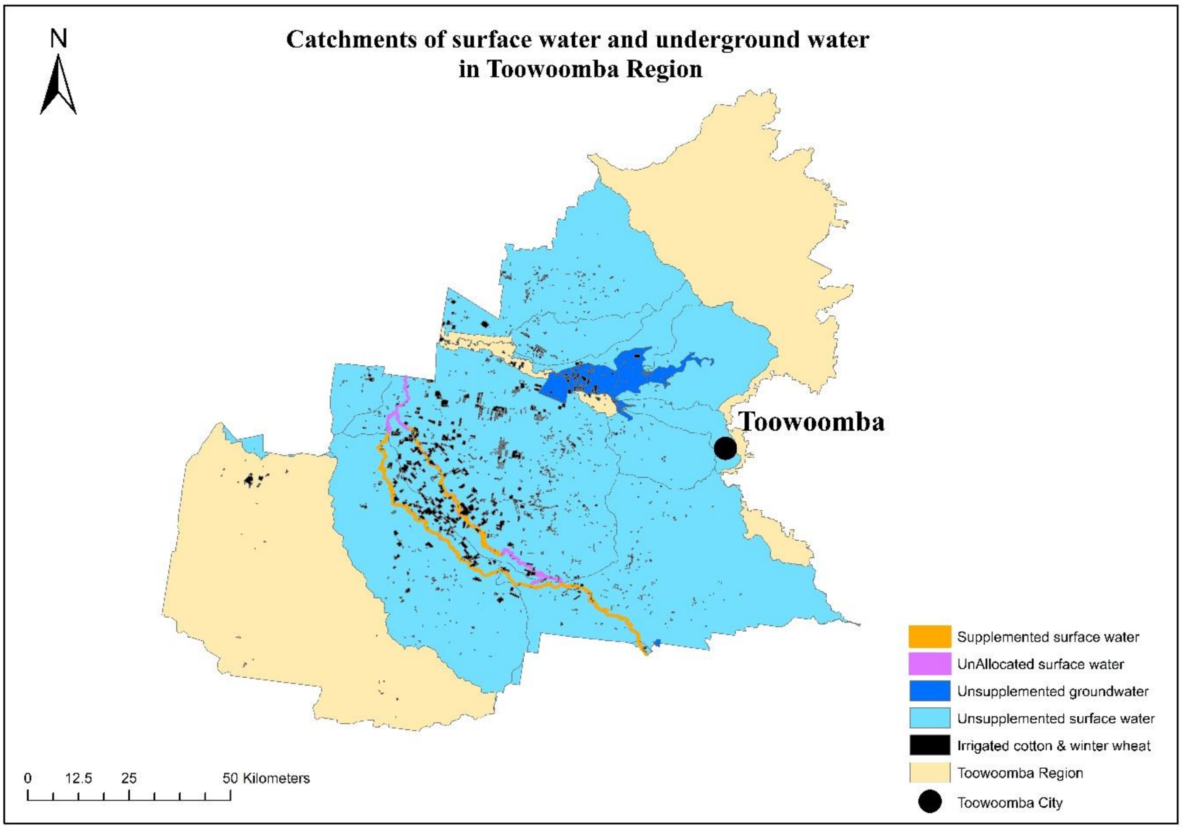


Figure 3.3. Catchments within Toowoomba Region, made by ArcMap 10.8.1, data sourced from (Queensland Government 2022c).

A water allocation is announced for water access entitlements on a seasonal basis depending on how much water is available in the water resource from which the allocation is drawn. Two different types of water allocations are recognized (BoM 2024):

- Supplemented allocations - water allocations supplied from water supply schemes;

- Un-supplemented allocations - water allocations taken from the natural flow of the river or from groundwater.

The Toowoomba Region has a warm and humid climatic condition (sub-tropical climate) with warm summers and cool winters (DES 2019). According to the Bureau of Meteorology (BOM), the average annual precipitation is 735 mm (28.9 in), normally reaching the peak in the warm season. Most rainfalls usually occur from November to March, during which January and February see the maximal downpour (BOM 2022).

As large geographical scales of regions can have various climatic conditions in different parts, they will present a disparity in climate data like precipitation and temperature (Queensland Government 2022a). This occurs in arid or semi-arid nations like Australia in particular, where it is much drier in the inland. However, Toowoomba Region, as a local scale, has similar climatic conditions in different geographical parts. This consistency of climatic situations on the geographical scale can reduce the uncertainty and deviation in parameters such as rainfall in developing the model.

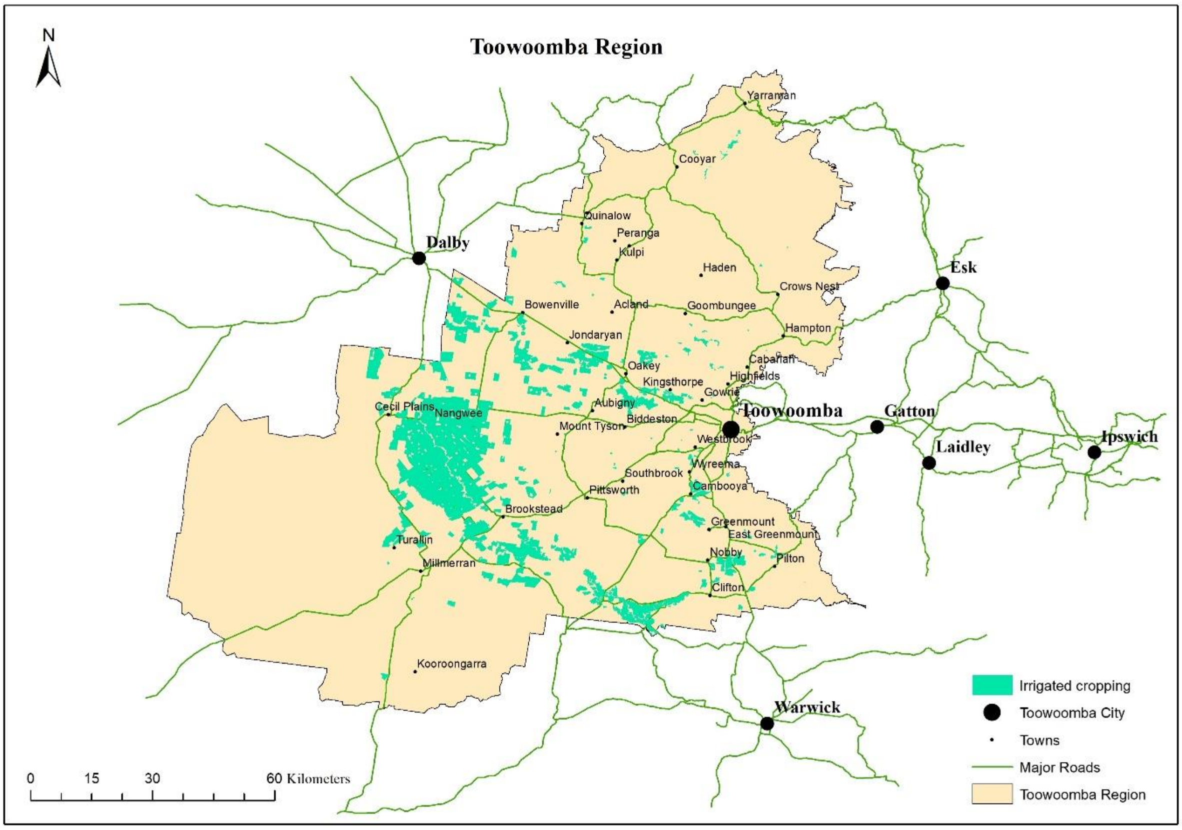
3.2.2. Crop selection

3.2.2.1. Background

ABARES (2022a) outlines yearly key crops for each state, including Queensland where farmers manage to plant grain sorghum and cotton in summers, and wheat, barley and chickpeas in winters (DAF et al. 2015; DAF 2018; ABARES 2020; DAWE 2020b). Among the top commodities by value in a larger Darling Downs – Maranoa Region, following cattle and calves, cotton and winter wheat are ranked at the second and the third places accounting for AU$457 million and AU$452 million of the total value, respectively, as the top two crops with the highest economic values. Across the distributions of land uses, the most intensive areas for cropping range from Dalby to Toowoomba, covering most part of Toowoomba Region (ABARES 2022b).

In southern Queensland, Toowoomba Region is where wheat and particularly cotton are most commonly grown (DAF et al. 2015; DAF 2018; DAWE 2019a; ABARES 2020; DAWE 2020b). Single crop rotation implementation of cotton grown in summer and wheat in winter is common as one of the most profitable rotation practices in Toowoomba Region. Give certain land for cropping, part of the areas are used for cultivating cotton in summer and subsequently left for fallow management, while the other part are used for growing wheat in winter (Graham 2022a; Scobie 2022). **Figure 3.4** indicates the major irrigated cropping areas including cotton and winter wheat mainly distributed in the south-east and middle within the Toowoomba Region coupled with natural catchments and schemed water resources in the vicinity.

Figure 3.4. Irrigated cropping areas, including cotton and winter wheat cultivation, within Toowoomba



Region, made by ArcMap 10.8.1, data sourced from QSpatial (Queensland Government 2022c).

3.2.2.2. Cotton

Cotton is among the top four water-intensive crops on Australian farms in 2018-19 (ABS 2020). The average irrigation demand for cotton cultivation in Australia is 6-7 ML per hectare (Cotton Australia 2022a). The growing season lasts approximately six months, commencing in September/October (planting) and ending in March/April (picking). Due to the large amount of water pumped and delivered by irrigation systems on farm, the irrigation activities require substantial energy use and therefore are energy intensive (Cotton Australia 2022a).

Agriculture is the main contributor to most countries' economy with cotton being one of the important crops in agriculture, and Australia is among the top ten cotton-producing countries (Khan et al. 2020). According to Cotton Australia (2022b), cotton is grown in over 100 Australian communities, crossing over both Queensland and New South Wales (NSW) which are the primary two states producing cotton for the nation. Smaller areas for growing cotton are in Northern Victoria as well as some cotton trials ongoing in northern Queensland, northern Western Australia, and the Northern Territory.

The number of cotton farms in Australia totals up to 1,500. Roughly 90% of them are family owned. The farms cultivate part of the finest quality and highest yielding cotton across the globe. The number of farms planting cotton fluctuates annually, dependent on available water resources and at the farmers' discretion of whether to grow cotton in that year, for instance, what is the likelihood to achieve the maximal profitability from cotton growing (Cotton Australia 2022c; QFF 2022).

3.2.2.3. Wheat

Wheat is the major winter crop grown in Australia with sowing commencing in autumn and harvesting in spring and summer (determined by seasonal conditions). The main wheat producing states are Queensland, NSW Victoria, South Australia, and Western Australia. Queensland and NSW are the major states producing wheat that is for domestic consumption and feedstock (DAFF 2021). Wheat Quality Australia (2021) divides primary wheat growing zones into four key areas as "Classification Zones". These Classification Zones features different environmental conditions where different classes of wheat are grown, based on which physical attributes and defects are evaluated other than the genetic attributes of the wheat variety.

Most wheat grown is rainfed. In Queensland specifically, irrigated wheat is a small proportion of wheat grown. Most irrigated land is set aside for cotton production as it is the most profitable irrigated broadacre crop. Irrigated wheat is grown as part of a rotation, normally with cotton, and to provide some groundcover (Graham 2022b). The irrigated wheat cultivation areas in Queensland during the 2020-21 period were 39,744 ha, around 2.3% of the total cereal cropping areas (ABS 2022b). In the Darling Downs-Maranoa region, the areas of irrigated cereals were 22,978 ha, nearly 1.7% of the total cereal area grown in 2020-21 (Graham 2022b).

3.2.2.4. Summary of reasons for selecting cotton and irrigated wheat

These two crops are selected firstly because they are two of the most commonly grown crops in the Toowoomba Region. Datasets about cotton and wheat are readily accessible in this local area. Organisations such as the Department of Agriculture and Fisheries (DAF), Grains Research and Development Corporation (GRDC), Cotton Australia have all set up branch offices in Toowoomba, as well as the University of Southern Queensland in Toowoomba. This makes it easier to collect data by interview.

Cotton is one of the most important cash crops in Australia, considerably contributing to the economy. Coupled with rotation of irrigated wheat, this will help to achieve our goals to study the Water-Energy-Food nexus, as the water-energy dual relationship is still one indispensable part in irrigated crop systems. Besides, cotton cropping consumes plenty of water and correspondingly cause intensive energy use in irrigation activities, which will incur large amount of GHG emissions due to traditional fossil fuel uses. Then it will be necessitated to correlate carbon policies and climate change with the nexus. Thus, this can help to improve the integrality of our model.

Moreover, a rotation practice of summer cotton and winter wheat is one of the most common methods in Toowoomba Region. Irrigated wheat grown in the Toowoomba Region in winter is usually supplementary to cotton grown in summer. Planting irrigated wheat separately in large areas is not as common as planting irrigated cotton. Compared with rainfed wheat, irrigated wheat is rarer, even in a greater area in Australia. This can be a research gap in combination of cotton and irrigated wheat in a rotation system.

It is of high significance to incorporate them into one single crop rotation system and explore optimal agronomic performances in conjunction with balanced resource use and environmental performances under a WEF nexus framework. Thus, the selected crops for this study are cotton, grown in summer, and wheat, grown in winter, in the Toowoomba Region in a single crop rotation practice.

3.2.3. Irrigation practices

Current predominant types of irrigation methods in Australia include surface, sprinkler and drip irrigation (Irrigation Australia 2020). Among them, surface irrigation (such as border check, furrow, flood, basin) occupies approximately 60% of total usage in contrast to sprinkler (large mobile machines with a centre pivot, linear or lateral movement) taking up 13% and drip or trickle (above ground) taking up 9% (Irrigation Australia 2020). In Toowoomba Region, above 80% of total irrigation systems are surface irrigation. Compared with that, the overhead irrigation (centre pivot/lateral move) takes up 10 to 20% out of total irrigation systems (Graham 2022a; Queensland Government 2022d). Hence, this study uses surface irrigation as the main irrigation practice and main datasets for this irrigation system are accessible from the database, AgMargins, as stated in the next section.

3.3. Data collection and tools

The data for input variables and parameters in the model is mainly collected from authentic online available databases, governmental and organisational websites (such as ABARES, ABS, BOM, DAWE, DAF, CSIRO, FAO, GRDC), peer literature review, local reports, and so on. **Table 3.1** lists major databases used in conjunction with modelling methods and tools for data processing and analysis.

Table 3.1. Major databases and associated tools used for data processing and analysis in this study.

Database	Data contents	Application	Associated tools	References
AgMargins	Rates and variable costs for activities in farming, crop yields and prices	Variable costs incurred by pre-farm, on-farm and off-farm activities	Excel	Queensland Government (2022c)
ABS, ABARES	Crop yields, water use on farm, land use	Water and land entitlements	Excel	ABS (2022b)
QSpatial	Mapping and GIS datasets	Map making	ArcGIS, QGIS	Queensland Government (2022c)
SILO	Evapotranspiration (ET), rainfall	Crop Water Production Functions (CWPFs) modelling	Excel	Queensland Government (2022e)
AusLCI	Resources and materials use during life cycles	Resources and materials use and associated GHG emissions caused by pre-farm, on-farm and off-farm activities	SimaPro, Farm Greenhouse Accounting Framework Tools, Excel	ALCAS (2020) Ekonomou et al. (2022a)

As mentioned above, the AgMargins database outlines major pre-farm, on-farm, and off-farm activities. It is a web-based gross margin calculator and reporting tool for broadacre and horticultural crops across Queensland. It enables landholders/farmers to readily update crop production profits and costs for further assessment and farm management decisions (Queensland Government 2022d). This database has most recently been updated in October 2022 and is maintained by the Broadacre Cropping Systems Team in the Department of Agriculture and Fisheries (DAF) (Queensland Government 2022d). To verify the validity and reliability of this database, email interviews have been conducted with the team leader, Graham Harris, who is also the Principal Development Extension Officer in DAF. The Team is responsible for collecting, recording, filing, rectifying and verifying the datasets (Graham 2022b).

Table 3.2 outlines a summary of variable costs (growing costs, excluding water cost) on cotton and winter wheat in Toowoomba Region with the latest available data in the annual period of 2020-2021. Both the cotton and winter wheat are watered in surface irrigation practices as the most common irrigation practice as well as other common cropping practices available within the Toowoomba Region (Graham 2022a, 2022b; Scobie 2022).

Table 3.2. Summary of variable costs (in AU$/ha) for irrigated cotton and winter wheat.

Crop	Planting	Nutrition	Crop Protection	Harvesting	Post-Harvest	Fallow Management	Other	Total Variable Costs
Cotton	488	357	143	281	730	63	193	2,831
Wheat	60	337	38	30	54	53	57	808

Note: The irrigation practice is surface irrigation. These median values are based on Toowoomba Region, 2020/21 and drawn from the database AgMargins (Queensland Government 2022d). “Post-Harvest” is separate from “Fallow Management”, mainly inclusive of cartage and ginning on cotton and cartage on wheat after harvest and before subsequent fallow. All the other fallow activities are included in “Fallow Management”, such as conventional crop residue management (incorporation into soil). The “Other” category includes crop insurance, contracts for consultancy, research & development (R&D) levy, voluntary levy.

3.4. Model development

The overall integrated optimization model is based on a profitability function. Within this model, sub-models are developed including crop yield models, water use simulation, energy use accounting and its responsive GHG emissions. On top of these, the integrated model is further developed aligned with scenario designs such as alternative energy sources (on-grid electricity, solar photovoltaic) and crop residue disposals.

Figure 3.5 shows a schematic diagram of the study framework, which consists of 4 core stages: (1) WEF nexus conceptualisation (study goals and scope definition, literature review), (2) model development paired with scenario designs, (3) model application to the selected study area and crops (or baseline scenario), and (4) scenario analysis compared with the baseline scenario.

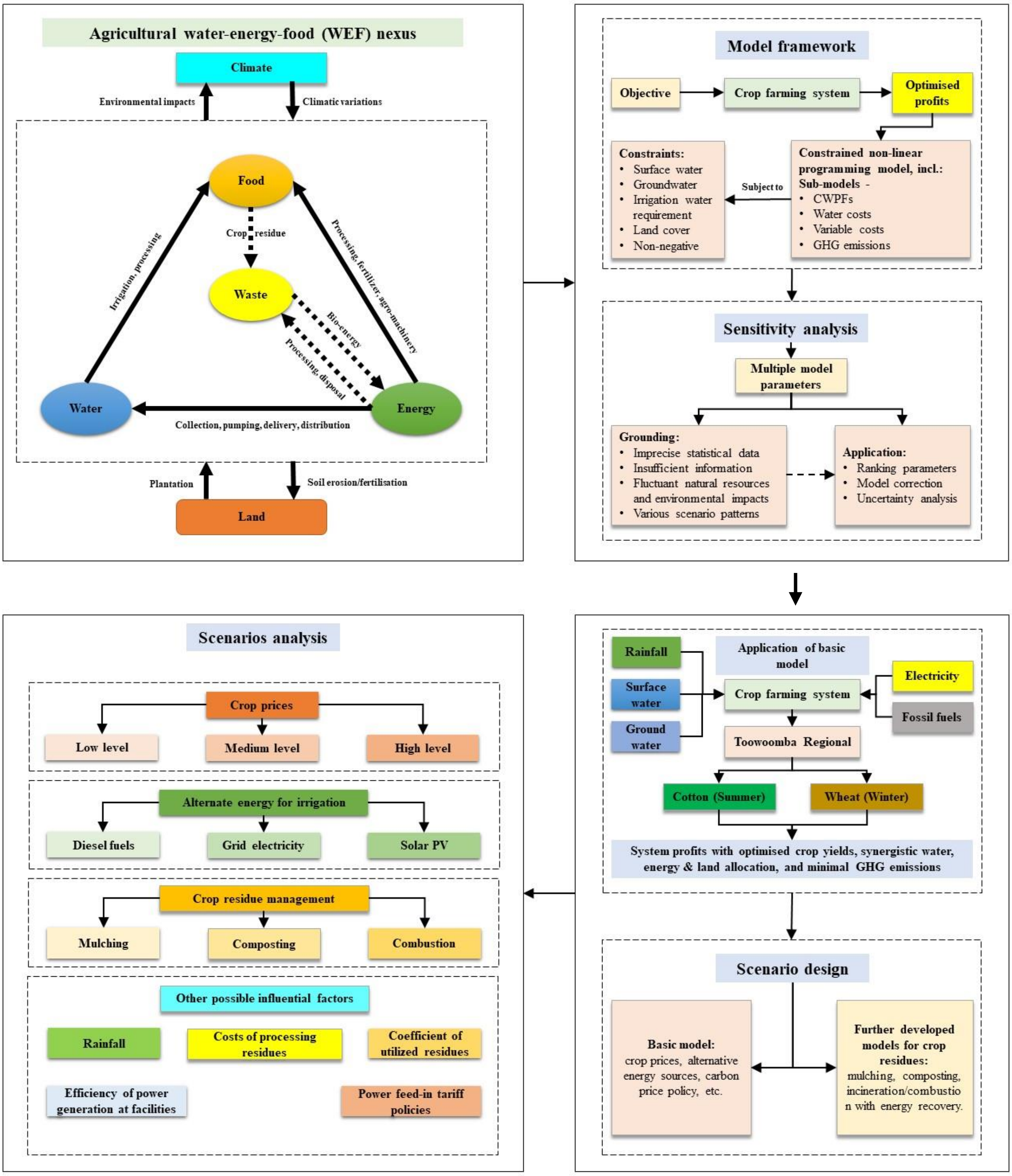


Figure 3.5. Study framework, including 4 main stages: (1) WEF nexus conceptualisation (study goals and scope definition, literature review), (2) model development paired with scenario designs, (3) basic model application as a baseline scenario (business as usual) to Toowoomba Region, and (4) scenario analysis compared with the baseline scenario.

In the conceptualisation, the main dual relationships between these internal sectors within the nexus system include water used for irrigating and processing crops (water-to-food), energy used to pump and deliver irrigation water (energy-to-water), energy consumed for processing, agrochemicals and agro-machinery on crops (energy-to-food), crop residue collected to generate bioenergy (waste-to-energy), and energy utilized to process and dispose crop residue (energy-to-waste). Outside of the WEF nexus, climatic factors and land use interact with the nexus system as external factors. The agricultural WEF nexus system itself influences the natural environment and resources, for example, by potentially causing climate change due to GHG emissions and land degradation due to land use. On the other way around, climate and land use change affect crop production, water resources and further economic returns.

A model framework is developed, subsequent to conceptualisation, in the form of non-linear mathematical programming subject to water and land constraints. Sub-models are synchronously developed for the sectors and their interconnectivities. Sensitivity analysis is implemented for analysing, determining, and sorting out uncertain parameters.

After the model development, the model will be applied to the selected single crop rotation system in Toowoomba Region with common farm practices in order to explore optimal land and water use, total profits, and associated GHG emissions. Relative to this baseline scenario, two series of scenarios are designed upon the basic model for potentially impactful factors like crop prices, energy sources in irrigation and carbon related policies, and upon further developed models for potentially impactful factors like alternative environmental methods to dispose crop residues.

3.4.1. Crop yield modelling

3.4.1.1. Crop Water Production Function (CWPF) selected for the study

A crop water production function refers to the functional relationship between the crop yields and the quantity of water resources consumed to produce the yields on the basis of consistent agricultural production level and techniques (Zhang 2009). It is a useful tool to develop proper irrigation strategies and determine potential crop yields in water deficiency situations (Kipkorir et al. 2002; Steduto et al. 2012; Garcia-Tejero et al. 2013; Pushpalatha et al. 2020).

On the basis of literature review, CWPFs are divided as follows:

(1) Empirical estimation models for predicting crop yields can be derived by employing curve fit methods for relationships between crop yields and different levels of applied irrigation water inputs. The data for different applied irrigation amount and the corresponding crop yields are observational, empirical and gleaned from real in-field experiments carried out on crops in years;

(2) Mathematical models (crop coefficient models):

These are existing mathematical functions structured by numbers of empirical studies in the past and indicate functional relationships between crop yields and water inputs yet with undetermined coefficients. These in-built coefficients can be obtained from empirical studies or estimated by curve fitting with experimental data.

(3) Process-based crop growth models:

They can be obtained using software. By simulating crop growth and further estimate crop yields, a functional relationship between crop yields and water inputs can be estimated.

In order to select the most appropriate CWPF for this study, advantages and disadvantages have been considered and summarized, based on the literature review in Chapter 2, as below:

- For empirical estimation models, they may be closer to real relationship of crop yield and water use on a small scale typical like a farm scale, in that the data for estimating the models are based on real in-field experiments. Nevertheless, obtaining these observational data will take numerous years to capture variability in the crop water production function caused by inter-annual differences in weather conditions during the growing season. The massive data collection and extensive experiments make it time consuming and costly. Besides, it is not applicable to larger geographic scales such as a regional scale.
- For process-based crop growth models, they are more readily obtained by using software and simulating crop growth. It can be much less time consuming. These crop growth models can much satisfy needs of researchers who study crop growing patterns interacting with surrounding and climatic environment. They are becoming more popular among

agricultural researchers. However, in terms of estimating process-based crop growth models, it similarly demands for extensive and precise experimental/observational data used for simulations in the software (such as APSIM, AquaCrop, CROPWAT). Also, it is challenging to ensure irrigation scheduling exactness for the daily intervals, in particular for high levels of climatic uncertainties farmers commonly face.

- In terms of crop coefficient models, those with evapotranspiration being the independent variable on individual each crop growth stage have included influences of water deficits between each stage. But they are complicated due to multiple uncertain coefficients. It would be impossible to determine them without massive experimental data inputs.
- In terms of crop coefficient models, those with irrigation water application rate as the independent variable on the whole crop growth period have revealed a general pattern on the crop water relationship. But they may be challenged against being limited to irrigation water sources without considering other water sources such as rainfall.
- In terms of crop coefficient models, those with evapotranspiration as the independent variable on the whole crop growth period share a similar simple model structure to those with irrigation water application rate as the independent variable on the whole crop growth period. The only challenge is still the determination on coefficients. These models are widely used in planning and design, and macroeconomic analysis.

Therefore, the CWPF selected in this study is the Stewart model (Doorenbos et al. 1979; Steduto et al. 2012), which is one of the crop coefficient models. The main reasons for selecting this model are as below:

- The CWPF with evapotranspiration on the whole crop growth period better unveils the real crop needs for water resources, taking on board effective rainfall, and macro-statistical relations between crop production and water use.
- Due to limited data sources for crop simulations, funds and timeframe in our study, determining models' coefficients by in-field experiments, farm surveys or software simulations would not be practical. Compared with the Stewart model, the other models still require massive empirical data to fit

in and determine the coefficients, which will be costly and take years to achieve.

- In contrast, the Stewart model coefficients can be derived from the Stewart model publication (Doorenbos et al. 1979). This publication has been regarded as one of FAO's milestone publications and widely used worldwide for a broad range of applications (Steduto et al. 2012; Varzi 2016). In this model, the in-built yield response factor (K_y) captures the essence of the complex linkages between crop yield and water use, in which multiple physical, chemical and biological processes are engaged.
- The model allows for the effects of water deficits on crop yield. This would help to examine effects of deficit irrigation practices on the WEF nexus system and to improve water efficiency and crop productivity of cotton, in particular, which is water demanding.

The Stewart model reveals relative yield reduction is in response to the corresponding relative reduction in evapotranspiration (ET), expressed as:

$$\left(1 - \frac{Y_a}{Y_{max}}\right) = K_y \left(1 - \frac{ET_a}{ET_{max}}\right) \tag{1}$$

where Y_{max} and Y_a are the maximum and actual yields; ET_{max} and ET_a are the maximum and actual evapotranspiration; K_y is a yield response factor representing the effect of a reduction in evapotranspiration on yield losses. Further breakdowns of the model and possible values of the involved parameters are discussed in the succeeding sections.

3.4.1.2. Yield response factor

In the FAO CWPF model, the yield response factor K_y values are crop specific and vary over the growing season with:

- K_y >1: crop response is very sensitive to water deficit with proportional larger yield reductions when water use is reduced because of stress.
- K_y <1: crop is more tolerant to water deficit, and recovers partially from stress, exhibiting less than proportional reductions in yield with reduced water use.
- K_y =1: yield reduction is directly proportional to reduced water use.

K_y values for various crops can be derived from the publication by Steduto et al. (2012), which has been listed in **Appendix B**. The values for cotton and winter wheat are displayed as below in **Table 3.3**.

Table 3.3. Seasonal Ky values for cotton and winter wheat (Steduto et al. 2012).

Crop	Ky	Crop	Ky
Cotton	0.85	Winter wheat	1.05

As aforementioned, coefficients in CWPFs are mostly estimated through either real massive and lengthy in-field experiments, which would take years, or simulations with software, which highly require precise datasets about soil profile and climatic conditions and specific decisions about cropping practice management. Because of limited precise data sources for estimation on the coefficients, limited funding and limited timeframe in the study, the coefficient K_y values are mainly derived from the publication by Steduto et al. (2012). This publication has been based on the analysis of an extensive quantity of studies on crop-yield and water relationships under deficit irrigation practices. These coefficients in conjunction with crop coefficients K_c have been systematically researched and estimated in extensive studies by Food and Agriculture Organization (FAO).

3.4.1.3. Estimation of CWPF model parameters

The maximum crop yield values (Y_{max}) are estimated from available data in both ABS database and AgMargins for the Toowoomba Region over the past five to ten years. The maximum crop evapotranspiration (ET_{max}) is estimated from a series of crop evapotranspiration (or, crop water need/requirement/demand, ET_c) values determined based on FAO guidelines for crop-water requirements, which can be calculated by:

$$ET_c = K_c \cdot ET_o \tag{2}$$

where ET_o is the reference crop evapotranspiration and K_c is the crop coefficient.

Table 3.4 lists K_c values for cotton and winter wheat. Other typical K_c values of various crops are listed in **Appendix C**. The values of ET_o for Toowoomba Region are derived from the web-based database, SILO (Queensland Government 2022e), from 2010/11-2020/21. The FAO Penman-Monteith equation is adopted for estimating the reference crop evapotranspiration (ET_c) (Allen et al. 1998b).

Table 3.4. Values of crop factors (K_c) for cotton and winter wheat and growth stages.

Crop	Initial	Crop development	Mid-season	Late-season
Cotton	0.45	0.75	1.15	0.75
Winter wheat	0.35	0.75	1.15	0.45

Note: The numbers indicate average values of K_c for crops on every growth stage, including initial, crop development, mid-season and late-season stage. The K_c also depends on climate and particularly relative humidity and windspeed. The values shown above should be decreased by 0.05 if the relative humidity is higher than 80% and the windspeed is lower than 2 m/sec, such as K_c = 1.15 turns K_c = 1.10. The values should be increased by 0.05 if the relative humidity is lower than 50% and the windspeed is higher than 5 m/sec, such as K_c = 1.05 turns K_c = 1.10. While the relative humidity is between 50% and 80% and the windspeed is between 2 m/sec and 5 m/sec, the values remain the same as in the table.

Figure 3.6 shows all the 16 climate stations that can be found and selected for this study in the best proximity of the major irrigated cropping areas within Toowoomba Region. Other large numbers of stations are distant from the centralized irrigated cropping areas that will not be able to represent the most accurate ET_o and effective rainfall (P_{Eff}) values for the irrigated cotton and winter wheat. Accordingly, **Appendix D** lists details about these stations, including names, serial numbers, and exact locations.

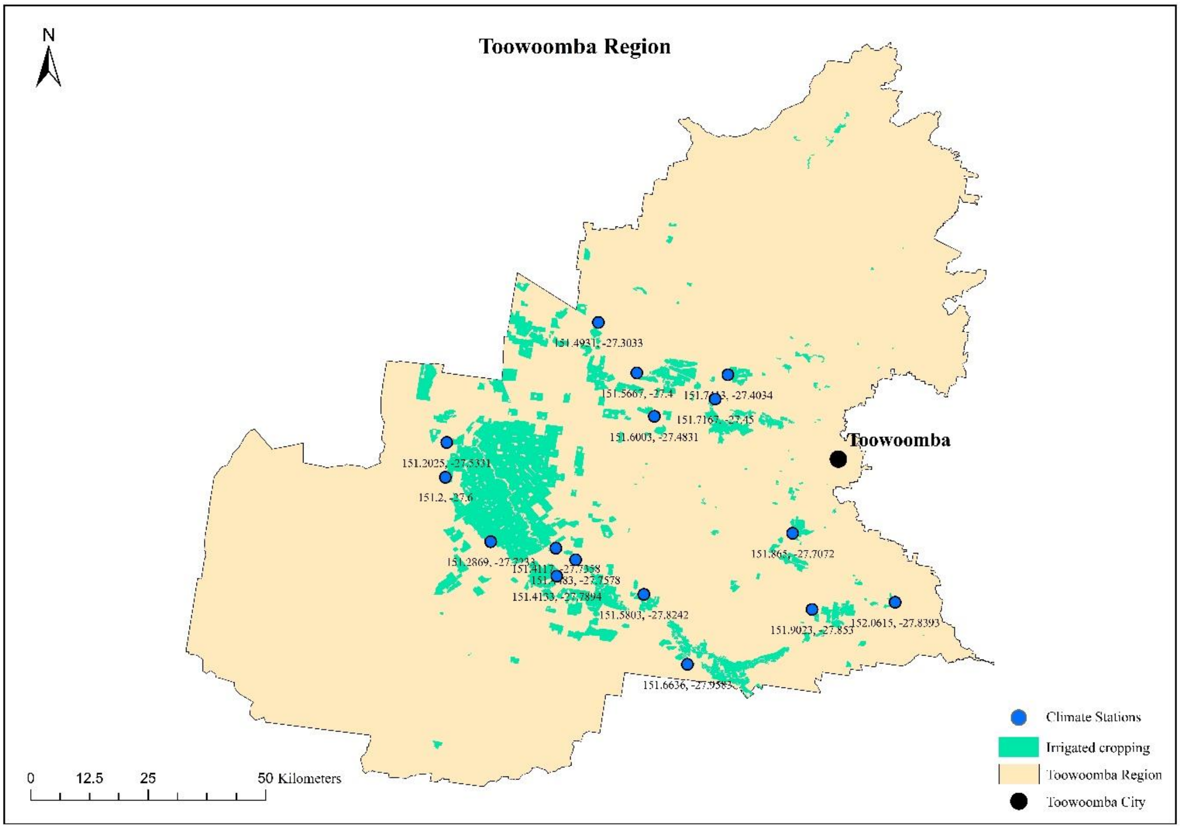


Figure 3.6. Selected climate stations for ET_o and P_{Eff} within Toowoomba Region, made by ArcMap 10.8.1, data sourced from QSpatial (Queensland Government 2022c)

Using the above equation, the ET_c values for each four growing stages on a daily basis are calculated. All the specific daily ET_c values in each growth stage add up to total values for the whole growth periods of cotton and wheat respectively. **Table 3.5** shows minimum, maximum and average values of evapotranspiration for cotton winter wheat recorded in Toowoomba Region during 2010/11 – 2020/2021. The ET_{max} values for cotton and wheat are estimated from these estimated ET_c values on the whole growth period.

Table 3.5. Minimum, maximum and average values of evapotranspiration (ET_c).

Crop	Min. (mm)	Max. (mm)	Ave. (mm)
Cotton	648.22	945.42	843.87
Winter wheat	224.42	326.40	271.92

Note: The data is for cotton and winter wheat on the whole growth period, based on 16 climate stations during 2010/11 – 2020/2021 (Queensland Government 2022e).

3.4.1.4. Modelling of crop water requirement

As the terms “crop evapotranspiration” and “crop water need” are often used interchangeably (Rao et al. 1977; Al-Kaisi 2000; Al-Kaisi et al. 2009; Smilovic et al. 2016; Satpute et al. 2021), the symbol ET_c is equating to crop water need (requirement, demand). Crop water demand (ET_c) consists of four major parts: 1) soil water, 2) groundwater, 3) rainfall and, 4) irrigation (Zhang 2009). During the whole period of crop growth, farmland water balance can be expressed as:

$$ET_c = P_{Eff} + W_{Irr} + \mathrm{S} + \mathrm{CR} - \mathrm{DP} \qquad (3)$$

where P_{Eff} is the effective precipitation during the whole crop growth period; W_{Irr} is the irrigation water application; S is the water stored by soil; CR is the water amount used by crops via underground water table through crops’ capillaries (Capillary Rise); DP is water through deep percolation.

When the build-up of soluble salts in the soil becomes or is expected to become excessive, the salts can be leached by applying more water than actual crop need during the growing season. This extra water moves at least a portion of the salts below the root zone by deep percolation (leaching). Leaching is the key factor in controlling soluble salts brought in by the irrigation water. Over time, salt removal by leaching must equal or exceed the salt additions from the applied water. Otherwise, salts will build up and eventually reach damaging concentrations. Hence, estimating a leaching requirement is necessary. The terms of “leaching fraction (LF)” and “leaching requirement (LR)” are often used interchangeably. They both refer to that portion of the irrigation which should pass through the root zone to control salts at a specific level. While LF indicates that the value be expressed as a fraction, LR can be expressed either as a fraction or percentage of irrigation water (Ayers et al. 1985).

Given there is a dynamic water balance in the farmland soil ecology between the leaching, the soil water and the water utilized by crops, the crop water need is primarily affected by effective precipitation and irrigation (Allen et al. 1998b; Scobie 2022). Thus, *Equation (3)* can be simplified as:

$$ET_c = P_{Eff} + W_{Irr} \tag{4}$$

3.4.1.5. Estimation of effective rainfall

When precipitation cannot suffice for crop growing, irrigation will be supplementary. Irrigated crops are watered either by combination of irrigation and rainfall or by irrigation alone, while rain-fed crops depend on natural rains as the main water source. Rains falling on the soils will not be fully utilized by the crops. Part of the rainwater percolates through the soil to the root zones, while part flows away over the land (run-off). Water via deep percolation and run-off cannot naturally be used by plants unless it is manually collected and used, which may be “ineffective”. Thus, the remainder stored in soil and used by plants is called “effective” rainfall. The ratio of effective precipitation is dependent on local climatic contexts, soil texture and structure, and the depth of the root zone. For example, if there is a high volume of rainfall, a relatively high proportion of water is lost via deep percolation and overland flows (Brouwer et al. 1986b). When taking into account effects of rainfall on crops yields, effective rainfall is an essential parameter to be factored in.

There are multiple existing effective rainfall estimation methods, which may well suit different purposes, such as direct measurement techniques, empirical methods, soil water balance methods (Patwardhan et al. 1990). Ali et al. (2017) has summarised a suite of effective precipitation calculation methods, including:

- United States Department of Agriculture Soil Conservation Service (USDA-SCS) method
- ET-Rainfall Ratio method

- U.S. Bureau of Reclamation method
- Soil Water Balance method
- Renfro Equation
- Other empirical methods, such as Indian-1 and Indian-2 methods, Japanese method, Vietnam method, Burma method

The comparative results from these methods for the rice growing period in the study by Ali et al. (2017) reveals a relatively low deviation from standard results by Japanese method and Indian-1 method for -2.2% and 6.8%, respectively.

Despite a better accuracy of estimation for Japanese and Indian-1 methods as well as their simplicity, other methods like USDA-SCS method in particular are more popular, which is also advised by FAO (2021b). Japanese and Indian-1 methods have limitations, which considerably restrict them to be applied for a broader range of situations. They are mainly applicable to specific local contexts in the northern hemisphere (Ali et al. 2017).

In contrast, the USDA-SCS method is selected for estimating the effective rainfall in this study, as it is widely used for effective rainfall estimation. Ali et al. (2017) also suggests the USDA-SCS method is robust in estimating effective precipitation by using correction coefficients that are embedded in the FAO's CropWat software. The data for precipitation in the Toowoomba Region during the crop growth periods are collected from SILO (Queensland Government 2022e).

$$P_{Eff} = (P_{Rain} * (125 - 0.2 * 3 * P_{Rain}))/125 \qquad \text{for } P_{Rain} \leq 250/3 \text{ mm} \qquad (5)$$

$$P_{Eff} = 125/3 + 0.1 * P_{Rain} \qquad \text{for } P_{Rain} > 250/3 \text{ mm} \qquad (6)$$

where P_{Rain} represents precipitation in mm, and in red are correction factors that the software CropWat applies to adjust formulas in the case of decade and daily rainfall data (for effective rainfall calculations daily data are aggregated per decade) (FAO 2021b).

The numerical ranges (minimum and maximum values) of P_{Rain} and P_{Eff} for cotton and winter wheat (whole growth period) during 2010/11-2020/21 are listed below in **Table 3.6**.

Table 3.6. Minimum, maximum and average values of rainfall (P_{Rain}) and effective rainfall (P_{Eff}) (Queensland Government 2022e).

Crop		Min. (mm)	Max. (mm)	Ave. (mm)
Cotton	P_{Rain}	180	1,118	465
	P_{Eff}	128	237	171
Winter wheat	P_{Rain}	16	240	126
	P_{Eff}	16	148	96

Note: The data is for cotton and winter wheat on the whole growth period derived from 16 climate stations during 2010/11 – 2020/2021.

3.4.2. Profit of cropping systems

The profit of a cropping system equals the difference between total revenues and total costs, specifically the net return after subtracting the input energy cost and water cost from the output income of that crop. The profit function is accordingly expressed as:

$$\mathrm{P}_{rofit} = \sum_{i=1}^{n} (R_i - C_i) \tag{7}$$

where P_{rofit} is the function for the total profit (AU$) of a cropping system, in which crops are planted; i is the index of one specific crop; R_i represents all revenues from crop i (AU$); C_i is all costs for growing crop i (AU$).

The revenues of growing crop i (R_i) at the irrigated level can be primarily denoted as follows:

$$R_i = p_{Yi} \cdot Y_i \cdot A_i \tag{8}$$

where p_{Yi} represents the price for the crop i (AU$/t); Y_i is the yield of crop i (t/ha); A_i is the irrigated area of crop i (ha).

The total variable costs C_i in the integrated model stem from three major parts:

(1) Water costs, meaning the costs of irrigation practices including those from surface water and groundwater use and those from energy use (diesel or electricity) of collecting, pumping and delivering water in irrigation;

(2) Greenhouse gas (GHG) emission costs, which are the costs of emissions from energy use in irrigation and from all the other pre-farm, on-farm, and off-farm energy use;

(3) All the other variable costs (excluding water costs), including:

- Seeding and planting;

- Nutrition;
- Crop protection;
- Harvesting;
- Post-harvesting;
- Fallow management and crop residue disposal (incorporation into soil)
- Other (labor, crop insurance, levies, and so on).

Thus, the total costs for growing crop i can be generally expressed as:

$$C_i = C_{Wi} + C_{Gi} + C_{Fi} \tag{9}$$

where C_{Wi} is the irrigation water cost for crop i; C_{Gi} is the GHG emission cost caused by crop i; C_{Fi} is all the other variable cost for growing crop i.

3.4.3. Irrigation water and energy use

The conjunctive consumable water (W_i, ML/ha) used for irrigation in the model consists of surface water and groundwater as well as overland flow water stored in ring tanks (An-Vo et al. 2015; Graham 2022b). It generates part of water costs relating to water allocations from irrigation supply schemes (such as Leslie Dam) or bores. Besides the free-of-charge overland flow water, rainfall is another water source without costs involved. Irrigation water license is in fact a fixed charge associated with a water permit or license allocation. It is not included in the water costs of the model, as this fixed cost for the water allocation must be paid irrespective of water applied in that water year (Graham 2022b). Irrigation related energy is predominantly diesel, as diesel pumping is common in Queensland irrigation, especially in the cotton industry where the pump stations are often remotely located (Scobie et al. 2020). Thus, the diesel cost is included in the water costs. In addition, oil, repairs and maintenance costs also apply to irrigation activities as part of water costs while applying water to cropping (Graham 2022b).

3.4.4. Energy and resource inputs from the other farm activities

These inputs are other variable costs in growing crops, excluding the expenditures related to irrigation practices and costs incurred by emitting GHGs. Together with inputs from irrigation (water and diesel fuels), datasets of these energy and resource inputs are accessible from AgMargins (Queensland Government 2022d). In conjunction with datasets from AgMargins, datasets from Australian Life

Cycle Inventory (AusLCI*)* (ALCAS 2020) are also accessed for each item of farming activities with given amount of resource, materials and energy used, such as agrochemicals, fertilizers, diesel and petrol. These itemed resource and energy inputs are for further GHG emissions calculation.

3.4.5. GHG emissions modelling

The itemed energy and resource uses are derived and estimated based on data from AgMargins and AusLCI, and entered into the model of the Greenhouse Accounting Frameworks (GAF) for Australian Primary Industries (Ekonomou et al. 2022a). This tool contains GHG accounting methods for various crops, including cotton and wheat, with different specific parameters and inputs, such as emission factors for on-grid electricity use in Scope 2 and Scope 3 from different states (**Appendix E**).

In this thesis, GHG emissions are divided into the emissions from irrigation water and the emissions from all the other activities for crop production. The GHG emissions for these two parts are calculated, respectively. The GAF tool takes cares of carbon emissions excluding the irrigation activities, while emissions from the irrigation are determined by Equation (10) below. The emissions from the direct energy use in irrigation (t/ha) is denoted as:

$$G_{Wi} = \mathrm{f}_{ED}^{e} \cdot E_i \tag{10}$$

where f_{ED}^{e} is the emission factor for diesel fuels. In the alternate energy scenario design, the on-grid electricity will be added in.

The total GHG emission from the whole cropping system is represented as:

$$G_i = \sum_{i=1}^{n} (G_{Wi} \cdot W_i \cdot A_i + G_{Fi} \cdot A_i) \tag{11}$$

where G_{Wi} is the GHG emissions from irrigation activities (tCO2e/ML); G_{Fi} is all the other GHG emissions for growing and producing crops (excluding emissions caused by irrigation activities) (tCO2e/ha).

Accordingly, the carbon costs for the cropping system (C_G) can then be expressed as:

$$C_G = \sum_{i=1}^{n} (p_G \cdot G_i) = \sum_{i=1}^{n} (p_G \cdot G_{Wi} \cdot W_i \cdot A_i + p_G \cdot G_{Fi} \cdot A_i) \tag{12}$$

where p_G represents carbon price (AU$/tCO2e). The data for carbon prices can be accessed via the Emissions Reduction Fund (ERF) website (Australian Government 2023).

3.4.6. The integrated optimization model

The gross profits denoted by $\mathrm{P}_{rofit}$for crop production of the whole cropping system is represented as:

$$\mathrm{P}_{rofit} = \sum_{i=1}^{n} P_i(\, W_i, A_i) \tag{13}$$

where the key independent variables are water application rate (W_i) and irrigated area (A_i).

3.4.6.1. Objective function

A nonlinear programming (NLP) model is hereby generated with the aim of maximizing the profits in the Equation (14), subject to several land, water, technical and administrative constraints. The model is denoted in the form of vector functions as follows:

$$\begin{aligned} &maximise\ \mathrm{P}_{rofit} = f(\boldsymbol{x}) \quad x \in R^n \\ &subject\ to\ c_i(\boldsymbol{x}) = 0, \qquad i \in E \\ &c_i(\boldsymbol{x}) \geq 0, \qquad i \in I. \end{aligned} \tag{14}$$

where the objective function $f(\boldsymbol{x})$ represents the right hand side of Equation (14) with $\boldsymbol{x}$ as a vector of the input variables including the water use and irrigated areas of each crop, and so on $c_i(\boldsymbol{x})$, i = 1, 2, . . . , n are additional constraint functions. E and I are the index sets of equality and inequality constraints respectively. The objective function is a nonlinear function while the constraint functions can be either linear or nonlinear.

3.4.6.2. Constraints

- Water Availability Constraint

Total water use should not exceed the corresponding announced water allocation or total water use available for the water year, as represented as:

$$\sum_{i=1}^{n} (W_i \cdot A_i) \ \leq \mathrm{W} \tag{15}$$

where W_i is the irrigation water application in field (ML/ha) of crop i and W is the water allocated (out of the total water entitlement) or total actual water use for the irrigation system during a certain water year. The allocated water entitlement (surface water +groundwater) for irrigation of both cotton and winter wheat within Toowoomba Region during the water year 2020-2021 is 50,719.33 Megalitres (ML) (ABS 2022b).

- Irrigation Water Constraints

As the CWPF (Stewart model) used for this study is mainly applicable to cropping with deficit irrigation, the irrigation water application rate (W_i) should not exceed the maximal rate (W_i^{max}) for each crop respectively, and should be non-negative, as denoted below:

$$0 \leq W_i \ \leq W_i^{max} \tag{16}$$

- Allowable Irrigated Area Constraints

Factors such as management considerations, market conditions, machinery capacity of the farm, and climatic conditions restrict the minimal or maximal land acreages for certain crops to meet the regulations on local land use in the area.

$$TA_i^{min} \leq A_i \ \leq TA_i^{max} \tag{17}$$

where TA_i^{min} and TA_i^{max} represent minimal and maximal values, respectively, of the irrigated area under crop i. The available arable land for irrigated cotton in Toowoomba Region during 2020-2021 is 11,651.59 ha with a numerical range from 55.51 ha to 14,766.28 ha during 2010/11-2020/2021. For irrigated cereal grains, it is 7,767.61 ha during 2020-2021 with a numerical range from 278.11 ha to 7,767.61 ha during 2010/11-2020/2021 (ABS 2022b).

- Non-Negativity Constraints

The non-negativity constraints ensure that the solution remains feasible.

$$W_i, A_i \ \geq 0 \tag{18}$$

3.4.7. Problem solving

There are several methods to solve a constrained non-linear optimization model. Some methods are designed to solve mathematical models with higher order parameters, which require complex calculations and skilled coding techniques, such as Sequential Least Squares Programming (SLSQP) and Trust-Region Constrained implemented in Python-based software, and Sequential Quadratic Programming

(SQP) implemented in C-language-based software. These methods require users to be highly familiar with the mathematical rationales and logics, and well skilled in coding. They are not friendly to all users.

In this thesis, the integrated model is developed with a simple structure with parameters being in no higher orders. It would not be necessary to adopt complex model solving methods like those mentioned above. Instead, for better operability, the method selected to solve the model is sourced from Excel to achieve the most probable optimums in a more cost effective manner. These methods and tools built in Excel are simple, cost-effective, user friendly, and ready to use with good visualization. There are three solving methods built in Excel. Comparisons between them are outlined in **Table 3.7**.

Table 3.7. Comparisons among different solving methods built in Excel.

Methods	Advantages	Disadvantages
Generalized Reduced Gradient (GRG) Nonlinear	Fastest, no high requirement for calculation capacit.	1. Highly dependent on initial condtions. 2. No secured values on global optimum solution. 3. Functions should be smooth.
Evolutionary	More robust than GRG Nonlinear and morel likely to spot a globally optimum solution.	Very slow and require high criteria for calculations
Simplex Linear Programming (LP)	Very robust for linear problems and secured globallyoptimum solution	Only limited to linear problems

Note: The in-built tool in Microsoft Excel is “Excel Solver”. Within the Slover, there are three main methods: GRG Nonlinear, Evolutionary, and Simplex LP.

The GRG Nonlinear and Evolutionary are better for nonlinear problems, while Simplex LP is limited to linear problems only. The Simplex LP is disadvantaged for a wider range of application due to restriction in programming types, as most cases are nonlinear programming based. To simplify Evolutionary calculations, some settings can be chosen, such as Mutation Rate and Population Size. However, it may reduce result returns to execute this solution simplification. Even though the speed of GRG Nonlinear brings a compromise on results returned, a GRG Multistart setting built in the Excel can bridge the gap, reaching a nice comprise between the robustness of Evolutionary and the speed of GRG Nonlinear (Díaz de los Ríos et al. 2020; Sen 2020; EngineerExcel 2022; Zakwan 2022). Therefore, the GRG Nonlinear method with a GRG Multistart setting is selected for solving the single objective constrained non-linear multivariate programming model in our study.

3.5. Sensitivity analysis

During the modelling process, there might be underlying errors or inaccessible parameters. This will lead to model uncertainties (Wagener et al. 2005; Sun et al. 2016). Due to the uncertainties of inputs and processes, it is essential to quantitatively ascertain and analyse the effects of model uncertainty on model reliability by examining model parameters (Boote et al. 1996; Green et al. 2003). In this regard, sensitivity analysis can be used in the construction, validation, and application of the model. It can determine sensitive parameters, help data mining and scenario setting, and reduce the model's simulative error level, so as to provide better support for decision making.

Chen et al. (2017) and Saltelli et al. (2019) compare different functions, mathematical theories and methods for Sensitivity Analysis coupled with summarized applications, advantages and limits. After comparative analysis on the methods (**Appendix F)**, it is determined that the Morris sensitivity analysis method is the most appropriate one for this study. It is suitable for non-linear models (non-linear response between inputs and outputs) with relatively low computational cost. It is easy for application and suitable for quickly identifying and screening potentially vital sensitive parameters in the model (Looss et al. 2015; Chen et al. 2017).

The sensitivity analysis is implemented via Python-based open-source software, SALib, by being coded into Python algorithms. SALib is an open-source library written in Python for performing sensitivity analysis. It contains Python-based implementations of commonly used sensitivity analysis methods, including Sobol (Sobol 2001; Saltelli 2002; Saltelli et al. 2010), Morris (Morris 1991; Campolongo et al. 2007), FAST (Cukier et al. 1973; Saltelli et al. 1999), and so on

3.6. Scenario design

3.6.1. Introduction

Scenarios are claimed to systematically envision and construct potential future situations in support of strategic decision making and for a better understanding the problems involved in the situations (Alcamo 2008). Likewise, scenario analysis are effective in dealing with uncertainties (Postma et al. 2005). It has become a popular approach in organizational planning and participatory exercises in pursuit of sustainable development (Duinker et al. 2007).

In order to investigate how different practices and policies influence optimized synergies of resource use (water and land), economic benefits, and associated environmental performances (GHG emissions) in the single crop rotation system, potential scenarios will be designed relative to a baseline scenario (business-as-usual) in Chapter 4. The scenarios will be divided into two series upon the developed models, presented, and discussed in detail in subsequent chapters respectively.

The integrated models developed in this study are (1) the basic core model that has developed in Section 3.4 Model Development, and (2) two further developed models upon the basic model (to be presented in Section 3.6.2). They involve an additional value chain commencing at the post-harvest or fallow stage, where usually farmers manage the crop residues by ploughing into soil, and ending at a disposal stage, where crop residues are processed, disposed, and utilized by being converted into certain end products.

In Chapter 4, the model developed in the above sections will be used in a baseline scenario with common conditions in Toowoomba Region. After preliminary result analysis, relevant discussions, and sensitivity analysis are conducted in Chapter 4, potentially influential factors will be accordingly considered for scenario design in Chapter 5, such as crop prices, rainfall, alternative energy sources and associated costs in irrigation, and carbon price policies. Thus, Chapter 4 and Chapter 5 are about applications of the basic core model to different scenarios.

Chapter 6 will present scenarios analysis for alternative crop residue disposal methods (mulching, composting, incineration/combustion with energy recovery) and compare them with the baseline scenario. In Chapter 7, other potentially impactful scenarios will be presented and discussed accordingly. So, these chapters will be about applications of the two further developed models to different scenarios.

The conventional and common crop residue management practice in Australia is mainly incorporating into soil, which is included in the stage of post-harvest and fallow management (Woods 2017; Graham 2022b). One of the further developed models will be used in scenarios with a mulching or a composting method displacing the conventional crop residue management practice (incorporating/ploughing into soil). The other model will be for scenarios with an incineration/combustion (with energy recovery) method replacing the conventional crop residue management practice. The model development of the extra components upon the basic model are described in the succeeding sections.

3.6.2. Environmental management in crop residues

As per literature review in Chapter 2, there has been a lack of studies on disposing crop residues incorporated in an agricultural WEF nexus system. It will be significant to compare and analyse different strategies for crop residue disposals regarding potential impacts on the WEF nexus based cropping system. In this regard, this series of scenarios implement optimization, upon the baseline situation, by considering 3 different environmental methods for crop residue disposals, (1) mulching, (2) composting, and (3) combustion/incineration with energy recovery. They are the main locally available disposal methods.

3.6.2.1. Yield of crop residues

Agricultural crop residues are divided into primary and secondary crop residues. Primary crop residues refer to the plant material available on the field after harvesting of the main product such as straw, stalk, stubble and leaves, while secondary crop residues refer to processed residues such as husks, hulls, bagasse, corncob, coffee pulp (Honorato-Salazar et al. 2020). The amount of primary residues is calculated by the Residue Index (RI) of each crop, which is defined as the ratio of the dry weight of the amount of residue generated to the total amount of primary crop harvested for a particular cultivar (Smeets et al. 2004; Rosillo-Calle et al. 2007; Honorato-Salazar et al. 2020). RI is generally obtained from the Harvest Index (HI), which is defined as the ratio of harvested product to total aboveground biomass of the crop at the time of harvesting (Smeets et al. 2004; Unkovich et al. 2010). So, RI equals (1/HI)-1. As for secondary residues, a processing residue coefficient (amount of residue/amount of raw material) is used to calculate the quantity of residue. Values of HI and processing residue coefficient have been obtained from peer studies about crop residues.

So, the quantity of crop residues yielded ($Q_{CR,i}$) that is usable for biofuel and biomass production is denoted as:

$$Q_{CR,i} = P_{C\&U,i} \cdot (RI_{i1} + RI_{i2}) \cdot Y_i \cdot A_i \tag{19}$$

where RI_{i1} and RI_{i2} are the primary and secondary residue index of crop i, respectively; $P_{C\&U,i}$ is the conjunctive coefficient for collectable and utilizable potential mass of the crop residues from crop i.

3.6.2.2. Life-cycle costs in crop residue management

The method to calculate the life cycle costs of a specific disposal method is based on and adapted from the study by Li et al. (2018). To specify the logistic processes of crop residues that are scattered around the cropping areas, several assumptions are made:

- Crop residues are evenly distributed within the cropping areas of the studied region without disparity in collection and transportation processes;
- The quantity of different types of crop residues is summable;
- The life cycle of one environmental disposal method is defined to be the workflow/process from the crop residue collections to the completed end products.

The major life-cycle costs for the disposals can include those associated with energy use, potential maintenance, potential labour, processing cost, transportation cost, and other cost (for instance loading and storage) (Li et al. 2018). According to situations in Toowoomba Region, these costs embedded within the crop residue disposal practices primarily comprise commercial costs of logistics, processing and disposal, and carbon costs of logistics, process and disposal (Zhang et al. 2020b).

The logistic costs can be calculated by the mean value of transport distance (freight to site) (L_i) multiplying the quantity of residues provided ($Q_{CR,i}$) and the charges for logistics ($p_{logi,i}$), expressed as below:

$$C_{logi,i} = p_{logi,i} \cdot Q_{CR,i} \cdot L_i \tag{20}$$

The processing and disposal costs can be calculated by the quantity of residues provided ($Q_{CR,i}$) multiplying the commercial charges per unit mass of residues for the disposal services ($P_{disp,i}$), expressed as below:

$$C_{disp,i} = p_{disp,i} \cdot Q_{CR,i} \tag{21}$$

3.6.2.3. GHG emissions in the crop residue disposal scenarios

Correspondingly, potential GHG emissions are estimated on these two major parts: (1) logistics; (2) pre-treating, processing, and disposal.

$$G_{logi,i} = g_{logi,i} \cdot Q_{CR,i} \cdot L_i \tag{22}$$

$$G_{disp,i} = g_{disp,i} \cdot Q_{CR,i} \tag{23}$$

where $G_{logi,i}$ is the GHG emissions from transporting residues of crop i, with $g_{logi,i}$ being the unit GHG emissions obtainable from the database AusLCI (ALCAS 2020); $G_{disp,i}$ is the GHG emissions from disposing residues of crop i, with $g_{disp,i}$ being the unit GHG emissions obtainable from AusLCI (ALCAS 2020).

3.6.2.4. End products and economic benefits

In this study, the three alternative crop residue disposal methods bring main end products of heavy and fine mulch, high-grade compost, which can be used as soil conditioner/booster back to farms, and electricity exported back to the grid or reused on farms (Phoenix Power Recycles 2022; Remondis 2022; WestRex 2023; Zilch Waste Recycles 2023). Through literature review about agricultural residues, economic benefits may be generated in such practices featuring biomass and/or bioenergy recovery. These benefits can be regarded as either revenues or avoided costs that will render the cropping system more profitable.

For mulching and composting, the benefits mainly include (1) avoided costs from conventional crop residue management (incorporation with soil in the basic scenario) and (2) avoided carbon costs imposed on GHG emissions from this conventional management (GHG emissions from ploughing into soil).

$$B_i = C_{avoi,i} \cdot A_i + \ p_G \cdot G_{avoi,i} \cdot A_i \tag{24}$$

where B_i is the avoided costs as benefits; $C_{avoi,i}$ is the avoided costs per ha land use by displacing the conventional practice; p_G is the carbon price (AU$/tCO2e); $G_{avoi,i}$ is the avoided GHG emissions per unit ha of land use.

For incineration/combustion with energy recovery, additional economic benefits are gained from recycling the power generated, including avoided costs by reusing the power and associated avoided carbon costs.

$$B_i = C_{avoi,i} \cdot A_i + \ p_G \cdot G_{avoi,i} \cdot A_i \ + \ (p_{elec} + \ p_G \cdot f) \cdot Q_{CR,i} \cdot LHI_i \cdot E_{elec} \tag{25}$$

where p_{elec} is the feed-in tariff for the power returned to the grid; f is the factor regarding how much GHG emissions would supposedly be incurred by generating one unit kWh of grid electricity (tCO2e/kWh) under local conditions and techniques; LHI_i is the lower heating value; E_{elec} is the efficiency for generating power at the waste facilities. A lower heating value (LHV) is adopted in this study given energy losses in water vapor, as opposed to a higher heating value (HHV). The energy loss is in the form of heat contained in water vapor discharged during and after processing the crop residues (Paul et al. 2020; Song et al. 2020).

3.7. Conclusion

This chapter has described the study scope, methods of data collection, and processes of model development and scenario design.

- Definitions of study boundary and data collection

The geographical scope of this study is defined by selecting the Toowoomba Region (local scale) as the study area. The temporal scope is confined to the water year of 2020-2021 (summer to winter). Crop selected are cotton and winter wheat, which constitute a suite of single crop rotation practices commonly implemented in Toowoomba Region. The most common irrigation system applied in Toowoomba Region is surface irrigation.

Core bulk datasets are drawn from SILO (Queensland Government 2022e) and AgMargins (Graham 2022b) for crop water yield model and variable costs. Other datasets are also utilized, such as AusLCI (ALCAS 2020) database for carbon emissions and crop residue scenarios, and other data from interviews, peer studies, websites, and so on.

- Model development

The overall model structure is to optimize the cropping profits with sub-models of crop water production function, water cost, other variable cost and carbon cost. The Stewart model (Doorenbos et al. 1979; Steduto et al. 2012) is adopted as the CWPF. The irrigation water combines surface water and underground water, and diesel fuels are commonly used in irrigation (basic situation). Other pre-farm, on-farm and off-farm activities incurring variable growing costs are included. GHG emissions are divided into those from irrigation and those from all the other activities except for irrigation. The whole model is structured as a constrained non-linear multivariate mathematical programming function, subject to water and land constraints. It is solved via Excel with an in-built modular solver, GRG Nonlinear.

- Sensitivity analysis method

The sensitivity analysis is performed via Morris Method (Morris 1991; Campolongo et al. 2007) on the Python-based open-source software, SALib, with coded Python algorithms.

- Scenario design

In Chapter 4, the model developed in above sections will be used in a baseline scenario with common conditions in Toowoomba Region. After preliminary result analysis, relevant discussions, and sensitivity analyses are conducted, in order to the key parameters or factors that impact the model outputs.

Potentially influential factors will be accordingly considered for scenario design in Chapter 5, such as crop prices, rainfall, alternative energy sources and associated costs in irrigation, and carbon price policies.

Chapter 6 will present scenarios analysis for alternative crop residue disposal methods (mulching, composting, incineration/combustion with energy recovery) and compare them with the baseline scenario. In Chapter 7, other potentially impactful situations will also be presented and discussed accordingly based on results in Chapter 4 - 6.

CHAPTER 4: APPLICATION OF THE BASIC MODEL FOR A SINGLE CROP ROTATION SYSTEM IN THE TOOWOOMBA REGION

4.1. Introduction

This chapter applies the basic core model developed in Chapter 3 to a single crop rotation system (cotton grown in summer and wheat grown in winter) within the Toowoomba Region with the most common situations. The general conclusions of this study may also apply to individual farms in this area. This is to achieve Objective (2) described in Chapter 1.

4.2. Model inputs

4.2.1. Crop yield and price

4.2.1.1. Maximum crop yield and maximum crop water requirement

The maximum crop yield values ($Y_{max,i}$) are 6.21 t/ha for cotton (lint and seed) and 6.00 t/ha for winter wheat within Toowoomba Region during 2015/16 and 2020/21. The maximum crop water requirement is 9.45 ML/ha for cotton and 3.26 ML/ha for wheat (Queensland Government 2022e).

4.2.1.2. Effective precipitation

The mean value of effective rainfall is 171 mm (1.71 ML/ha) for cotton and 125 mm (1.25 ML/ha) for wheat. Correspondingly, the mean value of actual rainfall is 462 mm (4.62 ML/ha) during cotton cultivation and 173 mm (1.73 ML/ha) during wheat cultivation (Queensland Government 2022e).

4.2.1.3. Maximum irrigation water application rate

Under a deficit irrigation practice, the combined uses of irrigation water application rate and effective precipitation should not exceed the maximum crop water requirement. Thus, the upper limit of irrigation water application rate should not be over 7.74 ML/ha for cotton and 2.02 ML/ha for wheat (Queensland Government 2022e).

4.2.1.4. Price of cotton and wheat

The most recent market price in the Toowoomba Region is AU$550/bale for cotton lint, AU$190/t for cotton seed, and AU$400/t for irrigated winter wheat (Woods 2017; Queensland Government 2022d). Cotton per unit mass can produce about 42% cotton lint and 58% cotton seed (Baffes 2021).

4.2.2. Water inputs and land use with associated costs

4.2.2.1. Water costs from irrigation

The conjunctive water used for irrigation in cropping are surface water and groundwater combined with overland flow water stored in ring tanks (An-Vo et al. 2015; Graham 2022b). Water costs mainly include charges for irrigation water used, diesel fuels used in operating the irrigation machinery (surface irrigation) and operations of machinery (oil, repairs and maintenance). The whole water costs for either cotton or wheat are AU$72/ML irrigation water applied (Woods 2017; Queensland Government 2022d), including:

- Cost of irrigation water used, AU$20/ML water applied;
- Cost of diesel used, AU$21.41/ML water applied, paired with bulk supply diesel price of AU$0.62/L diesel used;
- Cost of machinery operations, AU$30.59/ML water applied (Graham 2022a).

4.2.2.2. Water availability for irrigation

Total water use should not exceed the corresponding announced water allocation or total water uses available for the water year. The water sources for the irrigated cropping areas in Toowoomba Region can be broken down into:

- Surface water (57%) taken from irrigation channels or irrigation pipelines, on-farm dams or tanks, rivers, creeks, and lakes, recycled/re-used water from off-farm sources (such as re-use schemes, mines), town or reticulated mains supply;
- Groundwater (43%) taken from bores, springs, or wells (ABS 2022b).

The allocated water entitlement for irrigation of both cotton and wheat within Toowoomba Region during the water year 2020-2021 was 38.92 Gigalitres (GL)

(ABS 2022b). The maximal and minimal water use for irrigated cotton and wheat rotation was 66.04 GL in 2012/13 and 231.28 GL in 2015/16 (ABS 2022b).

4.2.2.3. Irrigated Area

The watered areas for irrigated cotton in Toowoomba Region ranges from 56 ha in 2015/16 to 11,652 ha in 2020/21 (ABS 2022b).

4.2.3. Energy and resource inputs from the other cropping activities

These inputs are from all the other pre-farm, on-farm and off-farm activities incurring costs in growing cotton and wheat, excluding the water costs and the costs incurred by emitting GHGs. These growing costs are AU$2,255/ha for cotton and AU$628/ha. The resource and energy inputs and associated costs are derived from the databases, AgMargins (Graham 2022b; Queensland Government 2022d) and Australian Life Cycle Inventory (AusLCI) (ALCAS 2020; lifecycles. 2020).

4.2.4. Estimation of GHG emissions and associated costs

The energy and resource inputs are entered into the tool of the Greenhouse Accounting Frameworks (GAF) for Australian Primary Industries (Ekonomou et al. 2022a). The estimated GHG emissions are 3.26 tCO2e/ha for cotton (0.10 tCO2e/ML/ha from irrigation and 2.48 tCO2e/ha from the other activities) and 2.74 tCO2e/ha for wheat (0.12 tCO2e /ML/ha from irrigation and 2.49 tCO2e/ha from the other activities).

Under this estimation, the intensities of GHG emissions from irrigation per ML irrigation water applied per ha irrigated area in cotton cultivation and in wheat cultivation are close. For instance, under an actual average irrigation water application rate of 8 ML/ha on cotton (Australian Government 2023), the intensity of GHG emissions from irrigation in cotton cultivation is 0.78 tCO2e/ha. Under an actual average irrigation water application rate of 2.5 ML/ha on wheat (Australian Government 2023), the intensity of GHG emissions from irrigation in wheat cultivation is 0.25 tCO2e/ha. Both are around 0.11 tCO2e/ML/ha after being converted to a “per ML per ha” unit.

Regarding carbon cost, the average carbon price (AU$15.99/tCO2e) from the latest auction of the Australian government's emission reduction funds is utilized (Australian Government 2021).

Given water application rates of 8 ML/ha on cotton and 2.5 ML/ha on wheat, an example of GHG emission intensity (tCO2e/ha) from variable resources applied estimated by this tool is shown in **Table 4.1** below.

Table 4.1. Summary of outputs from the Greenhouse Accounting Frameworks (GAF) Tool for cotton and wheat, GHG emission intensity in tCO2e/ha.

Crop	Cotton (tCO2e/ha)	Wheat (tCO2e/ha)
Scope 1: GHG emissions (on-farm)		
Fuel	1.03	0.36
Lime	-	-
Urea	0.19	0.34
Fertilizer	0.53	0.79
Atmospheric Deposition	0.06	0.09
Leaching and Runoff of Nitrogen	-	-
Crop residues (returned to soil)	0.57	0.27
Sub-total	2.38	1.85
Scope 2: GHG emissions (off-farm)		
Electricity	0.20	-
Sub-total	0.20	-
Scope 3: GHG emissions (pre-farm)		
Fertilizer (urea + superphosphate)	0.47	0.83
Herbicides/pesticides	0.12	0.04
Electricity	0.03	-
Fuel	0.05	0.02
Lime	-	-
Sub-total	0.68	0.89
Net GHG emissions	3.26	2.74

Note: The fuels used is mainly diesels with few petrol fuels. The major crop residue disposal method is ploughing to the soil, as field burning is rare now in Australia. The electricity for cotton cultivation (off-farm) is used by machinery except irrigation. Irrigation activities primarily use diesel fuels in this case (baseline scenario). There is no forestry system considered in this study, so carbon sequestration in trees is zero value and excluded in this table.

4.2.5. An overview of main model inputs

The major model inputs are outlined in conjunction with average values of latest data indicated below in **Table 4.2**. Except four key independent variables (irrigated areas and water application rates on both cotton and wheat), data for the key 13 parameters are entered into the model for running and solving in Excel.

Table 4.2. Summary of input parameters and mean values from the latest data in 2020/21.

No.	Inputs	Mean value	References
1	Price of cotton lint (AU$/bale)	550	Graham (2022b)
2	Price of cotton seed (AU$/t)	190	Graham (2022b)
3	Effective rainfall for cotton (ML/ha)	1.71	Queensland Government (2022e)
4	Water cost (AU$/ML water use)	72	Graham (2022b)
5	Growing cost of cotton (excl. water cost) (AU$/ha)	2,255	Graham (2022b)
6	Price of carbon (AU$/tCO2e)	15.99	Australian Government (2023)
7	GHG emissions from irrigation in cotton cultivation (tCO2e/ML/ha)	0.10	Queensland Government (2022d) Ekonomou et al. (2022b)
8	GHG Emissions from all other activities in cotton cultivation (tCO2e/ha)	2.48	Queensland Government (2022d) Ekonomou et al. (2022b)
9	Price of wheat (AU$/t)	400	Graham (2022b)
10	Effective rainfall for wheat (ML/ha)	1.25	Queensland Government (2022e)
11	Growing cost of wheat (excl. water cost) (AU $/ha)	628	ABS (2022b)
12	GHG emissions from irrigation in wheat cultivation (tCO2e/ML/ha)	0.10	Queensland Government (2022d) Ekonomou et al. (2022b)
13	GHG Emissions from all other activities in wheat cultivation (tCO2e/ha)	2.49	Queensland Government (2022d) Ekonomou et al. (2022b)

4.3. Sensitivity test inputs

The algorithms of sensitivity tests are written into Python language codes (**Appendix G**) and are run in the web-based software, Jupyter Notebook, embedded in the integrated software, Anaconda. Values of key input parameters are outlined below in **Table 4.3.** The model in this baseline scenario contains 13 key parameters with uncertainties, inclusive of the 4 key independent variables of the model, water application rates and irrigated areas for cotton and wheat respectively. These independent variables are also included in the sensitivity tests to examine and verify their comparative importance, as a benchmark, with other parameters. This will also help to better quantify and visualize the importance of other parameters and how they could potentially be interacting with each other.

Table 4.3. Summary of numerical ranges for each parameter in the model.

No.	Parameters	Lower value	Upper value	References
1	Water application rate of cotton (ML/ha)	0	8.17	Queensland Government (2022e)
2	Irrigated area of cotton (ha)	56	11,651	ABS (2022b)
3	Price of cotton lint (AU$/bale)	480	550	Graham (2022b)
4	Price of cotton seed (AU$/t)	0	190	Graham (2022b)
5	Effective rainfall for cotton (ML/ha)	1.28	2.37	Queensland Government (2022e)
6	Water cost (AU$/ML water use)	72	168	Graham (2022b)
7	Growing cost of cotton (excl. water cost) (AU$/ha)	1,483	2,257	Graham (2022b)
8	Price of carbon (AU$/tCO2e)	13.95	15.99	Australian Government (2023)
9	Water application rate of wheat (ML/ha)	0.00	3.11	Queensland Government (2022e)
10	Irrigated area of wheat (ha)	278	7,768	ABS (2022b)
11	Price of wheat (AU$/t)	220	400	Graham (2022b)
12	Effective rainfall for wheat (ML/ha)	0.16	1.48	Queensland Government (2022e)
13	Growing cost of wheat (excl. water cost) (AU$/ha)	573	639	ABS (2022b)

Note: The model in this baseline scenario contains 13 parameters with uncertainties. Among them, water application rates and irrigated areas for cotton and wheat are core independent variables. The importance of all these uncertain parameters listed in this table will be measured in the Sensitivity Analysis (SA).

In relation to scenarios of crop residue disposals, the basic core model is further developed into two more models, which contain extended value chains. One is for applications to mulching/composting related scenarios and the other is for applications to combustion related scenarios. As combustion involves energy recovery, four additional parameters are included on top of the mulching/composting model.

Table 4.4 lists extra components/parameters integrated into the model to study scenarios of crop residue disposals with mulching/composting and incineration/combustion associated scenarios, respectively.

Table 4.4. List of additional parameters for crop residue disposals related scenarios.

No.	Parameters	Lower value	Upper value	References
Disposal Method(s): Mulching or Composting				
1	Cost of logistics (AU$/hr)	130	250	Zilch Waste Recycles (2023) Cleanaway (2023) Phoenix Power Recycles (2022)
2	Average time of freight-to-site for crop residues (hr) [a]	0.57	1.03	Geographic Information System (GIS) based software [a]
3	Conjunctive coefficient of collected and utilized cotton straw/stalk	0.4	0.8	Graham (2022a) WestRex (2023)
4	Residue Index of cotton	0.0	1.9	Ekonomou et al. (2022b)
5	Cost of treatment, processing and disposal on residues (AU$/t)	10	90	SoilWealth (2017) WestRex (2023) Zilch Waste Recycles (2023) Remondis (2022) Cleanaway (2023) Phoenix Power Recycles (2022)
6	Cost of reapplying end products to farms (AU$/ha)	0.0	140	SoilWealth (2017)
7	Avoided cost from cotton straw/stalk (ploughing into soil) (AU$/ha)	0.0	63.5	Graham (2022b)
8	GHG emissions from logistics (tCO2e/tkm)	0.0	0.0004	ALCAS (2020)
9	Average distance of freight-to-site for crop residues (km) [b]	44.7	84.8	GIS based software [b]
10	GHG emissions from treatment, processing and disposal on residues (tCO2e/ha)	0.04	19.88	ALCAS (2020)
11	Avoided GHG emissions from cotton straw/stalk (ploughing into soil (tCO2e/ha)	0.0	0.6	Ekonomou et al. (2022b)
12	Conjunctive factor of collected and utilized wheat straw	0.4	0.8	Graham (2022a)
13	Residue Index of wheat	0.0	1.5	Ekonomou et al. (2022b)
14	Avoided cost from wheat straw (ploughing into soil) (AU$/ha)	0.0	53	Graham (2022b)
15	Avoided GHG emissions from wheat straw (ploughing into soil (tCO2e/ha)	0.0	0.3	Ekonomou et al. (2022b)
Disposal Method(s): Combustion				
16	Feed-in tariff of electricity (AU$/kWh)	0.12	0.26	Ergon Energy (2022b)
17	Lower heating value (LHV) of cotton straw/stalk (kWh/t) [c]	3800	4200	Kang et al. (2020) Paul et al. (2020) Song et al. (2020)
18	Efficiency for generating electricity by combustion in power plants [d]	0.2	0.6	Remondis (2022)
19	Lower heating value (LHV) for wheat straw (kWh/t)	3600	4100	Kang et al. (2020) Paul et al. (2020) Song et al. (2020)

Note: 28 parameters for the mulching/composting model and 32 parameters for the combustion model (inclusive of the 28 parameters) [e].

[a, b] The Average time (hr) and distance (km) of freight-to-site for collecting, transporting and delivering crop residues are estimated based on GIS software including ArcMap and QGIS in conjunction with Google Map.

[c] A lower heating value is used in this study given energy losses in water vapor, as opposed to a higher heating value (HHV). The energy loss is in the form of heat contained in water vapor discharged during and after processing the crop residues.

[d] The efficiency to generate electricity by combustion technology is used in conjunction with a LHV, namely in this study the percentage of electricity/power generated from crop residues per unit tonne.

[e] A list of additional 15 parameters included in the model with the numerical range of values. The extended model for mulching or composting contains 28 parameters for a sensitivity test inclusive of those 13 original parameters in the basic core model. The extended model for combustion contains 32 parameters for a sensitivity test inclusive of those 28 parameters in the mulching/composting model. Water application rates and irrigated areas for cotton and wheat are the two key independent variables. All the other uncertain parameters listed in this table are measured in this sensitivity analysis.

4.4. Key results and discussions

4.4.1. Application of the basic core model

This baseline simulation results are based on the total irrigated cropping area (11,652 ha) and total available water resource (surface + ground, 38.92 GL). Cropping is subject to a deficit irrigation practice employing regular surface irrigation systems in the Toowoomba Region. The maximal crop water requirement is 9.45ML/ha for cotton cultivation and 3.26ML/ha for wheat cultivation. These include average values of effective rainfall, 1.71ML/ha during cotton cultivation and 1.25ML/ha during wheat cultivation.

4.4.1.1. Resource use performances (land and water)

The optimal results for irrigated areas and water uses are presented in **Figure 4.1**. The irrigated areas total up to10,770 ha, nearly reaching the maximum (11,652 ha), where cotton cultivation occupies only 28% (3,003 ha) while wheat cultivation takes up 72% (7,768 ha). The total water uses are equal to the maximal water availability constraint 38.92 GL with cotton using 23.25 GL more than wheat using 15.67 GL. The water application rate on cotton (7.74ML/ha) is significantly higher than wheat (2.02ML/ha), both having reached the maximal water application rates.

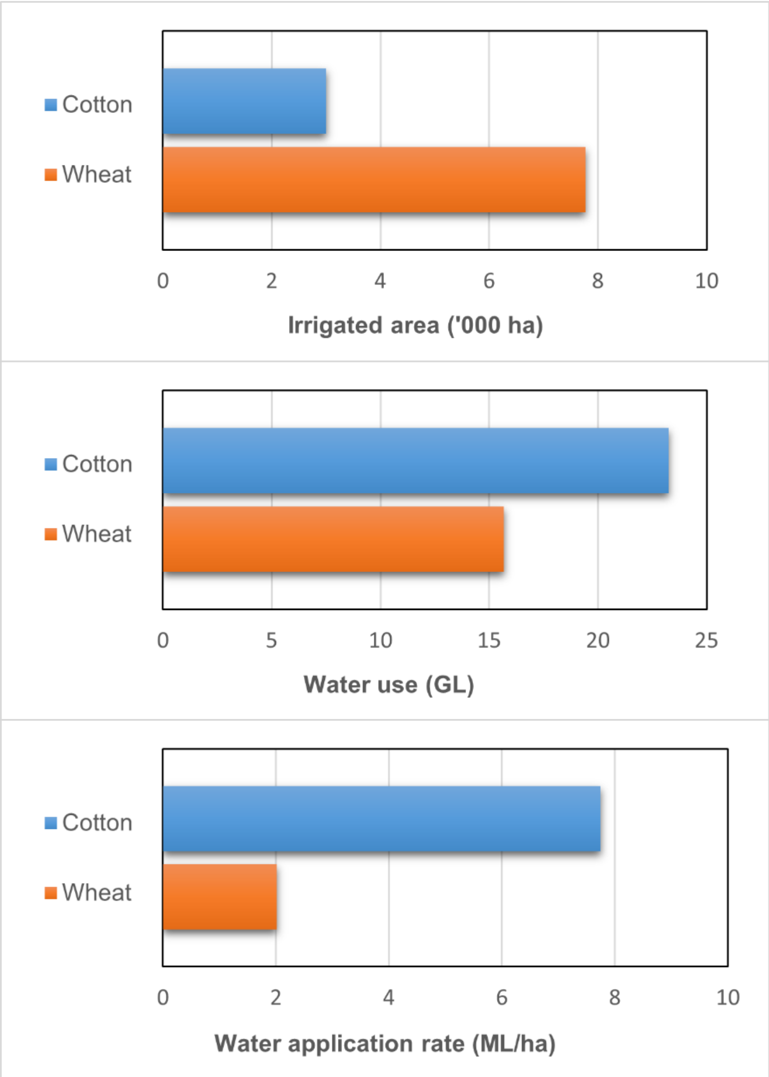


Figure 4.1. Optimal results for irrigated areas, water uses and water application rates in the basic core model applied to the single crop rotation (cotton grown in summer and wheat grown in winter) in Toowoomba Region.

4.4.1.2. Economic performances (gross margins and profits)

The optimal results for gross margins and profits are presented in **Figure 4.2**. While the water application rates on both crops peak, cotton and wheat yields reach the maximum, 6.21 t/ha (11.48 bale cotton lint/ha and 3.60 t cotton seed/ha) and 6t/ha, respectively. The gross margins per ML water used are AU$534/ML generated by cotton, smaller than AU$785/ML generated by wheat. The gross margins per hectare for cotton are AU$4,132, which are larger than the AU$1,584 per hectare for irrigated wheat. Under a cotton lint price AU$550/bale, cotton seed price AU$190/t and wheat price AU$400/t, total profits of AU$24.71 million are gained paired with total revenues of AU$39.65 million and total costs of AU$14.94 million. Cotton cultivation contributes to AU$12.41 million, which is close to wheat cultivation

AU$12.30 million. This is because the optimized water applied in cotton cultivation is approximately 3 times of that in wheat cultivation while optimized irrigated areas in cotton cultivation are only half of the optimized areas in wheat cultivation.

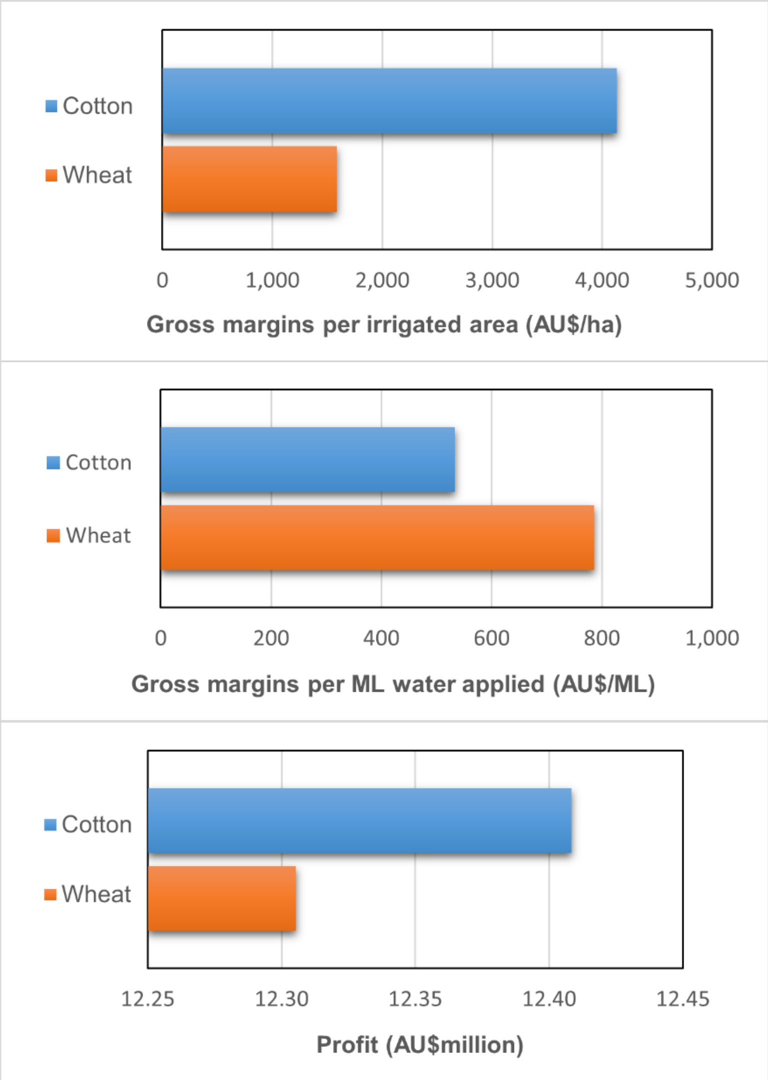


Figure 4.2. Optimal results for gross margins per hectare of irrigated areas and per megaliter of water applied and profits for cotton and wheat, respectively.

To examine the total variable costs (AU$14.94 million), a further breakdown is presented below in **Figure 4.3** inclusive of costs from main farming activities and items in conjunction with carbon cost. As a whole, the biggest part of total costs is incurred by applying nutrition (fertilizers) (24.65%), followed by irrigation (18.75%) and post-harvest (17.49%) activities. The post-harvest activity is set apart from crop residue management (ploughing into soil, 4.02%). The post-harvest mainly includes cartage of cotton and wheat and ginning of cotton. Irrigation does not contribute to a larger part than nutrition (fertilizers), as there is a low level of water cost in the Toowoomba Region (AU$72/ML water applied). The nutrition (fertilizers) cost is

AU$357 for cotton and AU$336 for wheat. Besides the major activities, crop residue management contributes to around 4% of the total costs, larger than the carbon cost (3.3%).

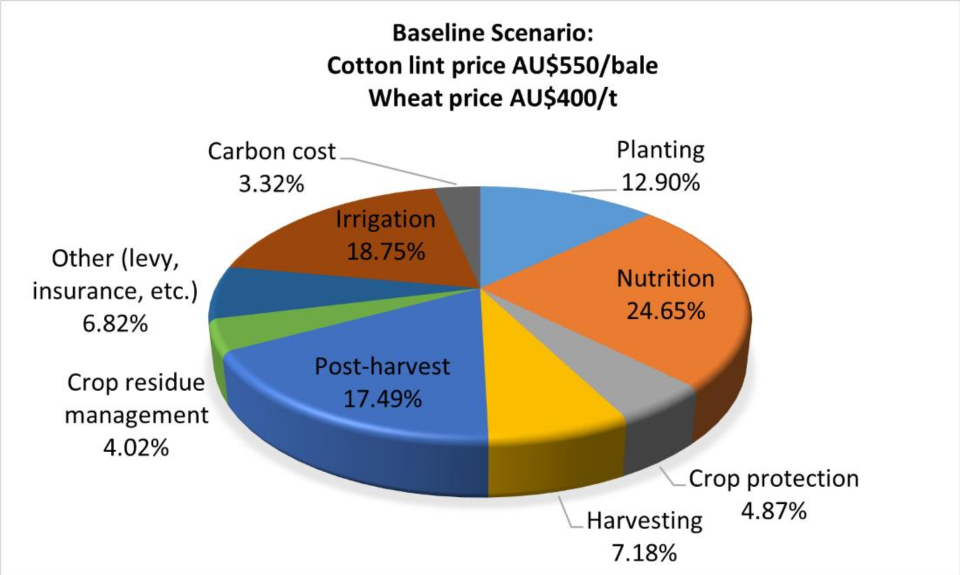


Figure 4.3. Breakdown of total variable costs from multiple growing activities inclusive of carbon cost imposed on GHG emissions from the cropping system.

4.4.1.3. Environmental performances (GHG emissions)

The optimal results for GHG emissions are presented in **Figure 4.4**. The total GHG emissions from wheat cultivation (21 ktCO_2e) are more than those from the cotton cultivation (9.8 ktCO_2e). These total up to 31 ktCO_2e. The GHG emission intensity of cotton cultivation per hectare is 3.25 tCO_2e/ha, higher than wheat cultivation at 2.69 tCO_2e/ha. This is caused by a significantly smaller irrigated land allocated to cotton than wheat. The GHG emission intensity from cotton is 0.52 tCO_2e/t cotton produced (equivalently 0.28 tCO_2e/bale cotton lint produced) higher than wheat 0.45 tCO_2e/t wheat produced.

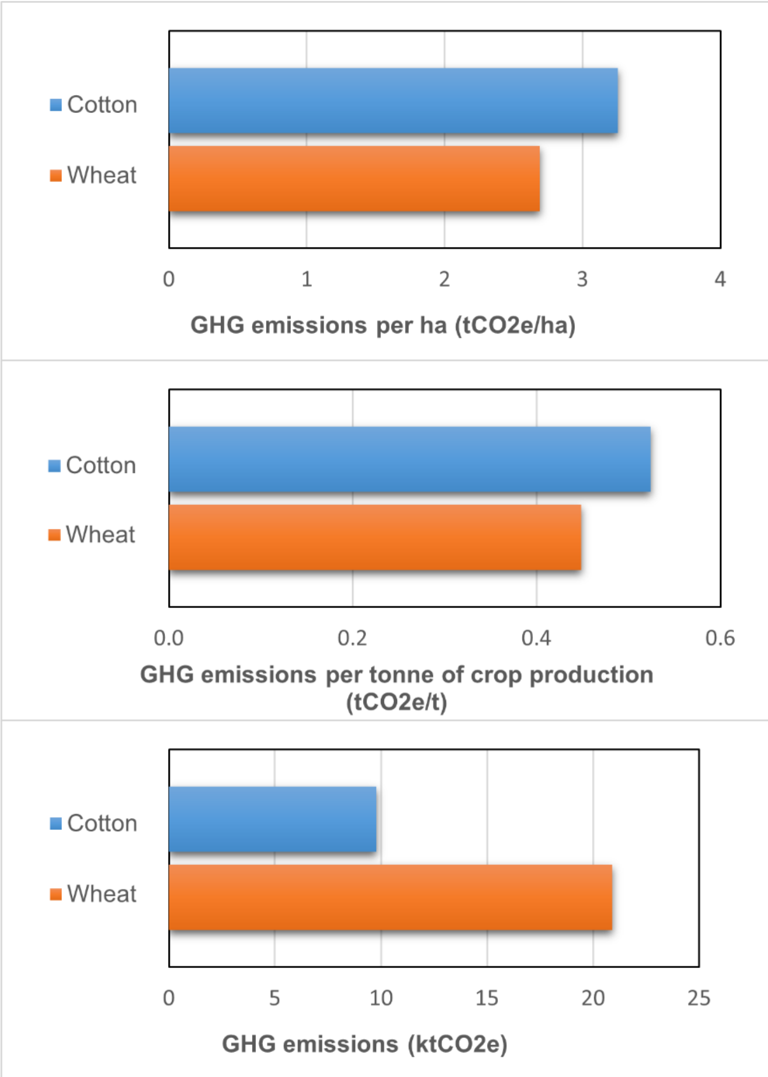


Figure 4.4. Optimal results for GHG emissions per hectare of irrigated areas, GHG emissions per tonne of crop production, and sub-total GHG emissions for each crop.

Figure 4.5 presents a breakdown of GHG emission sources from major resources and materials used and crop residues generated. The graph shows that nutrition (fertilizers) applied to on-farm and pre-farm activities (38% and 26% respectively) occupies most of the GHG emission sources, reaching above 60%. This is followed by conjunctive energy use (over 20%: diesel and petrol fuels 19%, electricity 2%) and crop residues (13%). In cotton cultivation, GHG emissions generated by combined energy usage is 40%, slightly higher than those by collective fertilizer application 38%. In wheat cultivation, there is a significantly lower percentage of GHG emissions by energy usage (13%) than emissions by fertilizer application (up to 76%). Crop residues show a noteworthy amount of GHG emissions in cotton (18%) compared with other GHG emission sources.

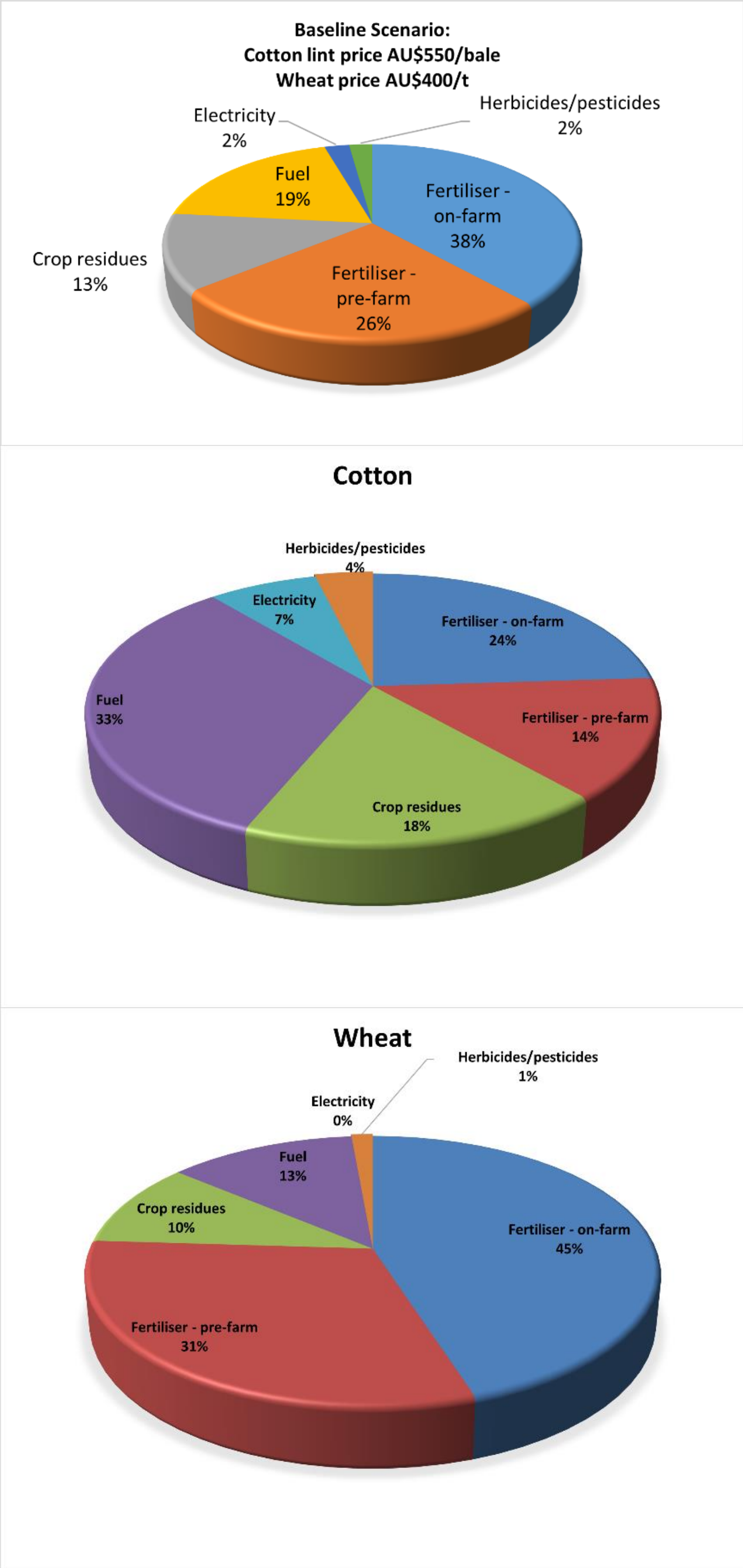


Figure 4.5. Breakdown of GHG emissions from resources and waste, including fertilizers both on-farm and off-farm, herbicides and/or pesticides, fuels (diesel and petrol) and on-grid electricity used for irrigation and other on-farm machinery, and crop residues incorporated into soil.

4.4.2. Sensitivity analysis

4.4.2.1. Results of sensitivity tests on the basic core model

Figure 4.6 shows the overall ranking of all 13 parameters involved in the basic core model.

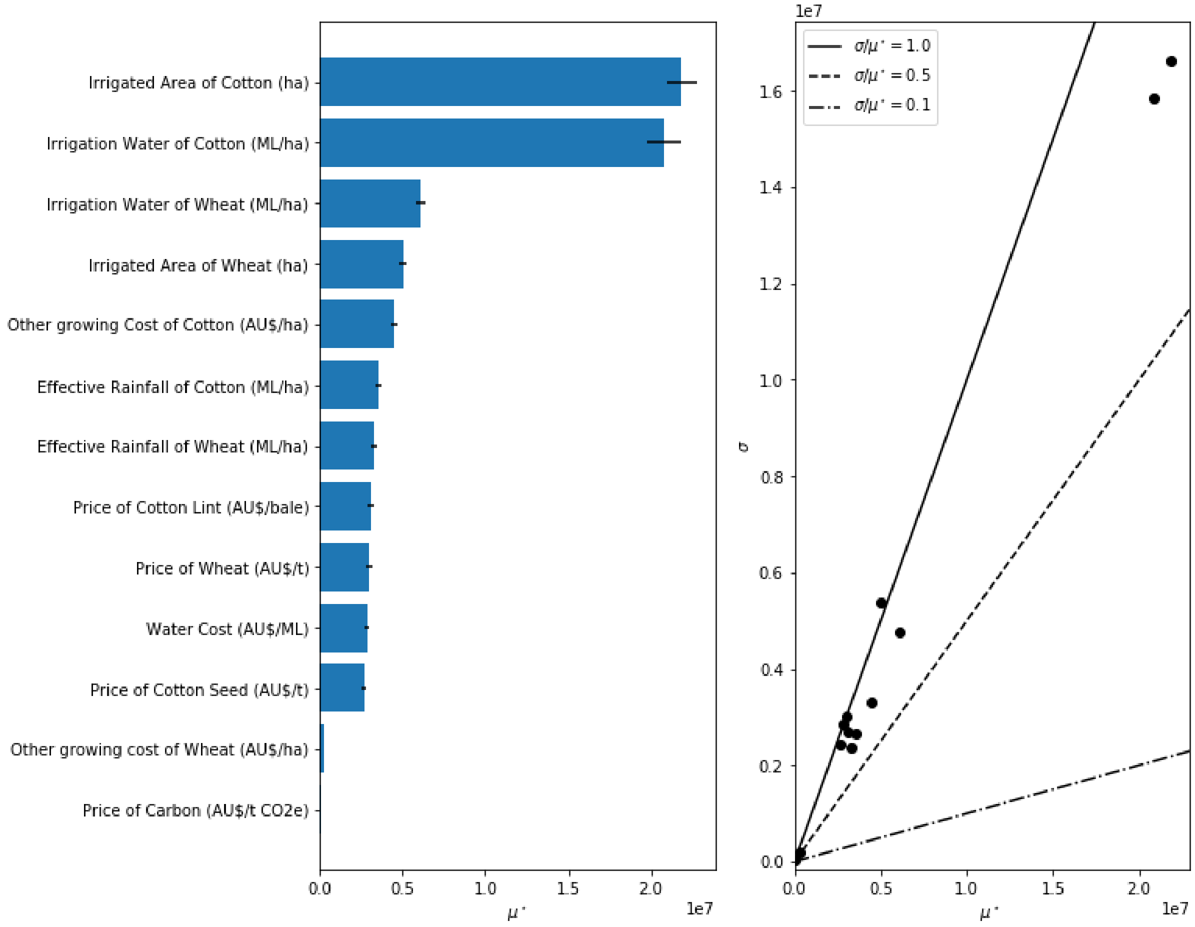


Figure 4.6. An overall ranking of the 13 parameters involved in the basic core model. The left-hand horizontal bar chart is the ranking of absolute mean values for each parameter's elementary effect (μ^*) from highest to lowest. The right-hand diagram provides comparisons of standard deviation (σ) and absolute mean value (μ^*) as σ/μ^* for elementary effects.

The left-hand bar chart shows the mean absolute value μ^* of elementary effects for each parameter. The elementary effects refer to the overall distribution of model outputs responsive to a certain parameter's inputs. By examining the dispersion of one input parameter's model output, the corresponding input parameter is estimated for its comparative sensitivity and ranked together with other parameters for their relative importance. Here in this thesis, the model output is total profits of the cropping system and thereby the elementary effects are specifically in the unit of AU$ million.

This μ^* metric indicates a general sensitivity of a parameter in the model. The higher the computed value of μ^* is, the more variable or uncertain the output of the model is to the input parameter and thus the more sensitive this parameter is to the model. In the right-hand graph, a standard deviation of elementary effect (σ) implies the nonlinear effects a parameter has on the output (Campolongo et al. 1999; Herman et al. 2019). Compared with μ^* metric and σ metric respectively, a conjunctive metric, σ/μ^*, is more accurate in measuring an overall importance/sensitivity of a parameter to the model. Each dot in the graph corresponds to a parameter with a value of σ/μ^*. The points close to the origin point refer to unimportant parameters. These parameters can be disregarded. By contrast, those deviated from the origin point are important. The farther away from the origin point in the y-axis, the stronger degree of nonlinearity or nonlinear interactions the parameters have on the model and therefore the more important/sensitive they are to the model.

In this basic model, the most five influential parameters in the order of importance/sensitivity are:

(1) irrigated area for cotton

(2) water application rate for cotton

(3) water application rate for winter wheat

(4) irrigated area for winter wheat.

(5) Growing costs of cotton, exclusive of water cost.

The first four are the core independent variables that are addressed in running and solving the integrated model. The first two are remarkably more sensitive than all the others. Except growing costs for wheat and carbon price, the others do not have very much difference in importance, which means their effects on the model are close and their importance are much lower than irrigation water and land use in cotton cultivation. Including the growing cost of cotton, all their μ^* values are below 0.5×10^7. In contrast, μ^* values for irrigated areas and water application rate in cotton growing are both more than 2.0×10^7.

On the right half of the figure, the two most discrete points correspond to the irrigated areas for cotton and the water application rate for cotton with σ values up to around 1.6×10^7. They have a larger non-linear effect on the model than the other parameters, followed by the water application rate for winter wheat and the irrigated areas for winter wheat. This is because the water and land use of cotton cultivation are intercorrelated with more variables than the other parameters in the model. In contrast, the other parameters are distributed around the solid line and the values of both σ and μ^* are much lower. So, they have significantly lower sensitivity and nonlinear effects on the model.

As such, these input parameters can be classified into three groups: (1) parameters with negligible effects, (2) parameters with linear effects on the model or fewer interactions with other parameters, and (3) parameters with nonlinear effects on the model or more interactions with other parameters (Franczyk 2019), as indicated in **Table 4.5**.

Table 4.5. Classification of input parameters in the basic core model as per the results of the sensitivity analysis.

Level	Category	Parameter
(1)	High effects	Water application rate for cotton Irrigated area for cotton
(2)	Medium effects	All the other parameters
(3)	Negligible or low effects	Growing cost for wheat (excl. water cost) Price for carbon

Note: (1) negligible or low effects, 2) medium effects, namely linear effects on the model or fewer interactions with other parameters, and (3) high effects, namely nonlinear effects or more interactions with other parameters.

4.4.2.2. Results of sensitivity tests on the two further developed models applied for crop residue disposals

As noted above, there are two further developed models upon the basic core model for crop residue disposals: one developed and applied for scenarios with mulching/composting, and the other for scenarios with combustion, both replacing the conventional agricultural disposals of ploughing crop residues into soil in the baseline scenario. **Figure 4.7** presents the result of sensitivity analysis on the mulching/composting scenario model. The first ten parameters in the order of importance/sensitivity are:

(1) Residue index (RI) of cotton

(2) Irrigated areas of cotton cultivation

(3) Costs of treatment, processing, and disposal on crop residues

(4) Water application rate of cotton

(5) Conjunctive factor of collected and utilized cotton straw/stalk

(6) Effective rainfall during cotton cultivation

(7) Price of cotton lint

(8) Cost of logistics

(9) Average time of freight to site for crop residues

(10) Price of cotton seed.

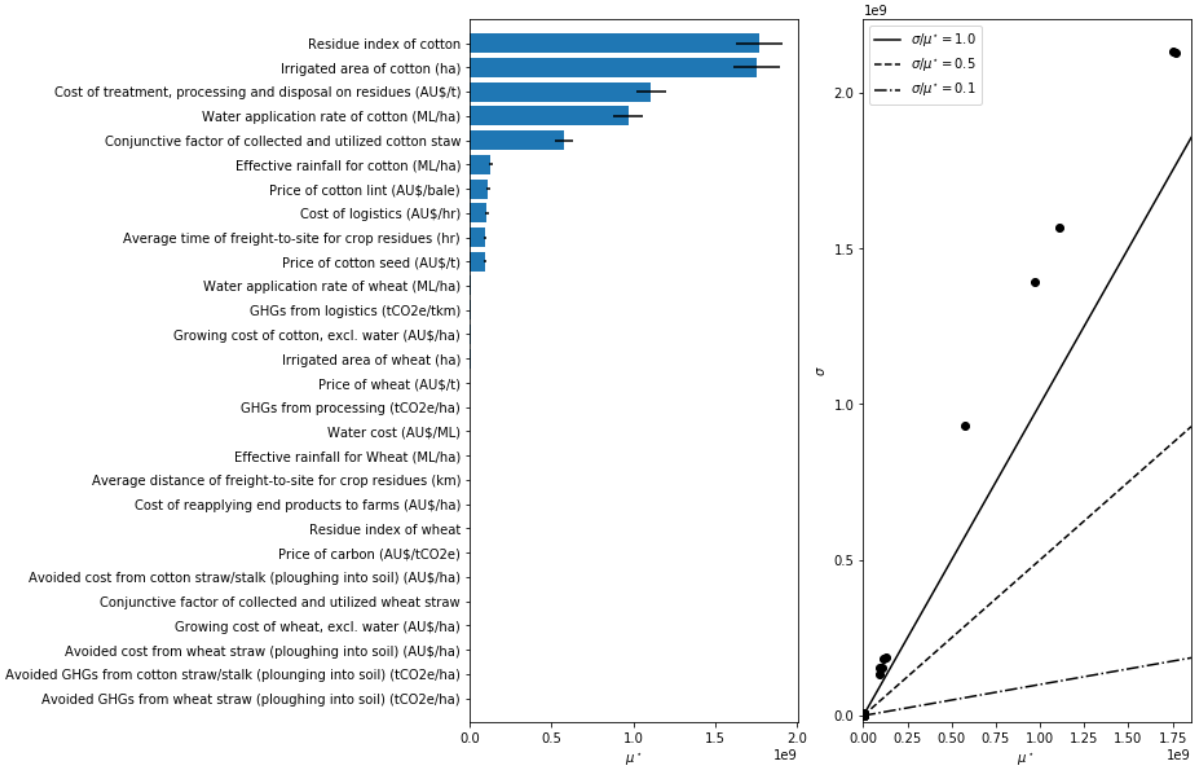


Figure 4.7. An overall ranking of totally 28 parameters involved in a further developed model for either mulching practice or composting practice with comparisons of standard deviation (σ) and mean absolute value (μ^*) as σ/μ^* for elementary effects.

μ^* values for these ten parameters range from 0.1×10^9 up to 1.7×10^9. μ^* values for all the other parameters are below 1.0×10^9. As opposed to the sensitivity test on the basic model, most parameters in this model are spread out beyond the solid line $\sigma/\mu^* = 1$. The values of σ range from about 0.1×10^9 up to approximately 2.2×10^9. This implies the parameters in this model have more interactive effects between each other and nonlinear effects on the model than those shown on the basic core model. This verifies that these parameters intertwine with more other variates in this further developed model than those in the basic core model.

In comparison, the first five are far more outstanding than the others, among which the irrigated land and water application rate of cotton are the key independent variables that are addressed in model running and solving. The other three can fall into two categories:

(1) Logistics on crop residues – RI of cotton, and conjunctive factor of

collected and utilized cotton straw/stalk

(2) Processing and utilization on crop residues – cost of treatment, processing and disposal on crop residues.

The RI reveals a main theoretical factor of crop residue yields generated directly from crop yields, while the conjunctive factor is the actual efficiency of utilizing residues towards converted end products after the disposal stage within the life cycle. The cost of treatment, processing and disposal on crop residues reflects a general situation of market price on organic residue disposals with privately owned businesses/facilities. Organic residue disposals are uncommon in Australia (Graham 2022b; Scobie 2022). The most common method of managing crop residue is to incorporate/plough the residues into soil. The cost of crop disposals has much variability in different localities and waste facilities due to immature market and price policies. This can explain why this cost is of high sensitivity in the model.

Relative to the sensitivity analysis on the basic core model, these three parameters associated with crop residue disposals are remarkable in sensitivity also due to their intricate relationships with higher orders of independent variables (water and land), thus making them non-linearly interacting with other parameters and influencing the model outcomes. **Table 4.6** lists the parameters classified into the three groups.

Table 4.6. Classification of input parameters (mulching/composting model) as per the results of the sensitivity analysis.

Level	Category	Parameter
(1)	High effects	Residue index (RI) of cotton Irrigated area of cotton cultivation Costs of treatment, processing, and disposal on crop residues Water application rate of cotton Conjunctive factor of collected and utilized cotton straw/stalk
(2)	Medium effects	Effective rainfall during cotton cultivation Price of cotton lint Cost of logistics Average time of freight to site for crop residues Price of cotton seed
(3)	Negligible or low effects	All the other parameters

Note: (1) negligible or low effects, (2) medium effects, namely linear effects on the model for fewer interactions with other parameters, and (3) high effects, namely nonlinear effects more interactions with other parameters.

Furthermore, **Figure 4.8** manifests the result of sensitivity analysis on the combustion scenario model. Comparatively, this combustion model shows a similar pattern of ranking to the mulching/composting model (**Figure 4.7**) with eleven remarkable parameters in the order of importance/sensitivity:

1) RI of cotton;
2) Irrigated areas of cotton;
3) Efficiency of electricity generation by power plant/waste facilities;
4) Feed-in tariffs on generated electricity returned to the grid;
5) Water application rate of cotton;
6) Conjunctive factor of collected and utilized cotton straw/stalk;
7) Cost of treatment, processing, and disposal on crop residues;
8) Effective rainfall during cotton cultivation;
9) Price of cotton lint;
10) Lower heating value (LHV) of cotton straw/stalk;
11) Price of cotton seed.

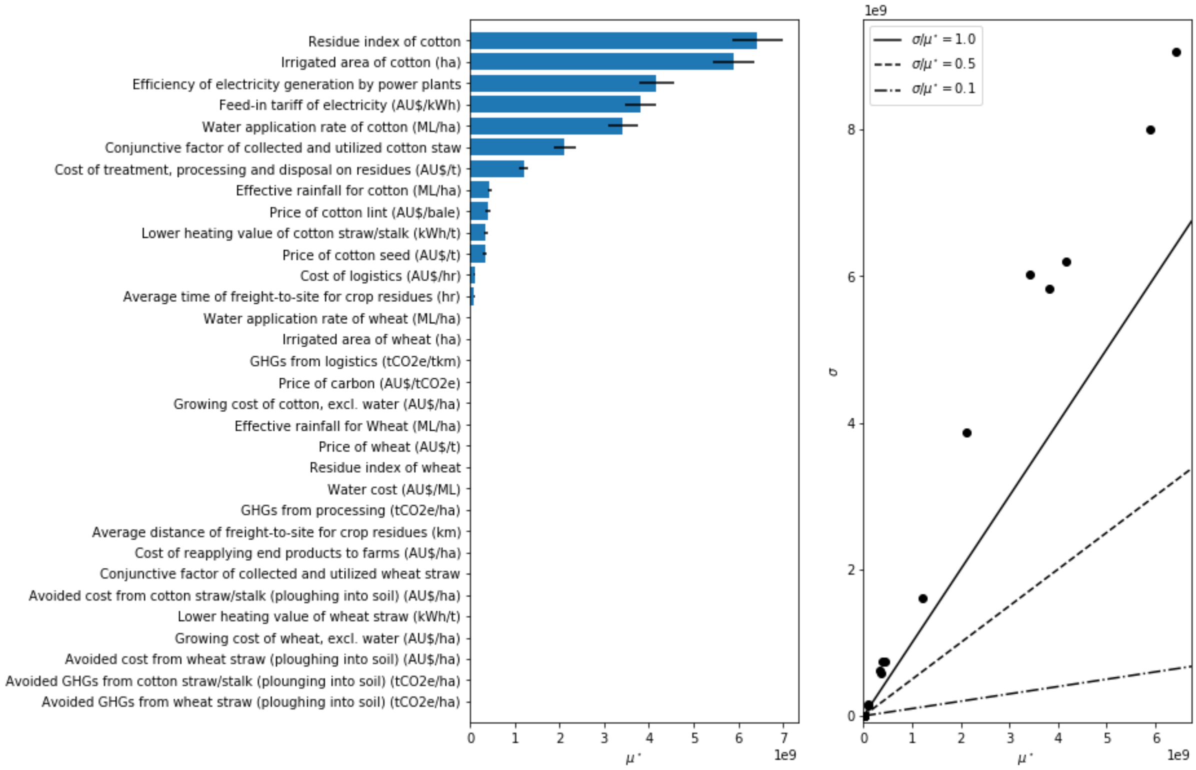


Figure 4.8. An overall ranking of totally 32 parameters involved in the further developed model for combustion practice with comparisons of standard deviation (σ) and absolute mean value (μ^*) for as σ/μ^* elementary effects.

The whole ranking in **Figure 4.8** varies slightly with 4 extra parameters included in this scenario. Two of them are specifically important: the efficiency of electricity generation by power plants/facilities that process and dispose the crop residues, and feed-in tariffs of electricity that is generated and exported back to the network. This means the energy recovery involved in incineration/combustion technically demonstrate important effects on the model outputs.

μ^* values for these eleven parameters range from around 0.5×10^9 up to approximately 6.5×10^9. Values of σ range from around 0.1×10^9 up to around 9.5×10^9. All the other parameters are close to the origin point. As opposed to the sensitivity tests on both the basic model and the mulching/composting model, most parameters in this model are even farther away and above from the solid line $\sigma/\mu^* = 1$. This unveils that parameters in this further developed model for incineration/combustion are more intertwined between each other, imposing stronger nonlinear effects on the model. These results of sensitivity analysis on both mulching/composing model and incineration/combustion scenario model indicate that the model outputs can be notably varied by identical levels of changes in parameter inputs. **Table 4.7** lists the parameters classified into the three groups.

Table 4.7. Classification of input parameters (Incineration/combustion model) as per the results of the sensitivity analysis.

Level	Category	Parameter
(1)	High effects	Residue index (RI) of cotton Irrigated area of cotton Efficiency of electricity generation by power plant/waste facilities Feed-in tariff on generated electricity returned to the grid Water application rate of cotton Conjunctive factor of collected and utilized cotton straw/stalk Costs of treatment, processing, and disposal on crop residues
(2)	Medium effects	Effective rainfall during cotton cultivation Price of cotton lint Lower heating value (LHV) of cotton straw/stalk Price of cotton seed
(3)	Negligible or low effects	All the other parameters

Note: (1) negligible or low effects, (2) medium effects, namely linear effects or fewer interactions with other parameters, and (3) high effects, namely nonlinear effects or more interactions with other parameters.

4.4.3. Discussions

4.4.3.1. Application of the basic core model (business as usual)

The core model developed in this study basically integrates water, energy, crop production, land, GHG emissions into one agronomic framework in the form of total profits. The key independent variables in this model are irrigated land use and water application rates for each crop in the cropping system. In essence, if these two key variables of each crop change, the other parameters will change accordingly as they are correlated to the independent variables. For instance, energy uses in irrigation (direct energy) and water costs are primarily determined by both irrigated land uses and water application rates. So are the GHG emissions from the direct energy and associated carbon costs from these emissions. The energy uses from other farming activities (indirect energy) and associated variable costs are primarily influenced by irrigated areas, and so are the GHG emissions from these indirect energy use in farming and related carbon costs. Crop yields are mainly determined by water application rates, given definite effective precipitation, while crop productions are affected by both irrigated land uses and water application rates.

What is noteworthy in this business-as-usual situation is that the optimized irrigated areas of wheat cultivation (7,768 ha, 72%) are significantly higher than those of cotton cultivation (3,003 ha, 28%). This is uncommon as cotton is usually one of the most profitable cash crops and thereby more land is supposed to be allocated to cotton cultivation. This often happens to crops rotated with rainfed wheat cultivation (Graham 2022a).

However, in this study the wheat cultivation is supplied with both irrigation and precipitation (irrigated wheat). Irrigated wheat is commonly working as a supplement to cotton cultivation in a single crop rotation across Darling Downs Region including Toowoomba Region (Graham 2022a, 2022b; Scobie 2022). The irrigated wheat yield in Toowoomba Region is as high as 6t/ha while the rainfed wheat is no more than 3.5t/ha. Moreover, irrigated wheat price is as high as AU$400/t while rainfed wheat price is no greater than AU$340/t. These two factors may have primarily led to an edge of irrigated wheat over rainfed wheat, thus narrowing the gap between cotton and wheat in market competitiveness. In particular, the price gap between cotton and irrigated wheat is reduced, thus making the wheat cultivation appear more profitable and economically viable. This can explain why more irrigated land is assigned to wheat cultivation.

In spite of significantly more land allocated to wheat, cotton growing maintains its economic advantage with over AU$4,000/ha gross margins generated and so makes its total profit a bit higher than that of irrigated wheat. The gross margins of cotton related to water use are over AU$500/ML, lower than wheat's AU$800/ML, having demonstrated cotton's characteristic in high water consuming. But mainly due to more land for wheat growing, the total GHG emissions from cotton growing are remarkably fewer than those from irrigated wheat growing. The emissions from wheat (over 20 ktCO2e) more than double those from cotton (below 10 ktCO2e).

With an overall analysis on performances of resource uses (land and water), economic benefits and environment (GHG emissions), cotton cultivation still has an edge over wheat cultivation in using fewer land, making higher profits and discharging less GHGs. This is generally aligned with other studies about benefits of cotton cultivation (DAWE 2019a; Lu et al. 2022; Scobie 2022; Rizwan et al. 2023). Even though the situation of allocated irrigated land to cotton and wheat may seem contradictory to normal studies, this can be incurred by a reduced advantage of cotton cultivation over wheat due to higher competitivity of the irrigated wheat.

4.4.3.2. Sensitivity analysis

Sensitivity reflects how important a parameter potentially is to the model. The greater change it incurs (within a certain numerical range of its inputs) on the model output, the more sensitive/important it will be to the model. Compare with Sobol method, sensitivity analysis with Morris method gauges the importance of parameters in a qualitative way but with less computational requirement. The values of sensitivity in the results indicate a relativity of importance between parameters. The results of sensitivity analysis on both the basic model and the further developed models have further verified the high importance of the irrigated land and water application rates as the independent variables. In contrast, the basic core model has a generally lower absolute mean values and standard deviation on parameters for elementary effects than the further developed models. This entails an overall higher sensitivity of parameters in the further developed models than that in the basic model.

A general higher sensitivity of multiple parameters also unveils complexity of the model. For example, the two additional models further developed for crop residue disposal related scenarios are much more complex than the basic core model. This is not only because they contain more parameters but also the parameters are interconnected, thus making interactions between them inclined to be nonlinear/irregular. This contributes to overall higher values of sensitivity for many parameters.

Parameters in the basic core model tend to be affecting the model in more of a linear pattern, while in the further developed models they tend to be influencing in more of a non-linear pattern. The more intertwined parameters are in the model, the higher orders of them are and therefore the more non-linear effects they will likely have on the model. Crops residues are closely related to crop yields which in turn are closely associated with water application rates and irrigated land. This makes some parameters particularly like GHG emissions from crop residue disposal activities become more correlated with the two key independent variables by multiple times of iteration (higher order).

4.5. Conclusion

This chapter has presented the application of the basic core model developed in Chapter 3, including key data inputs, sensitivity tests, and the results of optimization and sensitivity analysis. This basic model is applied to common conditions within the Toowoomba Region as a business-as-usual/baseline scenario. The optimized irrigated areas of wheat taking up 72% (7,768 ha) are greater than those of cotton which only occupies 28% (3,003 ha). The water use of cotton (23.25 GL) is more than that of wheat (15.67 GL) under a higher application rate of cotton 7.74 ML/ha than wheat 2.02 ML/ha. The gross margins per ha irrigated area are AU$4,132/ha by cotton, higher than AU$1,584/ha by wheat. GHG emissions in relation to water use and crop yields are higher from cotton cultivation (3.25 tCO_2e/ha, 0.52 tCO_2e/t) than from wheat cultivation (2.69 tCO_2e/ha, 0.45 tCO_2e/t), while total GHG emissions of wheat cultivation (21 $ktCO_2e$) are greater than cotton cultivation (9.8 $ktCO_2e$).

The results of sensitivity tests reveal that the key parameters or factors impacting the model outputs are water application rates and irrigated areas. The implications from these two factors are the most obvious on cotton cultivation with the largest μ^* values (mean absolute value for elementary effects), both above AU$20 million. These two parameters of cotton have large elementary and nonlinear/irregular effects on the model. In contrast, the effects of all the other parameters have close effects or sensitivity on the model and close to the origin point of the coordinate system, meaning they are not important.

Relative to the basic core model, two additional models are further developed particularly for scenarios of crop residue disposals, one for either mulching or composting scenario and the other for incineration/combustion scenario. As opposed to sensitivity tests in the basic core model, the results of the two models further developed unveil significantly higher impacts of parameters on model outputs. For mulching or composting, the mean absolute value (μ^*) is up to AU$1.7 billion and the standard deviation (σ) is up to Au$2.2 billion. For combustion, the mean absolute value (μ^*) is up to AU$6.5 billion and the standard deviation (σ) is up to AU$9.5 billion in σ. Inclusion of additional parameters in scenarios of crop residue disposals complicate the parameters' interactions and effects on model outputs.

Combined with the literature review, and the results of optimization and sensitivity analysis, scenarios on top of the basic model are designed and presented in Chapter 5 in relation to different crop prices and alternative energy sources plus their costs. In Chapter 6, the other two further developed models are employed and applied to scenarios regarding three alternative crop residue disposal methods, namely mulching, composting, and combustion with energy recovery, in addition with influences of logistics (transport on crop residues).

CHAPTER 5: IMPACT OF CROP PRICES AND ENERGY SOURCES

Drawing insights from the literature review, the ranking of major parameters' importance through sensitivity analysis, and the optimized results of the basic scenario presented in Chapter 4, this chapter focuses on investigating potential influences of the most critical factors/parameters on the single crop production system. As described in Chapter 3, scenarios will be implemented in two series within the subsequent chapters. This chapter will particularly explore impacts of crop prices (different prices of cotton lint and wheat), and alternative energy sources in irrigation and associated costs on optimization of the cropping system. This is to achieve Objective (3) described in Chapter 1.

5.1. Different cotton and wheat prices

Cotton is usually the main crop using more water when being rotated with rainfed wheat (Graham 2022a). However, from the preliminary results in Chapter 4, irrigated areas allocated to irrigated wheat cultivation are greater than those areas allocated to cotton cultivation. This is primarily caused by a higher yield (6t/ha) and higher market price (AU$400/t) of irrigated wheat adopted in this study, compared with rainfed wheat having a lower yield (below 3.5t/ha) and lower market price (below AU$340/t) in Toowoomba Region (Graham 2022a). The average wheat yield and market price across Australia over the last decade are mostly based on rainfed wheat with no more than 3t/ha and no higher than AU$300/t (ABARES 2022c, 2022a). However, the market price will be varying year to year. Thus, to determine how this will impact optimized performances of the cropping system, different levels of cotton lint and/or wheat prices are assumed in the following scenarios:

Baseline Scenario: Cotton lint price (AU$550/bale) and wheat price (AU$400/t).

Scenario 1: The same as baseline scenario but with different cotton lint prices (AU$400/bale, AU$450/bale, AU$500/bale, AU$600/bale, AU$650/bale, AU$700/bale).

Scenario 2: The same as baseline scenario but with different wheat prices (AU$200/t, AU$250/t, AU$300/t, AU$350/t, AU$450/t, AU$500/t).

5.2. Alternative energy sources and costs in irrigation

For variable costs, water costs stand out as a critical factor based on the ranking of the sensitivity test. Water costs are mainly affected by energy types used in irrigation and relevant energy rates/tariffs (García et al. 2019; Qin et al. 2020). Energy costs have been increasing significantly over the last few years, with the bulk diesel price from around AU$0.4/L in 2016 up to approximately AU$1.8/L in 2022 (Graham 2022a). In addition, GHG emissions from fuels used in irrigation activities (roughly one third of the total) are higher than those from the other activities in cropping (Ekonomou et al. 2022b). Different types of energy used in irrigation can have different levels of GHG emissions (Maraseni et al. 2012; Mushtaq et al. 2013; Hafeez et al. 2014; Zou et al. 2015; Jamali et al. 2021). Furthermore, changes in energy types can in turn affect costs associated with GHG emissions and influence total profits and total gross margins (TGMs) or gross margins (GMs) on cotton and wheat separately. The different types and amount of energy that can be consumed in irrigation are outlined below in **Table 5.1**.

Table 5.1. Different energy types and cost used in irrigation.

No.	Inputs	Mean value	References
1	Price of diesel (AU$/L)	0.62	Queensland Government (2022d) Graham (2022a)
2	Amount of diesel consumed per ML irrigation water applied (L/ML)	34	ALCAS (2020)
3	Price of on-grid electricity (AU$/kWh)	0.26	Ergon Energy (2022b)
4	Amount of on-grid electricity consumed per ML irrigation water applied (kWh/ML)	103	ALCAS (2020)
5	Cost of solar photovoltaic (PV) (AU$/ML)	51	Ergon Energy (2022b)
6	Amount of solar PV electricity consumed per ML irrigation water applied (kWh/ML)	103	ALCAS (2020)

Note: The costs of diesel and on-grid electricity are based on an average bulk price. The capital cost of solar PV is assumed to be averaged on an amount per ML irrigation water applied. The other costs included in models developed throughout the study are primarily variable costs.

The majority of pumps in irrigated agriculture operate on diesel (CottonInfo 2017; Graham 2022a; Murray 2022; Scobie 2022). Pumping with solar photovoltaic (PV) technology have been applied to the cotton industry (CottonInfo 2017). The basic scenario is to conduct optimization with diesel fuel use in irrigation. Here, other two alternative energy types replace the diesel use in irrigation activities, on-grid electricity or solar PV generated electricity. On top of that, different diesel and network electricity tariffs are assumed to explore how energy costs can impose impacts on the cropping system, including:

Baseline Scenario: Diesel price (AU$0.62/L) in irrigation.

Scenario 1: The same as baseline scenario but with different diesel prices (AU$0.3/L, AU$1.0/L, AU$1.5/L, AU$2.0/L, AU$3.0/L) in irrigation.

Scenario 2: The same as baseline scenario but replacing the diesel with on-grid electricity in irrigation activities with an average electricity tariff (AU$0.26/kWh).

Scenario 3: The same as baseline scenario but replacing the diesel with on-grid electricity in irrigation activities and setting different electricity tariffs (AU$0.1/kWh, AU$1.0/kWh, AU$1.5/kWh, AU$2.0/kWh, AU$3.0/kWh).

Scenario 4: The same as baseline scenario but replacing the diesel with solar PV power.

5.3. Key results and discussions

5.3.1. Changing cotton and wheat prices

5.3.1.1. Resource use performances (land and water)

The optimal results of irrigated areas and water applications are displayed as below in **Figure 5.1**. In the Baseline Scenario, the gap of cotton lint price (AU$550/bale) over the wheat price (AU$400/t) is not large enough, more land use is preferable to grow irrigated wheat rather than cotton (Chapter 4), when cotton cultivation only occupies less than 30%. This has a significant difference from usual cases where cotton cultivation takes precedence over wheat cultivation, probably because wheat is commonly grown in a rainfed mode in conjunction with low yields, less than 3.5t/ha, and low prices, less than AU$350/t, in Toowoomba Region (ABS 2022c; Queensland Government 2022d). In Scenario 1, when increasing the cotton lint price to around AU$600/bale and the same wheat price (AU$400/t), more land will be allocated to cotton cultivation (increased by 5%). The influences of prices begin to become more obvious when the cotton lint price continues to increase to above AU$650/bale. At this point, the land is almost used for cotton cultivation (increased to 98% of the total) within the land constraints and the wheat is shifted to a rainfed mode (zero irrigation water application rate). This means irrigated wheat is not so worthwhile to grow anymore. In Scenario 2, when setting the wheat price to a low level (below AU$300/t) and keeping the cotton lint price the same (AU$550/bale), the irrigated areas are mainly for cotton cultivation (95%). If the wheat price is increasing from AU$350/t to a high level, more land is allocated to irrigated wheat cultivation again, as same as the baseline scenario.

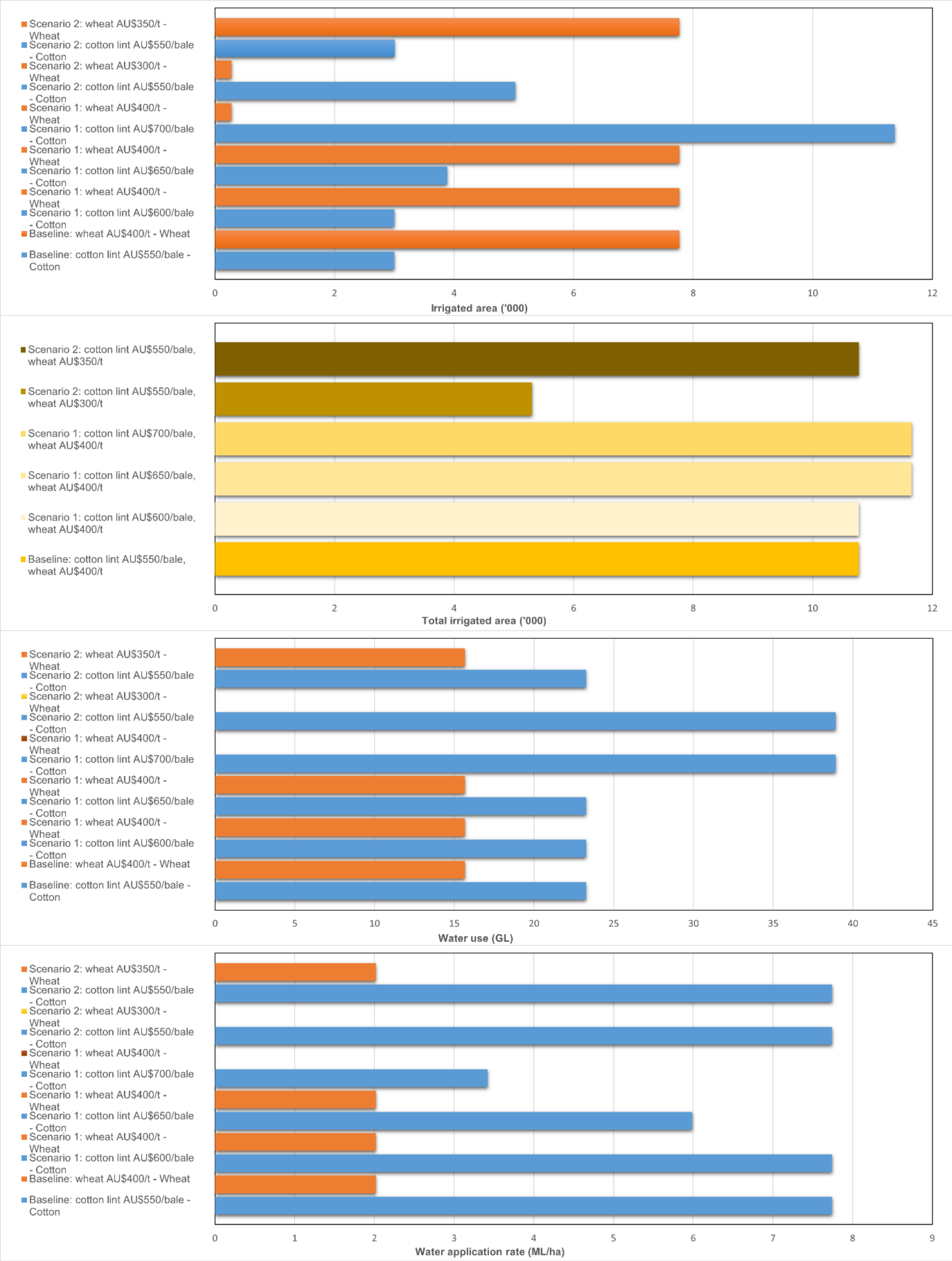


Figure 5.1. Optimal resource uses for cotton and wheat cultivation in the baseline simulation and optimization scenarios with different levels of cotton lint prices (Scenario 1) and wheat prices (Scenario 2). The legend on the left side of the figure shows different scenarios with different prices of cotton lint and wheat. This applies to the other relevant figures as well.

The total irrigated areas will peak at the maximum available irrigated land use as the prices of cotton and lint and wheat are relatively high (cotton lint above AU$650/bale and wheat above AU$350/t). Most available irrigated land will be utilized if the prices are at a medium level (cotton lint AU$500-650/bale and wheat AU$350-400/t). When the wheat price is below AU$300/t, 50% of total areas are used as the optimized land use for cotton and wheat cultivation. The rest of land is on a fallow practice or used for cultivation of other crops.

In most scenarios, the total water consumed reaches the maximal available water resources (38.92 GL). When the price gap between cotton and wheat is large enough, water is mainly consumed by cotton, for example cotton lint price over AU$650/bale and wheat price below AU$400/t, or cotton lint price over AU$550/bale and wheat price below AU$300/t. In high cotton lint price situation over AU$650/bale with wheat price below AU$400/t, the water application rate on cotton does not reach the maximal limit. It is becoming lower when cotton lint price is increasing (shifting to a deficit irrigation more).

5.3.1.2. Economic performances (gross margins and profits)

The optimal results of profits for both cotton and wheat, GMs and total profits are presented in **Figure 5.2**. The profits and GMs per hectare generated by wheat price changes are comparatively stable (AU$1,583/ha), while the profits and GMs from cotton increase as the cotton lint price increases. Those values for cotton cultivation reach the maximum at the point of cotton lint price AU$700/bale paired with few profits and GMs per hectare by wheat cultivation. GMs per hectare irrigated area for cotton is the highest with AU$4,706/ha at a cotton lint price of AU$600/bale, but they drop as the wheat price rises. This is mainly because of there being more irrigated areas allocated to cotton cultivation. The wheat price AU$300/t can be a break-even point for irrigated wheat cultivation, as the wheat cultivation does not make profits when its price is below AU$300/t. If its price rises above this level, the situation will be akin to the baseline scenario. For instance, in a situation with low wheat prices (below AU$300/t), the GMs of wheat decrease to AU$175/ha and in a situation with higher cotton lint prices (over AU$650/bale) it turns into negative. However, while increasing either cotton lint price or wheat price, the total profits will be increasing linearly. The total profits will be rising at a slightly larger rate by increasing cotton lint prices (total profits increased by 7-12%) than by increasing wheat prices (total profits increased by 7-8%).

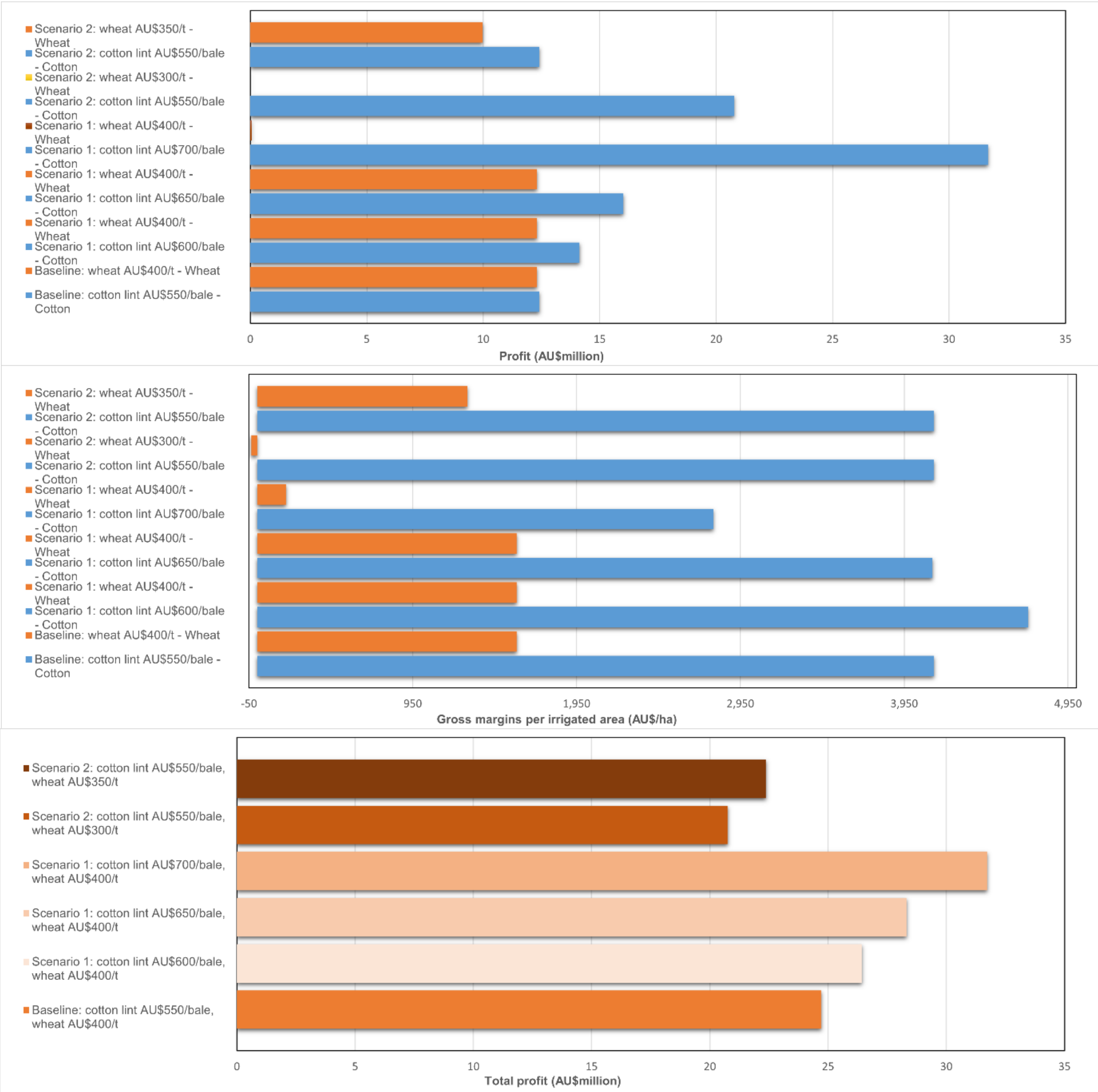


Figure 5.2. Profits, GMs per ha for cotton and wheat cultivation, and total profits in the baseline simulation and optimization scenarios with different levels of cotton lint prices (Scenario 1) and wheat prices (Scenario 2).

To examiner total costs generated by different farming activities in the cropping system, a breakdown is presented below in **Figure 5.3**. In most scenarios, the proportion of irrigation cost remains around 19%, except under cotton lint price AU$700/bale and wheat price AU$400/t where irrigation takes up less than 10%. In this situation, cotton has an obvious advantage over wheat in prices. The majority of irrigated land is allocated to cotton cultivation (98%) and the remainder is for wheat cultivation in a rainfed mode. Under a larger allocated land to cotton and idential total contrained available water resources, the water application rate of cotton is reduced to only 3.42ML/ha with a yield of 3.8t/ha (equivelantly cotton lint 7.02bale/ha). Mainly because of the reduced water application rate, the total irrigation cost accordingly decreases.

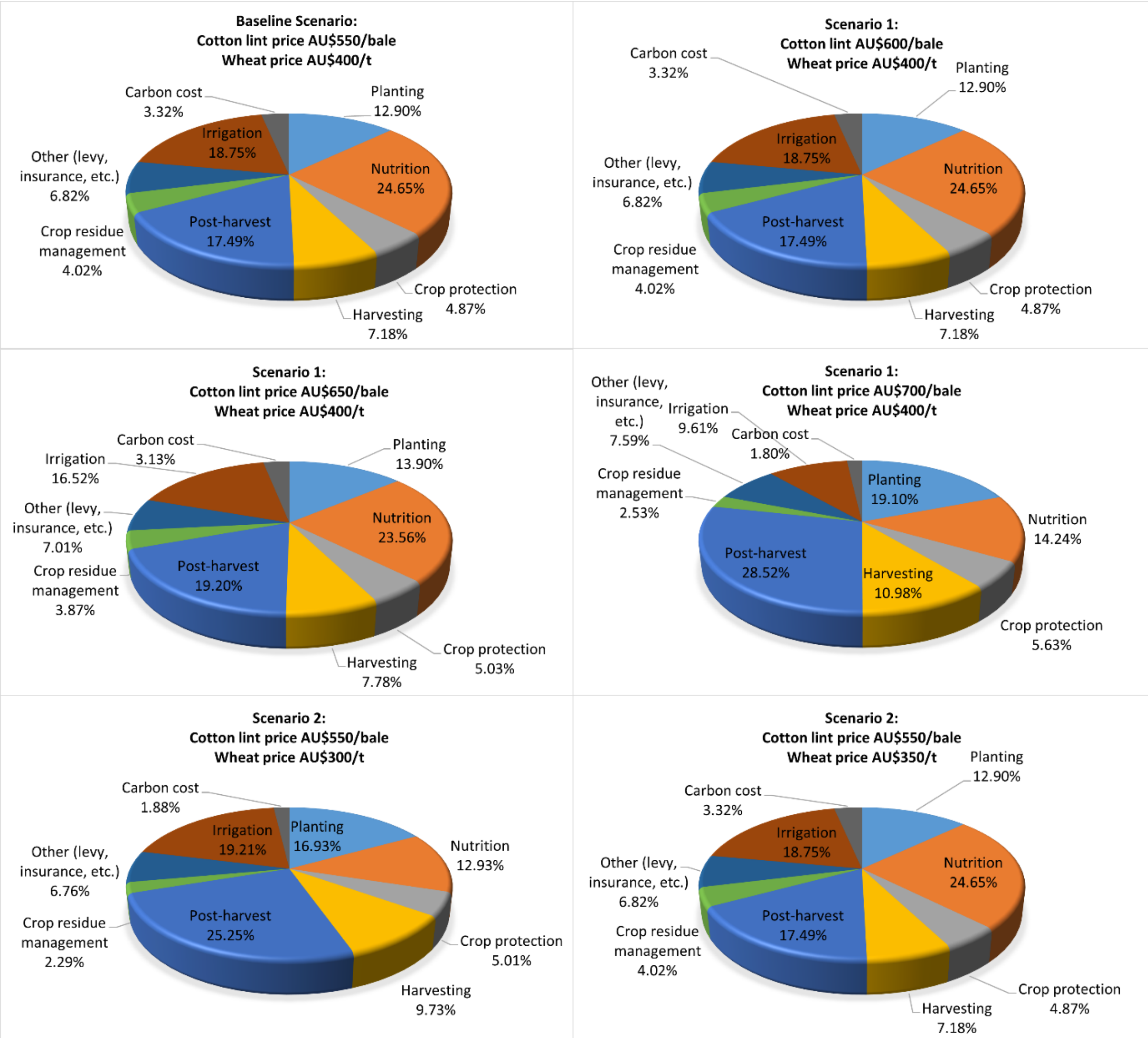


Figure 5.3. Breakdowns of total costs from multiple cultivation activities inclusive of carbon cost imposed on GHG emissions from the single crop rotation system in each scenario.

In contrast, costs of planting, crop protection, harvest, and post-harvest (mainly cartage and/or cotton ginning) increase as cotton price rises and decrease as wheat price rises. Cost of post-harvest varies most remarkably, increasing roughly by 0.5% corresponding to every AU$10/bale increase in cotton lint price and decreasing roughly by 1% corresponding to every AU$10/t increase in wheat price. It is an opposite situation for all the other costs, where they decrease as cotton price rises and increase as wheat price rises. Among them, cost of nutrition (fertilizers) varies notably, decreasing roughly by 0.8% corresponding to every AU$10/bale increase in cotton lint price and increasing roughly by 1.2% corresponding to every AU$10/t increase in wheat price.

5.3.1.3. Environmental performances (GHG emissions)

The optimal results of GHG emission intensities are presented below in **Figure 5.4**. The GHG emissions generated by wheat price changes do not differ much, while the emissions from cotton increase as the cotton lint price increases. The emissions reach the maximum at the point of cotton lint price AU$700/bale with few GHG emissions from wheat cultivation. When cotton lint price increases from AU$550/bale to above AU$650/bale, GHG emissions per hectare irrigated area for cotton decrease accordingly from 3.26tCO_2e/ha to 2.83tCO_2e/ha. If the wheat price is too low (below AU$300/t) or cotton lint price is relatively high enough (over AU$650/bale), the GHG emissions per hectare irrigated area for wheat fall from 2.74tCO_2e/ha to 2.49tCO_2e/ha.

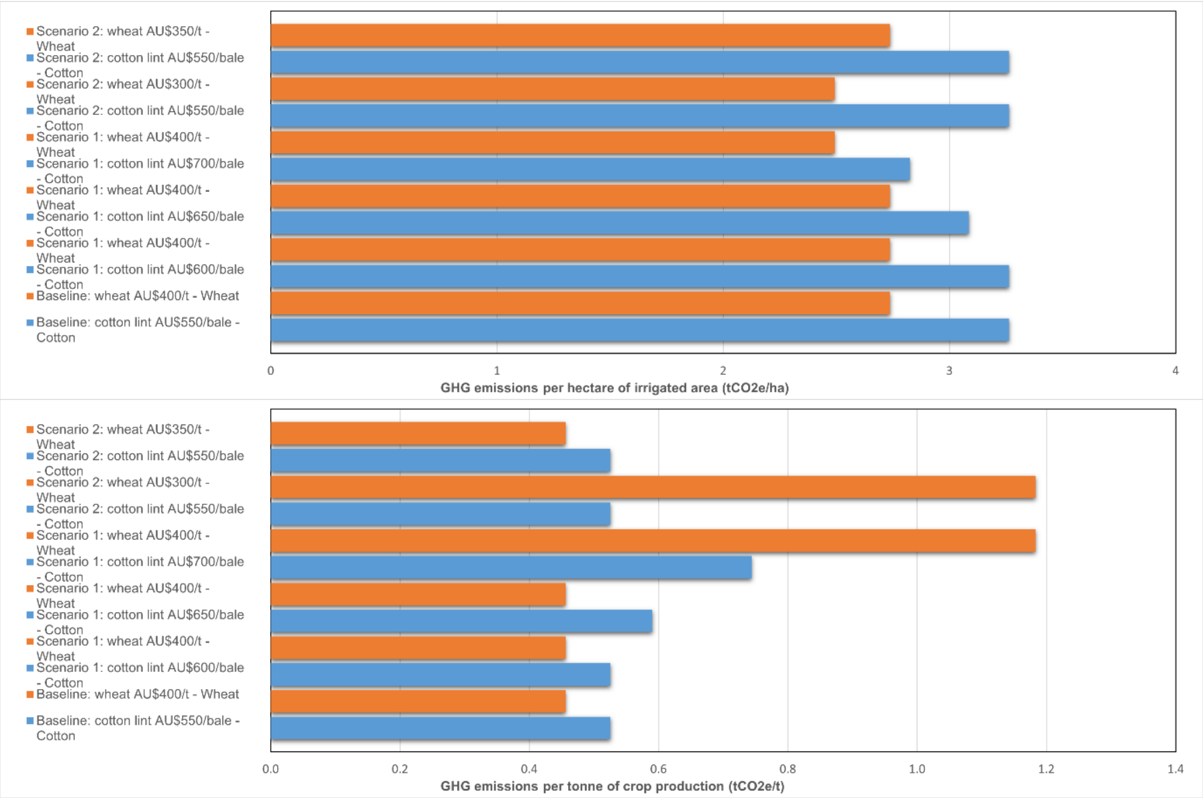


Figure 5.4. GHG emission intensities in units, per hectare of irrigated land use and per ton of crop produced, in the baseline simulation and optimization scenarios with different levels of cotton lint prices (Scenario 1) and wheat prices (Scenario 2).

The optimal results of GHG emissions for cotton and wheat, respectively, and total GHG emissions are shown in **Figure 5.5**. The total GHG emissions have the highest amount (31-33kt) when both prices are high (cotton lint price above

AU$600/bale and/or wheat price above AU$300/t); when the prices are low (cotton lint price below AU$600/bale and wheat price below AU$300/t), the GHG emissions are approximately half of the other scenarios. GHG emissions for either cotton or wheat are significantly influenced by irrigated areas. The highest levels of emissions in the cotton cultivation with a high price (cotton lint prices AU$700/bale) and in most wheat cultivation with high prices commonly are closely related to most irrigated areas being allocated and used (72% - 98%). This trend of allocation for irrigated land can be driven by the level of price for a crop alone or comparative advantage of prices between different crops.

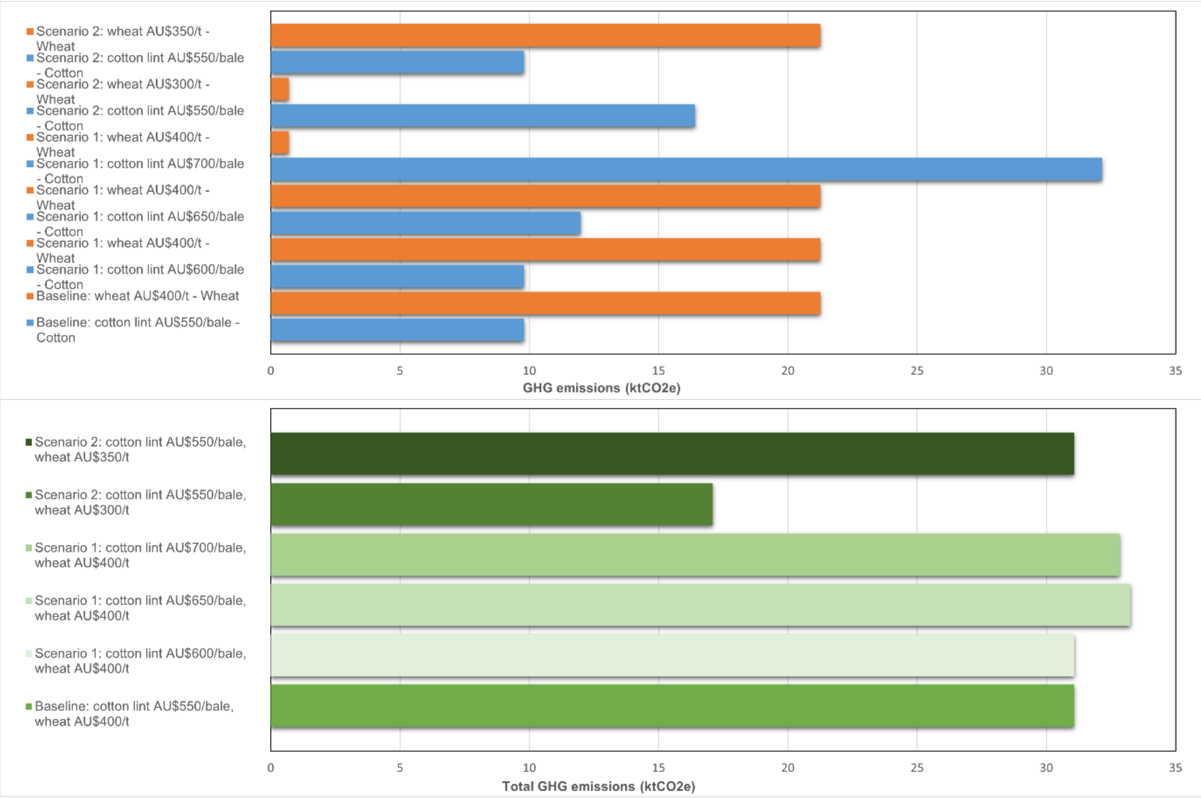


Figure 5.5. GHG emissions for cotton and wheat and total GHG emissions in the baseline simulation and optimization scenarios with different levels of cotton lint prices (Scenario 1) and wheat prices (Scenario 2).

To further examine how the GHG emissions can change between scenarios, **Figure 5.6** provides a breakdown of different emission sources for each scenario. In most scenarios, the top three GHG emission contributors are fertilizers applied on-farm (25%-38%), fertilizers applied pre-farm (15%-26%), and fuels (diesel and petrol) (19%-32%). While fuels cause more GHG emissions, fertilizers make less. The primary variable contributor is conjunctive energy sources (fuel and on-grid electricity). Their GHG emissions are determined mainly by irrigated land allocated to cotton cultivation. When cotton cultivation dominates, fuel and electricity uses are increased by 5%-13% and by 5%-7%, respectively, with irrigated areas allocated to cotton changing from 28% to 98%.

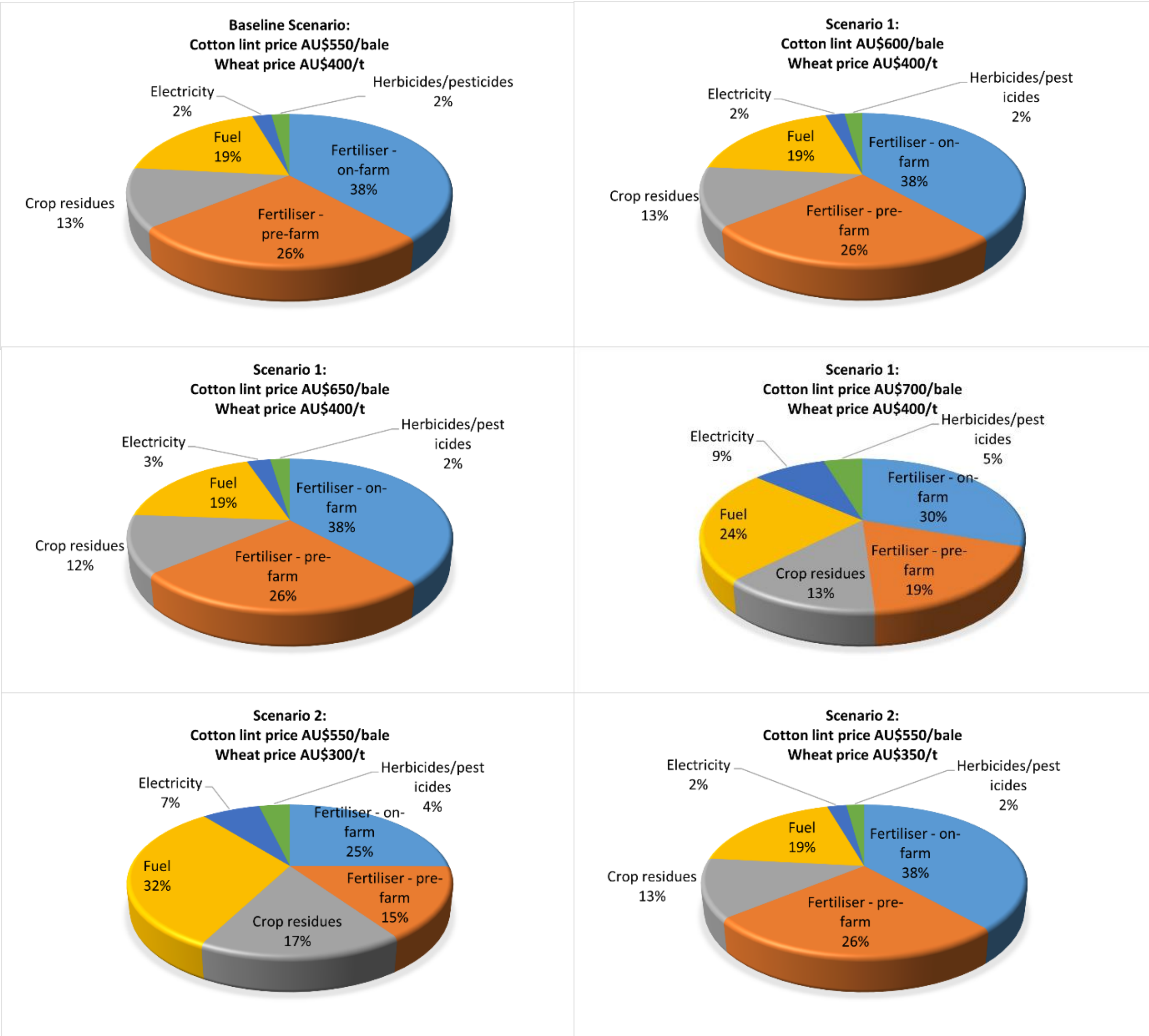


Figure 5.6. Breakdown of GHG emissions from different resources used pre-farm, on-farm and off-farm in Baseline Scenario, Scenario 1, and Scenario 2 with different levels of cotton lint prices and wheat prices.

5.3.1.4. Discussions

It has been found out that if the price gap between the cotton lint and wheat is relatively larger, such as cotton lint over AU$650/bale and wheat below AU$400/t or cotton lint over AU$550/bale and wheat below AU$300/t (a price gap larger than "250" in a numerical value), the irrigated areas are more likely to be allocated to cotton cultivation than wheat cultivation. Cotton cultivation is dominant (more than 95%) with very little wheat grown (less than 5%). This is because the cotton cultivation is more profitable than wheat cultivation in this case. The water application rate of cotton does not reach the cap of the constrained water use per hectare (deficit irrigation for cotton cultivation), while that of wheat is approximately zero or converted to rainfed wheat cultivation. Therefore, when the price gap is enlarged, the land allocation will be aligned with the usual cases where land use by cotton cultivation takes precedence over land use by wheat cultivation (Graham 2022b).

However, just as what is indicated in the baseline scenario (Chapter 4), if the price gap between the cotton lint and wheat is relatively smaller, for example with cotton lint below AU$650/bale and wheat over AU$400/t or cotton lint below AU$550/bale and wheat over AU$300/t (a price gap smaller than “250” in a numerical value), more irrigated areas are likely to be allocated to wheat cultivation than cotton cultivation. In this case, less than 30% of areas are for cotton cultivation and over 70% are for wheat cultivation. As such, wheat cultivation is more profitable than cotton cultivation. The water application rates of both cotton and wheat most likely reaches the cap of the constrained water use per hectare (full irrigation for both).

If the price gap continued to fall, the benefits of cultivation cotton would also decline and possibly the irrigated wheat would be the only crop. However, this situation is very rare. In reality, wheat is mostly grown in a rainfed mode and wheat price is much lower or wheat is much less economically competitive than cotton in market (Graham 2022a). However, this study discusses irrigated wheat, instead of rainfed wheat, as a supplement to cotton cultivation in the rotation. The irrigated wheat in the Toowoomba Region has a higher yield (up to 6t/ha) than rainfed wheat (less than 3.5t/ha) (Woods 2017; Graham 2022b; Queensland Government 2022d). These can explain why more land is allocated to irrigate wheat cultivation than cotton in the baseline scenario and part of the scenarios designed.

When focusing on the crop prices alone, the irrigated wheat cultivation will not make profits if its price is lower than AU$300/t. In the normal range of cotton lint prices in the market (over AU$450/bale), cotton cultivation will mostly be profitable. When cotton lint price is below AU$600/bale, more wheat is grown than cotton in areas (cotton less than 30% and wheat more than 70%); when cotton lint price is between AU$600/bale and AU$650/bale, still more wheat is grown than cotton but with a bit more cotton (cotton more than 30% and wheat less than 70%); when cotton lint price is beyond AU$650/bale, cotton will be the main crop (over 95%). In essence, the key issue here is not conflicting against usual cases where cotton cultivation is superior to wheat cultivation.

Among these scenarios, the optimal situations brought by price changes can be associated with relatively high cotton lint prices (over AU$600/bale) and low wheat prices (below AU$400/t). As seen from the results, in such situations, the resource uses in total amount and in intensity do not have much difference, as in most scenarios resource uses have reached the limit. The gross margins are higher and the GHG emission intensities are lower in these situations. Prices retaining at around these levels would most likely contribute to the highest profits and meanwhile the lowest GHG emissions.

5.3.2. Changing energy sources and costs in irrigation

5.3.2.1. Resource use performances (land and water)

Under the constrained water availability and deficit irrigation conditions, the water application rates and allocated irrigated areas are optimized. The water application rates for cotton and wheat cultivation both reach the highest amount, 7.74ML/ha and 2.02 ML/ha, respectively. The total water use gets to the maximal water availability 38.92GL. The irrigated areas for cotton cultivation are 3,003 ha, not reaching the upper limit, while the areas for wheat cultivation reach the maximal limit of 7,768 ha. Total irrigated areas amount to 10,771 ha.

5.3.2.2. Economic performances (gross margins and profits)

The optimal results of TGMs and total profits are displayed in **Figure 5.7**. By converting to on-grid electricity or solar PV generated electricity with different levels of diesel and electricity tariffs, differences are mainly showing up in profits and gross margins. Converting from the baseline scenario with diesel use in irrigation (diesel price AU$0.62/L) to a scenario with on-grid electricity use in irrigation (electricity tariff AU$0.26/kWh) causes 0.9% decrease in both total gross margins (TGMs) (from AU$2294/ha to AU$2273/ha) and total profits (from AU$24.71 million to AU$24.48 million). With unchanged total revenues in both scenarios (AU$39.65 million), water cost with diesel use is AU$557/ha, close to water cost with on-grid electricity use AU$602/ha.

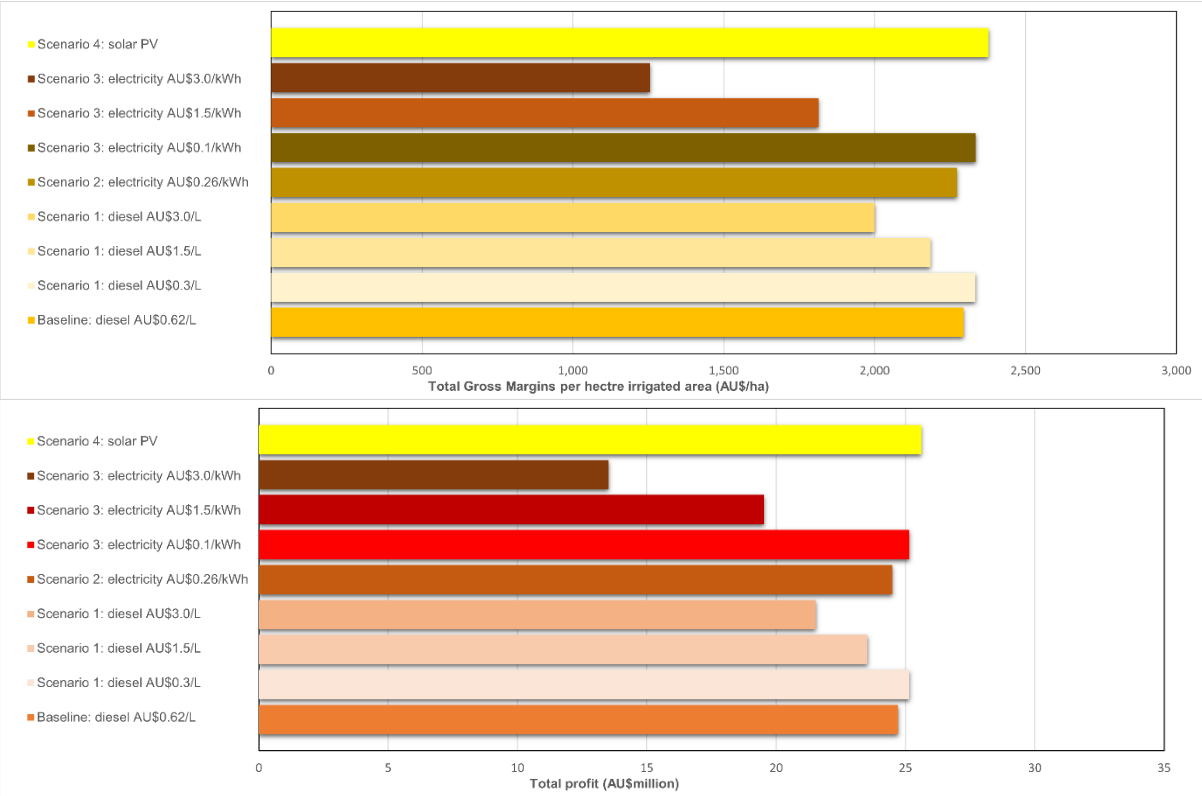


Figure 5.7. Total gross margins per hectare irrigated area (TGMs) and total profits in the baseline simulation (bulk diesel price AU$0.62/L) and optimization scenarios with alternative energy sources in irrigation and different corresponding energy tariffs: Scenario 1 – different diesel costs, Scenario 2 – converting to on-grid electricity with an average electricity tariff, Scenario 3 – electricity in irrigation with different levels of electricity tariffs, Scenario 4 – converting to solar PV generated electricity.

The solar PV in irrigation shows an outstanding economic performance, in contrast to the diesel and on-grid electricity use, due to low cost during water pumping and delivering. While converting to solar PV power use in irrigation from diesel use, the water cost is reduced by nearly 30% (from AU$557/ha to AU$392/ha). There is 3.6% increase in both TGMs (from AU$2294/ha to AU$2378) and total profits (from AU$24.71 million to AU$25.61 million). The profits are about AU$12.41 million generated by cotton cultivation and about AU$12.30 million by wheat. Gross margins are AU$4,132/ha generated by cotton and AU$1,583/ha by wheat. Within Scenario 1 with different diesel prices, TGMs decrease by AU$124/ha and total profits decrease by AU$1.34 million relative to each AU$ increase in diesel price. Within Scenario 2 with different on-grid electricity tariffs, TGMs decrease by AU$372/ha and total profits decrease by AU$4.01 million relative to each AU$ increase in on-grid electricity tariff.

Figure 5.8 gives a breakdown of the total costs incurred by various farming activities involved in the single-crop system.

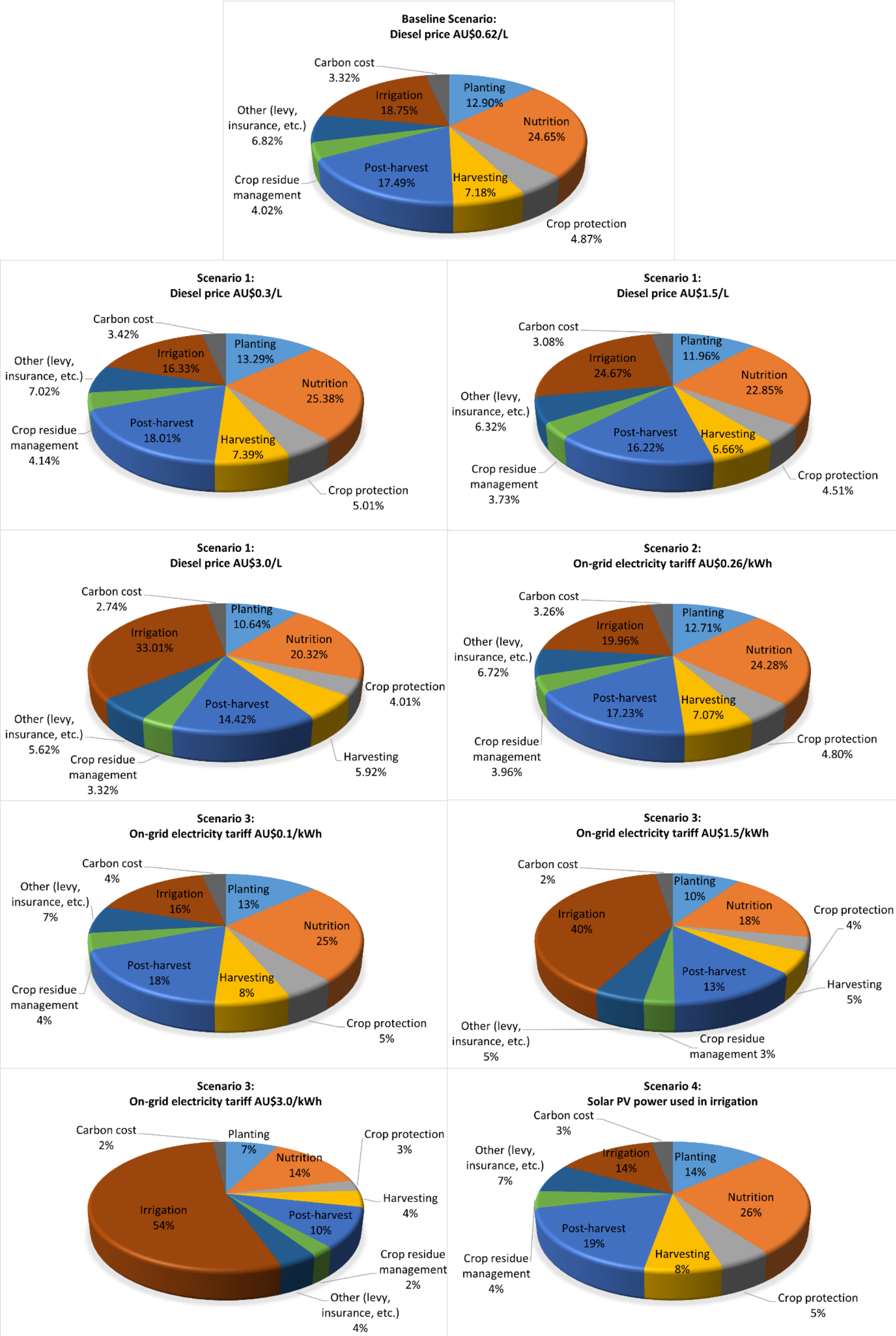


Figure 5.8. Breakdowns of total costs from multiple growing activities in each scenario.

It shows the dynamics as diesel price and electricity tariff increases. The changes incurred by electricity tariff increase (16%-54%) are more notable than those by diesel price increase (16%-33%). Water cost with solar PV power use is the lowest (14%) compared with water cost with diesel use for a low diesel price (AU$0.3/L) or on-grid electricity use for a low electricity tariff (AU$0.1/kWh).

5.3.2.3. Environmental performances (GHG emissions)

The different levels of energy prices/tariffs do not have a significant effect on GHG emissions. The total GHG emissions of the cropping system within the Toowoomba Region are around 31 ktCO2e for either diesel or on-grid electricity use, while they are about 27 ktCO2e for solar PV power use. This is mainly due to a close GHG emission intensity (per ha) between diesel use and on-grid electricity use scenarios (cotton 3.26 tCO2e/ha and wheat 2.74 tCO2e/ha) and a remarkably lower intensity in the solar PV power use scenario (2.48 tCO2e/ha) particularly from cotton cultivation:

- Diesel use: cotton 3.26 tCO2e/ha and wheat 2.74 tCO2e/ha;
- On-grid electricity use: cotton 3.25 tCO2e/ha and wheat 2.73 tCO2e/ha;
- Solar PV power use: cotton 2.48 tCO2e/ha and wheat 2.50 tCO2e/ha.

The subtle difference in emission intensity between diesel use and electricity use is caused by the irrigation activities, where on-grid electricity use in irrigation incurs 0.01 tCO2e/ha lower emission intensity than diesel use. **Figure 5.9** presents results for GHG emission intensity for cotton and wheat cultivation (per hectare of irrigated area, tCO2e/ha, and per tonne of crop production, tCO2e/t). The results for diesel and on-grid electricity use are close because of identical optimized water application rates and irrigated areas in all the scenarios. The results reveal that different types of energy sources in irrigation, particularly renewables, can affect the cropping system while the energy tariffs can have a limited effect. The effects show up mainly in economic performances. The essential factors that determine the substantial changes in the cropping system are primarily the two key parameters of water application rate and irrigated areas, as indicated in sensitivity analysis as well.

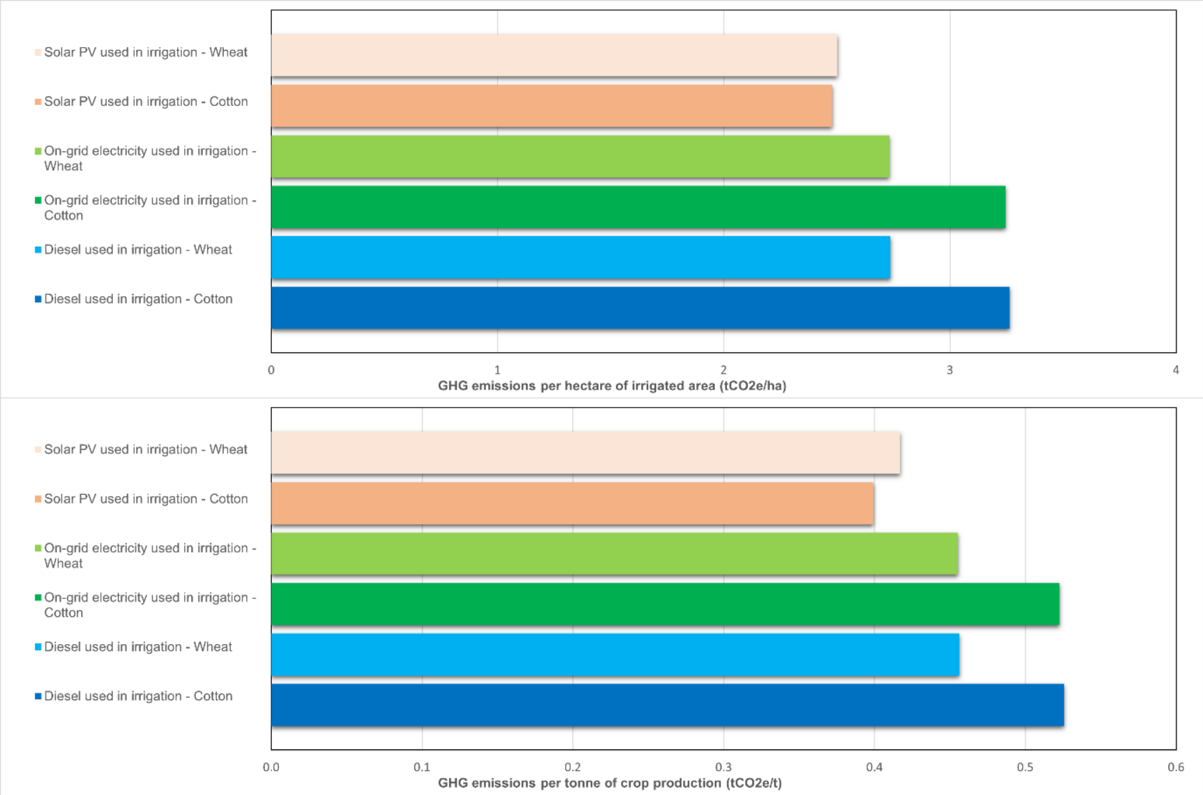


Figure 5.9. GHG emissions per hectare of irrigated area and per tonne of crop production for cotton and wheat cultivation in the baseline simulation and optimization scenarios with alternative energy sources in irrigation: diesel fuel, on-grid electricity, and solar PV.

Figure 5.10 provides a direct overview of GHG emissions sourced from different farming activities by diesel, on-grid electricity, and solar PV power use in irrigation. The electricity use in diesel scenario and solar PV power scenario refers to on-grid electricity applied to cotton ginning (2% and 3% respectively). The proportions of GHG emissions from conjunctive energy use (diesel and electricity) in the first two graphs are close (21%), while by changing to solar PV power the proportion is reduced to 10%.

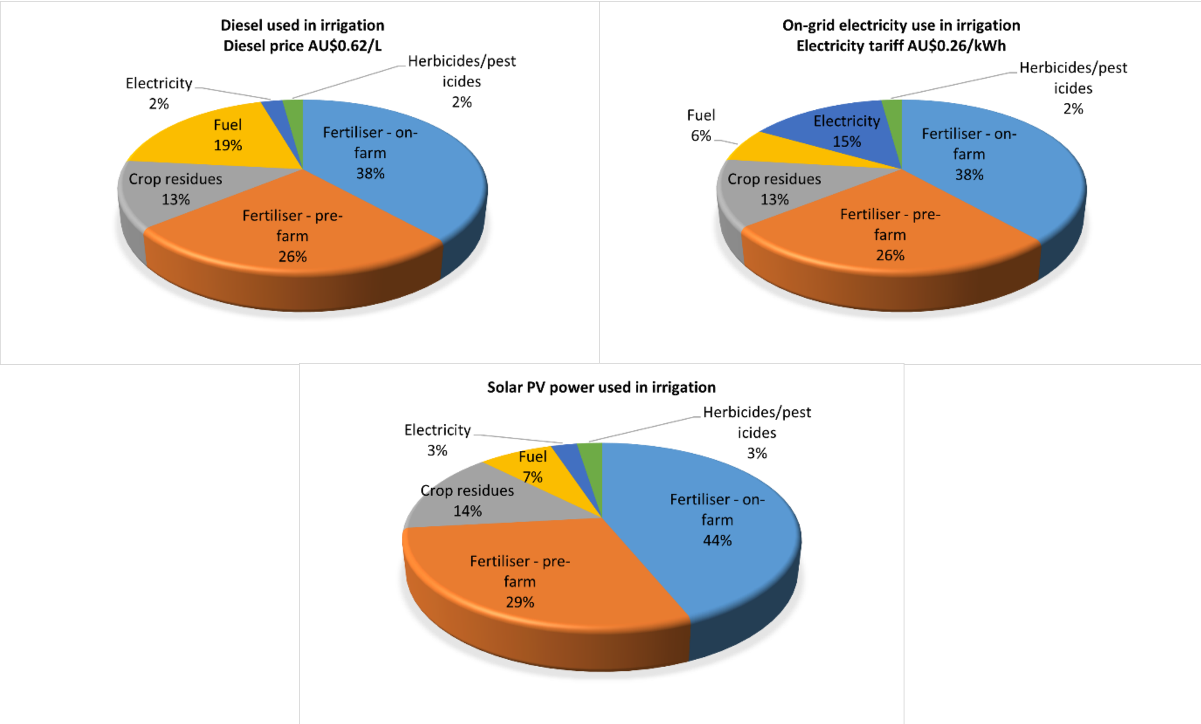


Figure 5.10. Breakdown of GHG emissions from different resources used pre-farm, on-farm and off-farm in scenarios with diesel, on-grid electricity and solar PV power used in irrigation respectively.

5.3.2.4. Discussions

Changes of energy types in irrigation primarily contribute to changes of water costs. The eventual effects on the optimal results tend to be in a linear way and mainly result in changes in economic performances and GHG emissions. Changing to a different energy source in irrigation does not significantly change optimized results, as different energy types do not influence water application rates and allocated irrigated land under deficit irrigation conditions. The water application rates and irrigated areas for cotton and wheat are close to those in the baseline scenario (cotton 7.74 ML/ha, 3,003 ha and wheat 2.02 ML/ha, 7,768 ha).

Changing to different levels of energy tariffs does not significantly change the optimal results. The energy tariffs can be regarded as factors within the water cost module in the integrated model that are more limited in interacting with the core factors (water application rate and irrigated areas) than energy types. The effects are only related to economic performances of the cropping system in a linear pattern. The water application rates and irrigated areas for cotton and wheat are also close to those indicated in the baseline scenario (cotton 7.74 ML/ha, 3,003 ha and wheat 2.02 ML/ha, 7,768 ha).

The optimal situation among all scenarios in this section regarding alternative energy uses is where solar PV power is used in irrigation. Given identical performances of resource uses, solar PV power can generate the highest profits and the least GHG emissions in contrast to the other energy sources. However, if cutting down the other two energy sources' costs/tariffs as low as possible, the optimized results would be close to those shown in solar PV power use.

5.4. Conclusion

This chapter has discussed critical factors that potentially influence the core model developed in this study. Based on literature review and the results of sensitivity analysis on the model in Chapter 4, two major categories of key parameters are selected, from the perspectives of food and energy respectively, to investigate how they would change the optimal outcomes of the single crop rotation system, namely (1) different levels of crop prices, (2) alternative energy types in irrigation activities and different levels of energy costs.

It has been found that in terms of effects by crop prices on the cropping system, the relative advantage of price for one crop over the other primarily affects the trade-offs and synergies of resource use and optimized economic performances. If the price gap between the cotton lint and wheat is relatively larger, such as cotton lint over AU$650/bale and wheat below AU$400/t or cotton lint over AU$550/bale and wheat below AU$300/t, the irrigated areas are more likely to be allocated to cotton cultivation than wheat cultivation. If the price gap between the cotton lint and wheat is relatively smaller, such as cotton lint below AU$650/bale and wheat over AU$400/t or cotton lint below AU$550/bale and wheat over AU$300/t, more irrigated areas are likely to be allocated to wheat cultivation than cotton cultivation. The highest profits can be generated in the scenario with cotton lint over AU$650/bale and wheat below AU$400/t, which is approximately AU$32 million. The land use and GHG emissions are almost the highest as well among all scenarios, which are 11,651 ha and 32.84 ktCO2e.

Regarding alternative energy sources in irrigation and different tariffs, it has been found that they mainly have impact on profits, gross margins and GHG emissions. Optimal results brought by changes in energy types are close in diesel and network electricity use, while solar PV application can incur less water cost (AU$14.04 million) and less GHG emissions (27 ktCO2e). Solar PV application can make a total profit up to AU$26 million. When incremental tariffs are imposed on energy sources (diesel and on-grid electricity), obvious changes can be only seen in profits and TMGs. If making the energy costs as low as possible, the profits and GHG emissions will be close to the solar PV scenario.

The above results are obtained upon the basic core model developed in this thesis. The next chapter will apply two further developed integrated models to scenarios with alternative crop residue disposal methods. The value chain involved in the model has been extended. The three alternative environmental methods to dispose crop residues are mulching, composting, and combustion (with energy recovery) paired with different transport distances in each disposal method considered.

CHAPTER 6: IMPACT OF ALTERNATIVE CROP RESIDUE MANAGEMENT PRACTICES

Relative to the baseline scenario in Chapter 4, this chapter will explore how conversions to alternative environmental practices for disposing crop residues would influence the optimized outcomes of the cropping system. The two integrated models in this chapter are developed on the basis of the core model that has been applied to the baseline scenario in Chapter 4 and scenarios in Chapter 5. This is to achieve Objective (4) described in Chapter 1.

6.1. Managing crop residues with and without carbon costs

In the baseline scenario, the optimization contains a conventional method of managing crop residues (cotton straw/stalk and wheat straw), which is direct incorporation into soil when and after harvesting, which is common in Australia. This is part of the practices involved in crop residue retention as one of the three key principles of conservative agriculture (Findlater et al. 2019; FAO 2022; Sumberg et al. 2022). When changing to a different crop residue disposal practice that extends the value chain to a disposal stage in the life cycle, additional GHG emissions are incurred both by logistics and disposal (Iye et al. 2013a; Iye et al. 2013b; Zhao et al. 2016; Maraveas 2020).

However, most of the methods designing the existing waste facilities or biomass power plant locations and supply chains only consider the minimization of transportation costs, having disregarded the GHG emissions during the logistics (Zhao et al. 2016). The processes of treating and disposing residues in waste facilities do not take GHG emissions into account, either (Phoenix Power Recycles 2022; Remondis 2022; Cleanaway 2023; WestRex 2023; Zilch Waste Recycles 2023). Relevant avoided costs and avoided GHG emissions can also be considered in conjunction with GHG emissions and associated carbon costs incurred during the processes of disposing the residues. In a combustion/incineration disposal method, a certain amount of power can be generated and returned to the electricity network, which generated avoided GHG emissions and associated avoided carbon costs for generating this amount of power.

Relevant parameters for logistics of commercial crop residue disposal services with data gleaned from local private businesses are shown in **Appendix H**.

These parameters are integrated in the further developed models and are outlined with their values below in **Table 6.1**.

Table 6.1. List of additional parameters for all three practices.

No.	Inputs	Mean value	References
1	Cost of collection & transport [a] (AU$/hr)	190	Zilch Waste Recycles (2023) Cleanaway (2023) Phoenix Power Recycles (2022)
2	Average time for freight to site [b] (hr)	0.83	See note b
3	Average distance for freight to site [c] (km)	67	See note c
4	Conjunctive coefficient of collected, utilized and disposed residues to the total yielded residues [d]	0.50	Graham (2022a); WestRex (2023)
5	Residue index (RI)	Cotton: 1.90 Wheat: 1.50	Ekonomou et al. (2022a)
6	Cost of spreading mulches/composts/ashes (AU$/ha)	140	SoilWealth (2017)
7	Avoided cost (AU$/ha) [e]	Cotton: 63 Wheat: 53	Graham (2022b)
8	GHG emissions from collection & transport (tCO_2e/tkm)	0.0004	ALCAS (2020)
9	Avoided GHG emissions (tCO_2e/ha) [f]	Cotton: 0.60 Wheat: 0.30	Ekonomou et al. (2022a)

Note: The parameters are integrated on top of the basic core model and remain the same for the three scenarios, namely relevant costs and GHG emissions by logistics, and avoided cost and GHG emission in a conversion from “incorporation of residues into soil” to either mulching, composting, or combustion.

[a] The cost for services of logistics (collecting, transporting and delivering residues) are based on general time spent on the road.

[b,c] The average time and distance for freight to site are estimated by means of ArcMap and Google Map with an average limited speed around 80km/hr.

[d] The coefficient of disposed residues to total residues means there is an up to 50% residue loss from collecting to end products in a typical process, and the rest 50% are disposed in the facilities.

[e,f] The avoided cost and GHG emissions are from the conventional crop residue management practice, namely ploughing into soil directly, due to conversion to mulching.

The major differences between these disposal methods exist in the different technologies for treating, processing and disposing the waste/residues. Accordingly, the GHG emissions and associated carbon costs incurred during the processes of each disposal method will vary. The different parameters and data are listed below in **Table 6.2**.

Table 6.2. List of additional parameters that differ in the three practices.

No.	Inputs	Mean value	References
1	Cost of treatment and disposal (AU$/t)	Mulching: 40 Composting: 45 Combustion: 50	SoilWealth (2017) Zilch Waste Recycles (2023) Remondis (2022) Cleanaway (2023) Phoenix Power Recycles (2022)
2	GHG emissions from treatment & disposal	Mulching: 0.04 (tCO_2e/ha) Composting: 2.60 (tCO_2e/ha) Combustion: 6.36 (tCO_2e/ha)	ALCAS (2020)
3	Lower heating value (LHV) (kWh/t) [a]	For combustion only: Cotton straw: 4,161 Wheat straw: 4,102	Kang et al. (2020) Paul et al. (2020) Song et al. (2020)
4	Efficiency for generating electricity by combustion [b]	For combustion only: 30%	Remondis (2022)

Note: These parameters are integrated on top of the basic core model but vary from each of the three scenarios, namely cost for treating, processing and disposing the crop residues and GHG emissions during the process of treatment and disposal. Particularly, combustion can generate a certain amount of electricity that can be reused for cropping.

[a] A lower heating value is used in this study given energy losses in water vapor, as opposed to a higher heating value (HHV). The energy loss is in the form of heat contained in water vapor discharged during and after processing the crop residues.

[b] The efficiency to generate electricity by combustion technology is used in conjunction with a LHV, namely in this study the percentage of electricity/power generated from crop residues per unit tonne.

Here, these three methods to dispose crop residues are incorporated into the scenarios, replacing the conventional ploughing-into-soil method, namely mulching, composting, and incineration/combustion (with power recovery). These are the main disposal methods available in Toowoomba Region. Regular GHG emissions are integrated with or without considering an average carbon price policy in the three scenarios of crop residue disposals as below:

- Baseline Scenario: The common conventional crop residue management practice (ploughing into soil) with and without carbon cost.
- Scenario 1: Substituting mulching for the ploughing practice in the baseline scenario with and without carbon cost.
- Scenario 2: Substituting composting for the ploughing practice in the baseline scenario with and without carbon cost.
- Scenario 3: Substituting combustion for the ploughing practice in the baseline scenario with and without carbon cost.

6.2. Impact of logistic distances (freight to site from waste facilities)

Among the additional factors considered for the crop residue management scenarios, the logistics/transport proves to be another important aspect other than the disposal methods that can be impactful on optimized land and water uses, profits and GHG emissions of the cropping system. There have been numerous studies worldwide investigating how transport distances and distribution of crop residues affect biomass and bioenergy potentials and development (Iye et al. 2013b; Monforti et al. 2013; Okello et al. 2013; Bentsen et al. 2018; Scarlat et al. 2019b). They have demonstrated locations of waste facilities or power plants are of vital importance to crop residues' potentials. In particular, transportation costs and logistical distances can significantly impact the economic viability and interest in converting crop residues to biomass/bioenergy (Jiang et al. 2012; Qiu et al. 2014; Pastori et al. 2021). To make crop residues an economically viable option, areas producing crop residues are supposed to be geographically close to the waste facilities or power plants. This can significantly reduce biomass transportation cost and enhance utilization of the residues (Chen 2016).

The nearest local waste facility to the major irrigated cropping areas in Toowoomba Region is situated around Toowoomba City with an average distance of 66.7km (approximately 50 minutes one way), which is regarded as a long distance for delivering crop residues to processing and disposal. Here, different freight-to-site distances in lengths of time (min) from main irrigated cropping areas of cotton and wheat up to the waste facilities are incorporated into each of the three disposal scenarios above. This is to investigate how the distances of waste facilities to cropping areas/farms would impact the optimized land and water uses, profits and GHG emissions of the single-crop rotation system. Different distances are set as short distance (10 min), medium distance (30 min), and long distance (50 min).

6.3. Results and discussions

6.3.1. Changing to a different crop residue management practice

While transferring to a different crop residue disposal practice, GHG emissions are considered throughout the life cycle from seeding up to the final disposal stage. Meanwhile, the scenarios are designed with and without carbon costs to examine if a regular carbon price policy would be impactful on the optimal results of our extended models.

6.3.1.1. Resource use performances (land and water)

In terms of relevant resource use performances (mainly irrigated land use and water use) within Toowoomba Region in these scenarios, total water use amounts to the maximal water availability (38.92GL), in which cotton cultivation consumes 23.25GL and wheat cultivation consumes 15.67GL. Optimized total irrigated areas are close for the baseline scenario, mulching scenario and composting scenario (10,771 ha) with cotton cultivation taking up 3,003 ha and wheat cultivation taking up 7,768 ha. In these scenarios, water applications reach the upper limit with 7.74 ML/ha for cotton and 2.02 ML/ha for wheat.

The irrigated areas reach the upper limit of the available irrigated land in the combustion scenario (11,652 ha). This slight difference from the other three scenarios is mainly caused by the change in cotton cultivation taking up 3,884 ha and wheat cultivation remaining at 7,768 ha. The water application rate of cotton is reduced to 5.99 ML/ha compared with that of wheat remaining at 2.02 ML/ha.

6.3.1.2. Economic performances (gross margins and profits)

The optimal results of gross margins (GMs) and total profits are shown in **Figure 6.1.** The results indicate that, within the given land resource and water availability constraints, changing the method of crop residue disposal would notably change the economic performances. In contrast, removal of a regular carbon pricing policy (AU$15.99/tCO2e) in each scenario (including the baseline scenario) would promote the economic performances but in a very limited degree. When converting an “incorporation into soil” practice (baseline scenario) to a mulching practice (scenario 1), the total profits decrease from AU$24.71 million to AU$21.01 million (with a carbon price) and from AU$25.20 million to AU$21.53 million (without a carbon price). Compared with the baseline scenario, under a carbon price policy, the GMs for cotton decrease from AU$4,132/ha to AU$3,751/ha, while the GMs for wheat decrease from AU$1,583/ha to AU$1,262/ha; with no carbon price, the GMs for cotton decline from AU$4,184/ha to AU$3,797/ha, while the GMs for wheat decline from AU$1,627/ha to AU$1,303/ha.

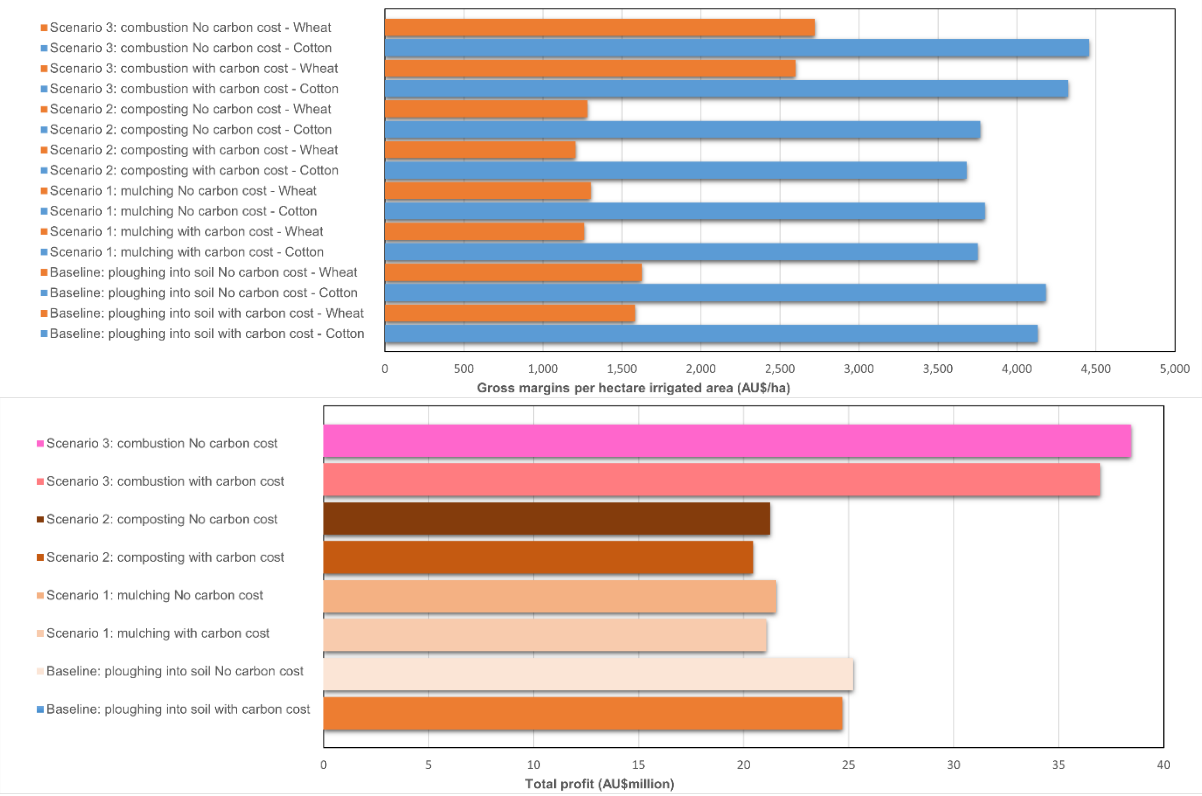


Figure 6.1. GMs for cotton and wheat cultivation, respectively, and total profit in the baseline simulation (ploughing into soil) and optimization scenarios of scenario 1: mulching, scenario 2: composting and scenario 3 combustion with and without a carbon price policy.

When converting an “incorporation into soil” practice (baseline scenario) to a composting practice (scenario 2), the total profits decrease from AU$24.71 million to AU$20.44 million (with a carbon price) and from AU$25.20 million to AU$21.26 million (without a carbon price). Under a carbon price policy, the GMs for cotton reduce from AU$4,132/ha to AU$3,681/ha, while the GMs for wheat reduce from AU$1,583/ha to AU$1,208/ha; with no carbon price, the GMs for cotton reduce from AU$4,184/ha to AU$3,768/ha, while the GMs for wheat reduce from AU$1,627/ha to AU$1,281/ha.

When converting an “incorporation into soil” practice (baseline scenario) to a combustion practice (scenario 3), the total profits increase from AU$24.71 million to AU$36.97 million (with a carbon price) and from AU$25.20 million to AU$38.44 million (without a carbon price). This is mainly caused by an increase in irrigated land uses in cotton and avoided energy cost from energy recovery during combustion processes. Compared with the baseline scenario, under a carbon price policy, the GMs for cotton rise from AU$4,132/ha to AU$4,324/ha, while the GMs for wheat rise from AU$1,583/ha to AU$2,598/ha; with no carbon price, the GMs for cotton rise from AU$4,184/ha to AU$4,456/ha, while the GMs for wheat rise from AU$1,627/ha to AU$2,720/ha.

It can be found out that the carbon price policy does not incur a significant impact on either profits or GMs. A comparison of changes for a removal of carbon costs caused by these different disposal methods are presented below:

- Baseline Scenario: An exclusion of the carbon price from the ploughing-into-soil practice gives rise to a sharp increase in profits by 2.0%, in GMs for cotton by 1.2% and in GMs for wheat by 2.8%.
- Scenario 1: An exclusion of the carbon price from the mulching practice brings a slight burgeon in profits by 2.5%, in GMs for cotton by 1.2% and in GMs for wheat by 3.2%.
- Scenario 2: An exclusion of the carbon price from the composting practice brings a slight burgeon in profits by 4.0%, in GMs for cotton by 2.4% and in GMs for wheat by 6.0%.
- Scenario 3: An exclusion of the carbon price from the combustion practice incurs a small increase in profits by 4.0%, in GMs for cotton by 3.1% and in GMs for wheat by 4.7%.

In brief, composting is the least profitable option compared with the other three: ploughing into soil (baseline/business-as-usual), mulching, and combustion. If converting to a mulching practice for disposing crop residues, the total profits will be reduced by 14%-15%; if converting to a composting practice, the total profits will be reduced by 15%-17%; if converting to a combustion practice, the total profits will be noteworthily beneficial in economic returns, increased by 49%-53%. When looking at the GMs for either crop, the values for cotton do not present a big disparity between each disposal practice (a gap less than AU$800/ha), but the results for wheat are a bit outstanding in converting to the combustion practice (a gap approximately AU$1,500/ha). Consistent to the results of total profits, composting shows the lowest GMs in both cotton and wheat while combustion has the highest GMs.

6.3.1.3. Environmental performances (GHG emissions)

In terms of GHG emissions, the optimized results are presented in **Figure 6.2**. The results reveal that a combustion practice incurs higher GHG emissions than the other three practices, approximately three times of the ploughing practice and mulching practice and twice of the composting.

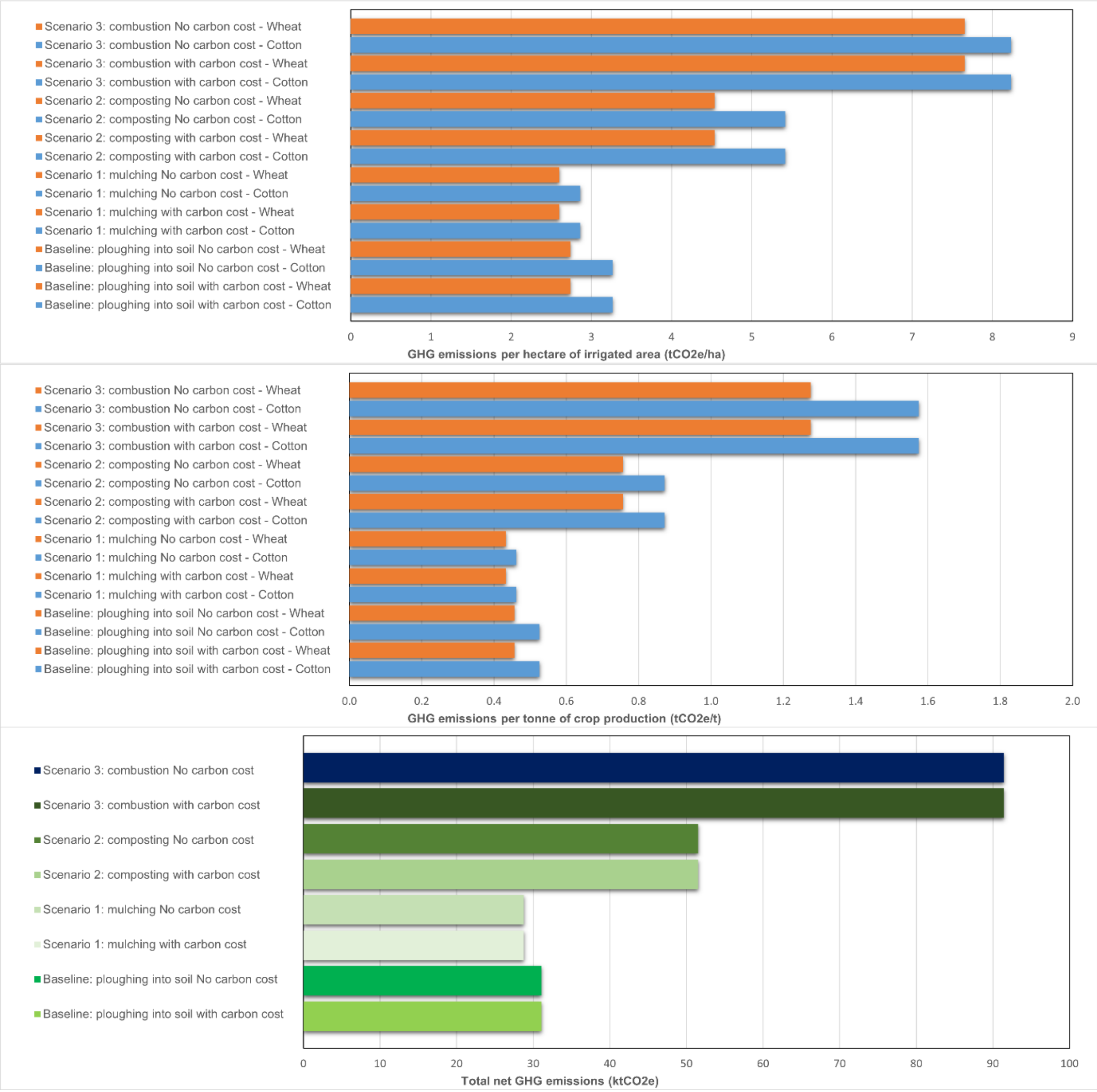


Figure 6.2. Total net GHG emissions from the whole cropping system, GHG emissions per hectare of irrigated land, and GHG emission per tonne of crop production for cotton and wheat cultivation, respectively, in the baseline simulation (ploughing into soil) and optimization scenarios: 1. mulching, 2. composting, and 3. combustion, with and without a carbon price policy.

Since all scenarios involve a regular carbon price policy, an exclusion of this regular carbon price policy is imposed as well to examine if the policy would have any influences on the outcome. The carbon pricing policy does not result in significant changes in GHG emissions. This is a single variate in the model that does not have an essential effect on the key independent variables (land and water) and thus does affect associated GHG emissions directly. The effect is in a limited linear manner on the optimal outcomes of the model.

By transferring an “incorporation into soil” practice (baseline scenario) to a mulching practice (scenario 1), the total net GHG emissions decrease from 31 ktCO2e to 29 ktCO2e. The GHG emission per hectare of irrigated area for cotton reduces from 3.26 tCO2e/ha to 2.86 tCO2e/ha, while this data for wheat reduces from 2.74 tCO2e/ha to 2.60 tCO2e/ha. The GHG emission per ton of crop production for cotton reduces from 0.53 tCO2e/t cotton produced (eq. 0.28 tCO2e/bale) to 0.46 tCO2e/t cotton produced (eq. 0.25 tCO2e/bale), while this data for wheat reduces from 0.46 tCO2e/ha to 0.43 tCO2e/ha.

When converting an “incorporation into soil” practice (baseline scenario) to a “composting practice” (scenario 2), the total net GHG emissions increase from 31 ktCO2e to 52 ktCO2e. The GHG emission per hectare of irrigated area for cotton rises from 3.26 tCO2e/ha to 5.42 tCO2e/ha, while that for wheat reduces from 2.74 tCO2e/ha to 4.54 tCO2e/ha. The GHG emission per ton of crop production for cotton rises from 0.53 tCO2e/t cotton produced (eq. 0.28 tCO2e/bale) to 0.87 tCO2e/t cotton produced (eq. 0.47 tCO2e/bale), while that for wheat rises from 0.46 tCO2e/ha to 0.76 tCO2e/ha.

When converting an “incorporation into soil” practice (baseline scenario) to a combustion practice (scenario 3), the total net GHG emissions surge from 31 ktCO2e to 91 ktCO2e. The GHG emission per hectare of irrigated area for cotton spikes from 3.26 tCO2e/ha to 8.23 tCO2e/ha, while that for wheat reduces from 2.74 tCO2e/ha to 7.65 tCO2e/ha. The GHG emission per ton of crop production for cotton rises from 0.53 tCO2e/t cotton produced (eq. 0.28 tCO2e/bale) to 1.57 tCO2e/t cotton produced (eq. 0.85 tCO2e/bale), while that for wheat rises from 0.46 tCO2e/ha to 1.28 tCO2e/ha.

Generally, mulching practice discharges the least total GHG emissions in contrast to the other three, which is slightly lower than the baseline scenario. However, replacement with a composting or combustion practice implemented on the residues will roughly double or triple the emissions. Likewise, the GHG emission intensities show the highest level in the combustion practice followed by composting. The GHG emission intensities in ploughing-into-soil and mulching are nearly equal. In all four scenarios, it can be noted that the GHG emission intensities close between cotton and wheat. The total emissions of combustion are considerably greater than the others.

6.3.1.4. Discussions

On the whole, changing the type of crop residue disposal method would exert significant influences on the optimal results of our studied cropping system. The most remarkable influences are caused by combustion/incineration (with energy recovery) related scenarios. In particular, when converting to a combustion scenario, the optimal irrigated land use and water application rate in cotton cultivation change from 3,003 ha and 7.74ML/ha to 3,884 ha and 5.99ML/ha. This mild change, instead, considerably increase the total profits (around AU$38 million) and total GHG emissions (over 90 ktCO2e), doubling or tripling the other scenarios.

The outstanding economic performance indicates that converting to a different crop residue disposal practice especially with economic returns would have a major impact on the optimal outcomes of the cropping system. This impact tends to be non-linear, which means the key independent variables (land and water) have been reallocated. Contrastingly, disposal practices such as mulching and composting do not incur changes in the key variable land and water resources.

Regarding the total GHG emissions, the techniques involved in combustion within Toowoomba Region contain high GHG emission intensity, 6.36 tCO2e/ha, as opposed to mulching 0.04 tCO2e/ha and composting 2.60 (tCO2e/ha) (ALCAS 2020; lifecycles. 2020). This primarily leads to the high levels of GHG emissions in all combustion scenarios. It implies that a combustion with energy recovery practice would be a financially beneficial option for farmers while it would not be adequately environmentally friendly under current treatment techniques on residues. From an angle of resource and energy reuse, it can be environmentally sustainable, but the avoided GHG emissions (0.74 tCO2e/ha) are insufficiently offsetting the emissions from the disposal itself.

As opposed to the notable impacts incurred by changes on the type of disposal method, a carbon price policy would change the optimized profits slightly by less than 5%. The carbon price, as a univariate parameter, does not essentially impact the key variables and so the limited effects only show up in economic performances. The carbon price imposed on the system is a regular price in 2021 and has increased to AU$17.12 in 2023 (Australian Government 2023). As the carbon price policy offers a low level of carbon charging rates, the effects on cropping system are limited.

6.3.2. Different transport distances in logistics

This section further discusses how distances of transport to collect and deliver crop residues could affect the optimal results of the single crop rotation system. In the baseline scenario, the average distance is 66.7km (approximately 50 minutes one way) from the waste facilities in Toowoomba City to the major irrigated cropping areas. Different distances are set as short distance (10 min), medium distance (30 min), and long distance (50 min).

6.3.2.1. Resource use performances (land and water)

In relation to resource uses, total water uses amount to the cap of the constrained water availability (38.92GL), in which cotton cultivation consumes 23.25GL and wheat cultivation consumes 15.67GL. Total irrigated areas are close among the baseline scenario, mulching scenario and composting scenario (10,771 ha) with cotton cultivation taking up 3,003 ha and wheat cultivation taking up 7,768 ha. The water applied reaches the maximal allowable amount, 7.74ML/ha for cotton and 2.02ML/ha for wheat.

The irrigated areas in the combustion scenario reaches the upper limit of the constrained available irrigated land (11,652 ha) with the primary change in cotton cultivation taking up 3,884 ha and wheat cultivation remaining at 7,768 ha. The water application rate of cotton is correspondingly reduced to 5.99ML/ha with that of wheat maintaining at 2.02ML/ha.

6.3.2.2. Economic performances (gross margins and profits)

Figure 6.3 shows the trends of impacts that different logistic distances in lengths of time (min) would have on total profits. The total profits made by implementing a combustion practice on crop residues are significantly more than profits incurred by implementing ploughing into soil, mulching, and composting. The baseline scenario has the second highest total profits. The transport distance does not have remarkable influences on the profits. On each km increase in logistic/transport distance, the total profits will decline by AU$10,072 for mulching, AU$10,258 for composting, and AU$10,631 for combustion.

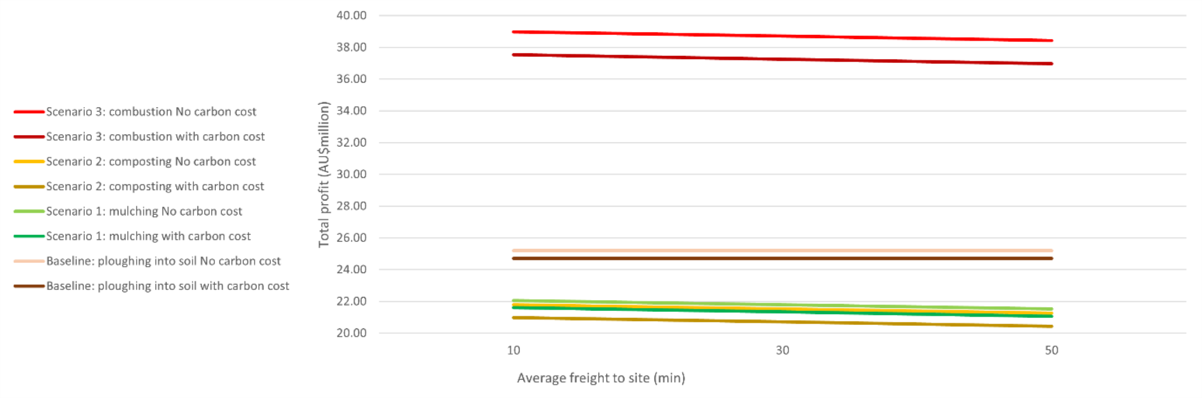


Figure 6.3. Total profits on different average freight to site distances for the baseline scenario (ploughing into soil) and optimization scenarios: 1. mulching, 2. composting, and 3. combustion.

To examine how the distance would change the total costs, a breakdown of total charged costs and avoided costs generated by different farming activities in the cropping system is presented below in **Figure 6.4**. Proportions in different charged costs do not vary significantly in all three alternative disposal scenarios as the distance from cropping areas to waste facilities increases, such as logistic cost ranging from 0.7% to 3%. Avoided costs are primarily incurred by changing the original crop residue management practice (costs of ploughing into soil, around 3%) and associated GHG emissions (carbon cost, about 0.3%). The avoided energy cost in the combustion scenario, which can offset approximately 80% of the total charged costs. This avoided energy cost is incurred by major energy recovery (electricity) from waste facilities. This can clarify why all combustion/incineration (with energy recovery) related scenarios contribute to total profits significantly with an economic edge of AU$13 million – AU$18 million over the other scenarios.

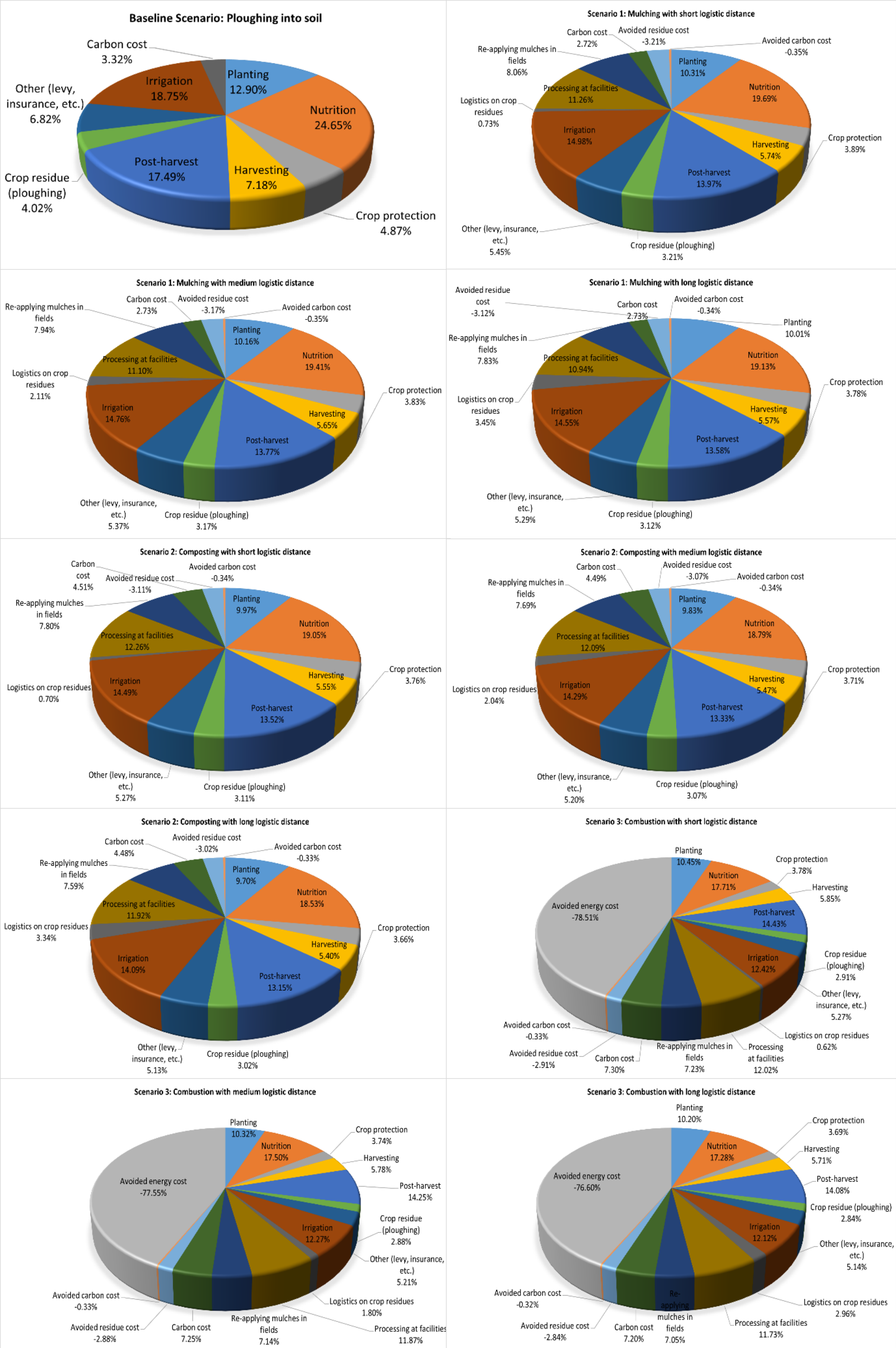


Figure 6.4. Breakdown of total charged costs an avoided costs involved in each scenario of crop

residue disposal with different logistic distances in Toowoomba Region. A short distance for transport of crop residues is approximately 14 km on average (0.17 hr), while a medium one is 40 km (0.5 hr) and a long one is 67 km (0.83 hr).

6.3.2.3. Environmental performances (GHG emissions)

Generally, the level of total GHG emissions caused by conducting a combustion practice are remarkably higher (between 90 ktCO2e and 95 ktCO2e) than those by the other three scenarios. Though the baseline scenario has the second highest total profit, the associated GHG emissions (between 30 ktCO2e and 35 ktCO2e) are much lower than the composting scenario (50 ktCO2e and 55 ktCO2e). The mulching scenario makes the lowest level of GHG emissions (25 ktCO2e and 30 ktCO2e).

Likewise, the transport distance has no obvious influences on the emissions. Within the Toowoomba Region, on each km increased transport distance, the total GHG emissions increase by 20.89 tCO2e for mulching, 20.70 tCO2e for composting and 21.64 tCO2e for combustion. The effects are in a linear pattern with a mild upward trend (**Figure 6.5**).

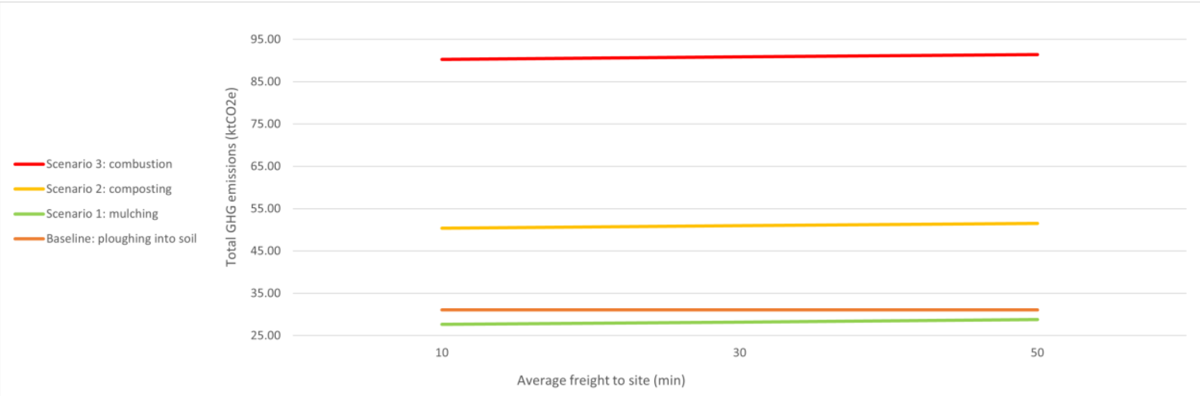


Figure 6.5. Total GHG emissions on different average freight-to-site distances for the baseline scenario (ploughing into soil) and optimization scenarios: 1. mulching, 2. composting, and 3. combustion.

Figure 6.6 gives a breakdown of GHG emission sources for all activities. Apart from all the major farming related activities as the main GHG emission sources in all the three scenarios, processing crop residues in composting and combustion scenarios cause significant GHG emissions, around 41% and 67.5% respectively.

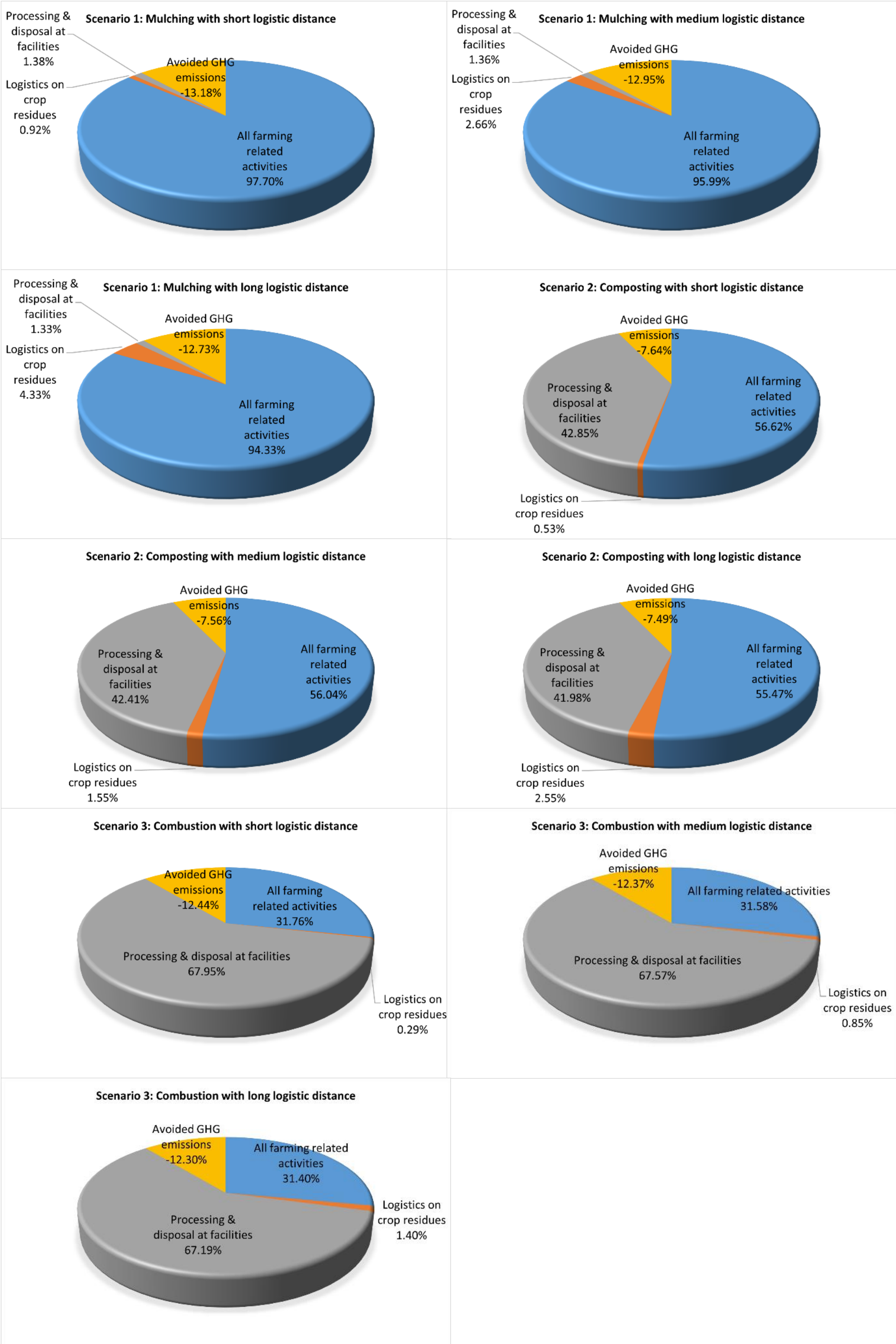


Figure 6.6. Breakdown of GHG emissions from major farming related activities, additional crop residue

management related activities, and avoided GHG emissions. The biggest part, all farming related activities, refers to GHG emissions from all pre-farm, on-farm, and off-farm activities.

The proportion of GHG emissions caused by logistics is changed slightly between each scenario (below 5%). The avoided GHG emissions contribute to a certain part in all three scenarios (around 10%). Despite a significant amount of total GHG emissions generated in combustion (up to 91 ktCO2e), the avoided GHG emissions are 12.7 ktCO2e. With the same amount of avoided GHG emissions (4.1 ktCO2e), composting causes 51 ktCO2e while mulching brings up to 28 ktCO2e. By contrast, mulching shows a better GHG emission performance by offsetting a higher percentage of GHG emissions.

6.3.2.4. Discussions

With an overview, the limited effects incurred by logistics mainly present in economic and environmental performances, as changes to different transport distances does not result in changes in the core independent resource variables. In this case, impacts of distances are in a linear mode with a subtle downward trend. Like the carbon price, transport distance is also a univariate factor that appears to be not sensitive to the system and has not correlated with many other parameters/factors in the system (low order).

The trend of profits indicates that changing from a near location (short distance) of waste facilities to a remote location (long distance) incurs a decrease by less than AU$2 million, which is mainly shown in an increase in the logistic cost. As to the GHG emissions, the trend shows that changing from a near location (short distance) of waste facilities to a remote location (long distance) incurs an increase by less than 2 ktCO2e. These changes are comparatively small to the total profits and total GHG emissions of the whole system, but by examining the results alone they are actually consistent with other studies researching logistic costs engaged in transporting crop residues (Ramamurthi et al. 2014; Suardi et al. 2019; Wang et al. 2021). Thus, it implies that transport distance would not be the major parameter/factor affecting the optimal performances of the cropping compared to the other parameters/factors in the system.

6.4. Conclusion

This chapter has discussed critical factors that potentially influence the extended models regarding crop residue disposals. Based on literature review and the results of sensitivity analysis on the model in Chapter 4, three main factors are considered in this chapter, to investigate how they would change the optimal outcomes of the single crop rotation system: (1) alternative crop residues (mulching, composting, combustion), (2) a regular carbon price policy on each practice, and (3) different logistic distances to collect and deliver crop residues.

By reviewing the results within this chapter, it has been found out that changing to a different practice of disposing crop residues is impactful on economic returns and GHG emissions. Under identical constrained resource use, the economic performances are the best in a combustion practice (total profits around AU$38.44 million without carbon cost), followed by the conventional agricultural practice, ploughing into soil (total profits around AU$25.20 million without carbon cost), and appear the worst in a composting practice (total profits around AU$21.26 million without carbon cost). The GHG emissions manifest the best outcomes in the mulching practice (28 ktCO2e), closely followed by ploughing into soil (31 ktCO2e). Emissions from composting and combustion almost double and triple as opposed to ploughing (51 ktCO2e and 91 ktCO2e, respectively). A regular carbon price policy (AU$15.99/tCO2e) or different logistic distances imposes limited linear changes on optimized outcomes in profits, GMs and GHG emissions.

Given the key results in Chapter 4, 5 and 6, the next chapter will further discuss potential factors that may affect the optimal results. Also, limitations throughout this study are to be discussed to provide advice about further peer studies in the future.

CHAPTER 7: FURTHER DISCUSSIONS

Drawing insights from key results and preliminary discussions in the previous three chapters, this chapter will explore other factors that are possibly influential on optimized model outcomes and their potential implications. These potentially impactful parameters have been selected from the ranking in the Sensitivity Analysis in Chapter 4 conjunctively considering findings in the Scenario Analysis in Chapter 5 and 6. Subsequently, limitations of the study will be discussed in conjunction with possibilities of reducing the gaps. This is to achieve Objective (5) described in Chapter 1.

7.1. Other possibly impactful factors and potential implications

7.1.1. Rainfall

Rains falling on soils will not be fully used by crops. Some of the rainwater percolates through the soil to the root zones, while some runs away over the land (run-off). Water via deep percolation and run-off cannot naturally be used by plants (unless manually collected and used), which claims to be “ineffective”. Therefore, the remainder stored in soil and used by plants is called “effective” rainfall (Ali et al. 2017; Luo et al. 2022). The effective rainfall will likely affect water application rates in irrigation activities in a direct way, in particular under a deficit irrigation practices as in this study. As the water application is constrained under the maximal crop water requirements, certain amount of effective rainfall will change the water application rates.

As per the ranking in the sensitivity analysis on the basic model, the sensitivity of effective rainfall as a parameter in the models is remarkable, close to water application rates and irrigated land. This factor has not been selected for scenario analysis in the previous chapters, as rainfall is usually closely associated with water allocation for the water year (Bewsher Consulting Pty Ltd 2019; MDBA 2022a). The water allocation may vary from year to year, depending on what year it is, namely wet year or dry year (Sunwater 2019b; MDBA 2022b). Estimation of water allocations is a complicated process with decision making given various factors (MDBA 2022b). There has not been a reliable model to build up a relationship between rainfall and water allocations.

Thus, in this scenario analysis it is assumed that the water allocations remain the same under different precipitation conditions. Different levels of rainfall are designed for a dry, moderate, and wet year respectively in **Table 7.1** to generally examine how effective rainfall affects the optimized system performances/outcomes.

Table 7.1. Rainfall and corresponding effective rainfalls during each crop cultivation in a dry, moderate, and wet year, respectively, in Toowoomba Region.

	Dry year	Moderate year	Wet year	Average year
Summer rainfall (mm)	180	433	1,118	465
Effective rainfall during cotton cultivation (mm)	128	168	237	171
Winter rainfall (mm)	16	139	240	126
Effective rainfall during wheat cultivation (mm)	16	108	148	96

Key results show that the values of irrigated land, profits and greenhouse gas (GHG) emissions do not have significant differences among the baseline scenario (average rainfall), the moderate year, and the wet year. But in the dry year, total irrigated land is below 5,000 ha; total profits are below AU$20 million; total GHG emissions are roughly half of those in other three scenarios. In a dry year, irrigated land allocated to cotton is more than that in a moderate or wet year, and water is more supplied via irrigation for cotton. Combined with results and discussions in Chapter 4 and 5, this has weakened the advantage of wheat cultivation over cotton cultivation. It indicates in this case cotton cultivation will take precedence over wheat cultivation. However, when there is more rainfall supplementary to irrigation in wheat cultivation, wheat will be grown in more allocated irrigated areas than cotton under a high wheat price (AU$400/t) as indicated in the scenarios discussed in previous chapters.

The crop water requirements in all these effective rainfall related scenarios reach the maximal amount (cotton: 9.45 ML/ha; wheat: 3.26 ML/ha), except for cotton in a wet summer (8.81 ML/ha). Accordingly, maximal crop yields have been reached (cotton: 6.21 t/ha, or cotton lint: 11.48 bale/ha; wheat: 6 t/ha), except in a wet summer (cotton: 5.85 t/ha, or cotton lint: 10.82 bale/ha). The total water uses reach the maximal water availability 38.92GL for all. Results of water application rates and irrigated land for cotton and wheat in years with a dry, moderate, and wet year are listed below:

- In a dry year,

water application rate: cotton 8.17 ML/ha, wheat 3.11 ML/ha;

irrigated land: cotton 4,657 ha, wheat 278 ha.

- In a moderate year,

water application rate: cotton 7.77 ML/ha, wheat 2.19 ML/ha;

irrigated land: cotton 2,823 ha, wheat 7,768 ha.

- In a wet year,

water application rate: cotton 6.45 ML/ha, wheat 1.79 ML/ha;

irrigated land: cotton 3,884 ha, wheat 7,768 ha.

Figure 7.1 shows the total irrigated areas, total profits and total GHG emissions in the three different types of water years.

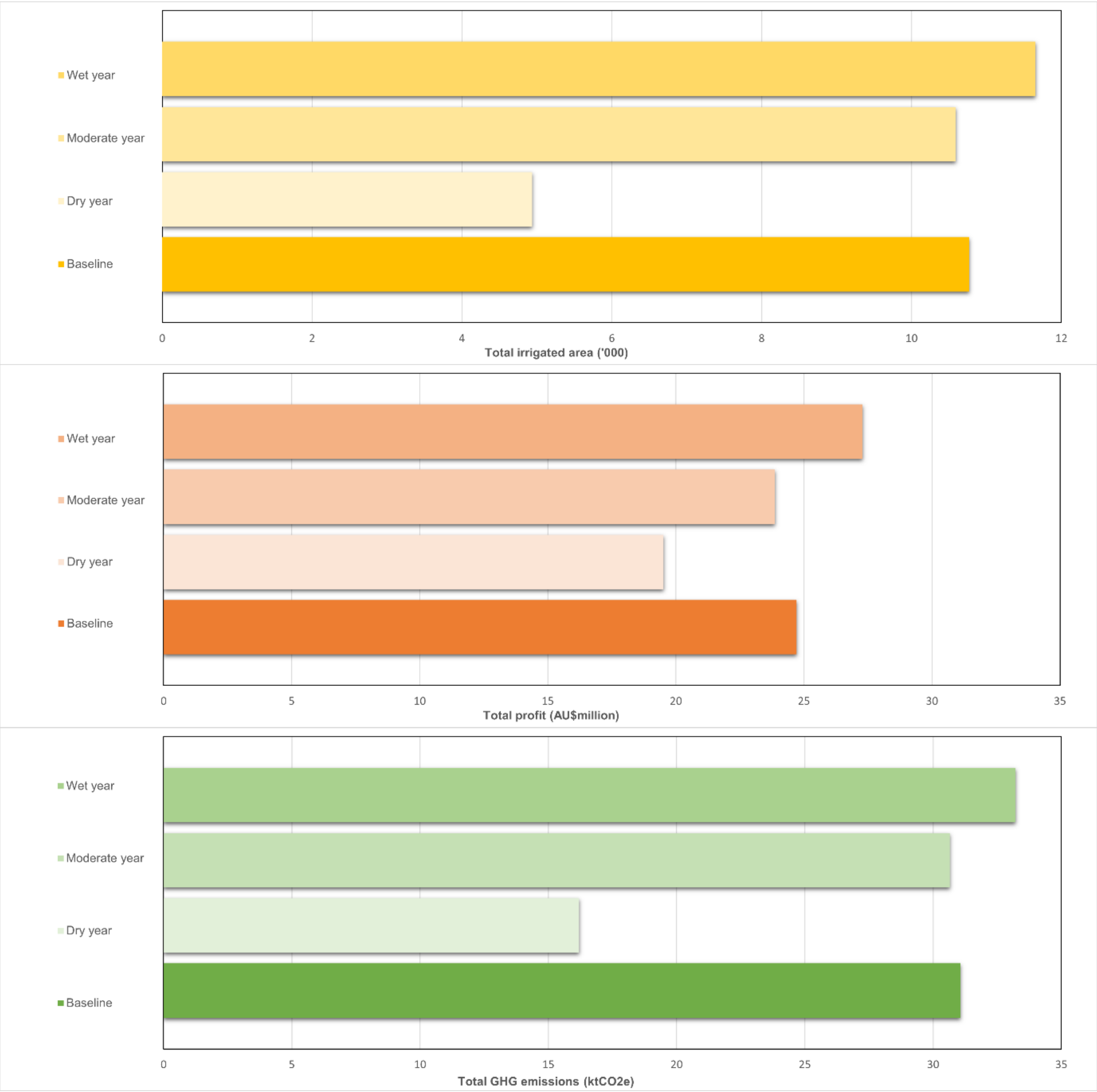


Figure 7.1. Total irrigated areas, total profits, and total GHG emissions in a dry, moderate, and wet year. On top of the baseline scenario, the other three represent the dry year, the moderate year, and the wet year, respectively.

Under a deficit irrigation practice and highly restricted water resource conditions, the rainfall, or effective rainfall, essentially changes the upper limit of water application rates on the crops, which in turn changes the optimal water application rates. This is different from scenarios with parameters that appear not so impactful, such as energy costs and logistic distances for transporting crop residues, where the upper limits of water application rates remain fixed. If there is no significant change caused by a certain factor on the actual water application rates and irrigated land, this factor will have limited effects on the optimized outcomes. The effects will present in a linear pattern, which means when continuing changing (increasing/decreasing) the parameter the optimized outcomes (either profits or GHG emissions) will change (increasing/decreasing) linearly.

7.1.2. Cost of processing and disposing crop residues

Costs imposed on crop residue treatment, processing and disposal (mulching, composting, and combustion with energy recovery at facilities) vary widely, ranging from AU$0/t to AU$90/t crop residues, depending on the individual business and market. For instance, composting can be free in some private businesses like WestRex (2023), while can be up to AU$90/t like Phoenix Power Recycles (2022). WestRex (2023) mainly charge for logistics and re-sale of end products, high-grade and certified compost, which can be re-applied to farms. In contrast, Phoenix Power Recycles (2022) charge fees not only for the treatment and disposal work but also for logistics and re-sale (prescription compost as soil conditioner/booster).

There has been a lack of policies and regulations of this kind of costs imposed on crop residue disposals. The pricing for disposing crop residues is estimated under other types of green residues. A very common and typical mode about this in Australia is that local municipalities or regional councils take in green wastes and send them to landfill. These green wastes are commonly forestry residues and green residues collected from local residential communities (Toowoomba Regional Council 2022a). The commercial charges on disposing these green wastes can be as high as AU$50/t and beyond (Toowoomba Regional Council 2022b).

As per the sensitivity analysis on the two extended models related to crop residue disposals, the costs of disposing crop residues are important compared to other factors/parameters. According to the wide range of commercial quotes on disposing crop residues in either mulching, composting or combustion, here low, median and high charges are imposed to investigate how these different costs would affect the optimized outcomes of the models. **Table 7.2** outlines a low, median, and high level of commercial fees charged by the private businesses for the three alternative disposal services.

Table 7.2. Low, median, high commercial charges for mulching, composting, and combustion (energy recovery), as well as crop residue management costs in the baseline scenario.

		Low charge	Median charge	High charge
Baseline: Ploughing into soil (AU$/t)	Cotton stalk: 63 Wheat straw: 53			
Mulching (AU$/t)		10	40	70
Composting (AU$/t)		0	45	90
Combustion (AU$/t)		30	50	70

As the costs of processing and disposing crop residues increase on the same numerical range from AU$0/t to AU$90/t, the combustion scenarios are the most profitable, decreasing in the slowest way from AU$38.06 million to AU$35.89 million (AU$24,111 decreased on each AU$1/t increased). It is followed by mulching scenarios, decreasing from AU$22.65 million to AU$19.49 million (AU$53,670 decreased on each AU$1/t increased). Composting scenarios can be the least economically beneficial, decreasing in the fastest way from AU$22.81 million to AU$18.07 million (AU$35,113 decreased on each AU$1/t increased) (**Figure 7.2**).

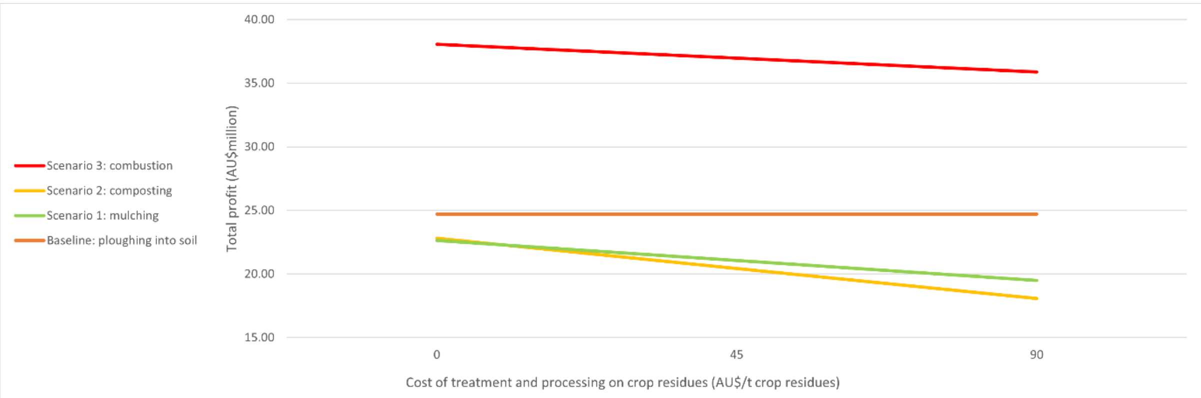


Figure 7.2. Total profits in trends for the four major crop residue management/disposal methods in this study: ploughing crop residues into soil (baseline), mulching, composting, and combustion (energy recovery) with different levels of commercial charges imposed on each method.

These costs of processing crop residues do not create direct effects on GHG emissions, because this factor, cost of treating, processing, and disposing cotton stalk/straw, is an economic parameter and affects the economic performances most directly. While converting an “incorporation into soil” practice (baseline scenario) to a mulching practice (scenario 1) in disposing the residues, the total net GHG emissions decrease from 31 ktCO2e to 29 ktCO2e; when converting an “incorporation into soil” practice (baseline scenario) to a “composting practice” (scenario 2), the total net GHG emissions increase from 31 ktCO2e to 52 ktCO2e; when converting an “incorporation into soil” practice (baseline scenario) to a combustion practice (scenario 3), the total net GHG emissions surge from 31 ktCO2e to 91 ktCO2e.

These key results and trends indicate that the costs of processing and disposing crop residues have a limited effect on the optimized outcomes. The major effect shows up mainly on optimized profits and it is in a linearly decreasing pattern as this cost is increasing.

7.1.3. Coefficient of collected and utilized residues

Throughout the logistics process from collecting crop residues on farms to disposing the crop residues at facilities, there is a considerable quantity of residues lost (Chen 2016; Ali et al. 2019; Scarlat et al. 2019a; Flower et al. 2022). The ratio of crop residues that are collected on a farm and utilized for end products at waste facilities to the total theoretical crop residues yielded from crops is roughly 50% (WestRex 2023), which is named the conjunctive coefficient of collected and utilized crop residues in this thesis. According to the sensitivity analysis, the coefficient of utilized cotton stalk/straw is significantly more sensitive than that of utilized wheat straw. The coefficient of utilized wheat straw is close to the origin point and can be disregarded (**Figure 4.7** and **Figure 4.8**). In addition, this efficiency in collecting and utilizing/converting crop residues during logistics are essential to potentials of biomass (Ramamurthi et al. 2014; Scarlat et al. 2019b; Wang et al. 2021). Thus, the coefficient of utilized cotton stalk/straw will be tested to examine how increased efficiency about collecting and utilizing cotton straw/stalk would influence the optimized outcomes. Here, three values of the coefficient are set in each residue disposal practice: 50%, 70%, and 90%.

Key results show that the overall effects are limited, showing primarily on profits and GHG emissions. Total profits generated by scenarios with composting are a bit lower than those generated by mulching (about an average gap of AU$0.6 million). As the efficiency increases, total profits by mulching decrease from AU$21.07 million to AU$20.31 million (AU$18,794 decreased per 1% efficiency of utilization on cotton residues increased), while total profits by composting decrease from AU$20.44 million to AU$19.52 million (AU$23,058 decreased per 1% efficiency of utilization on cotton residues increased). On the contrary, total profits by combustion increase remarkably from AU$36.97 million to AU$40.81 million (AU$95,888 increased per 1% efficiency of utilization on cotton residues increased). The downtrend of total profits generated in either mulching or composting at an incremental efficiency of cotton residues utilization is caused by an increasing commercial cost imposed on processing these residues. The uptrend shown in combustion is primarily due to the avoided costs in combustion, from energy recovery offsetting a considerable part of energy costs (up to AU$2,947/ha for cotton cultivation and AU$1,462/ha for wheat cultivation) and a certain amount of avoided carbon costs (up to AU$21.42/ha for cotton cultivation and AU$10.62/ha for wheat cultivation) (**Figure 7.3**).

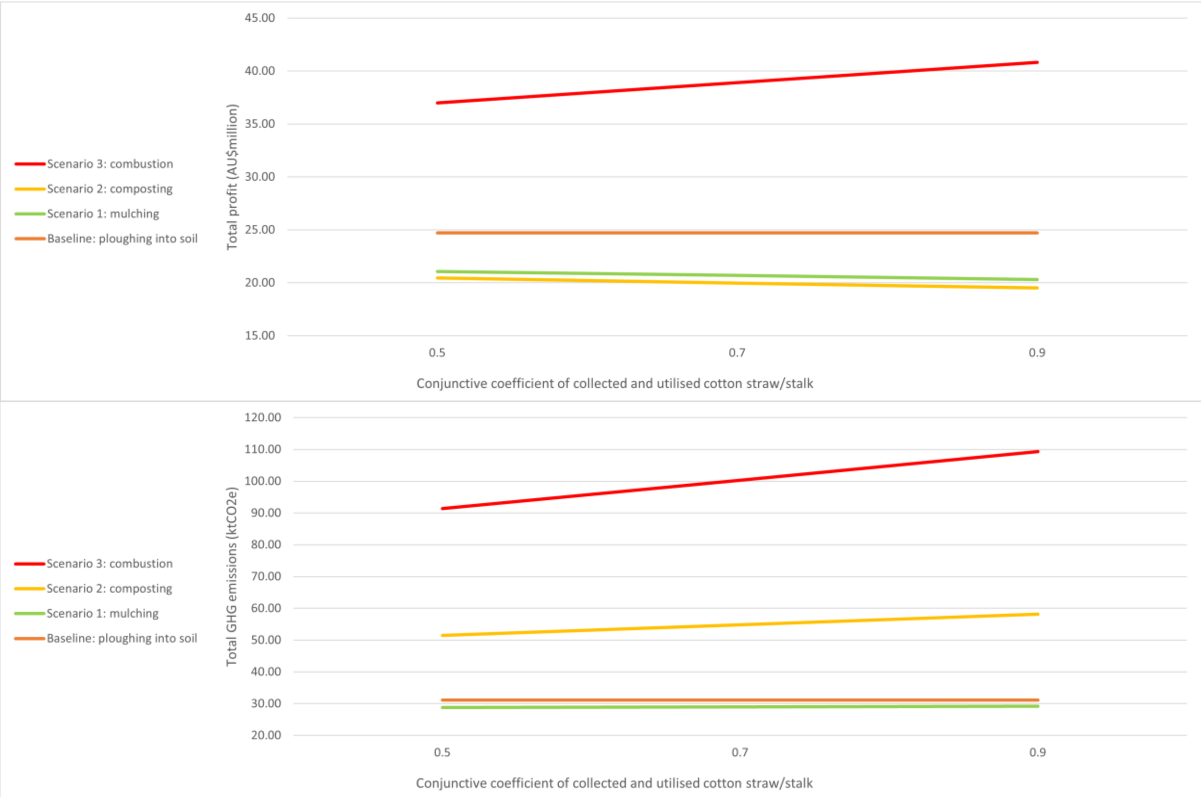


Figure 7.3. Total profits and total GHG emissions for different conjunctive coefficient of collected and utilized cotton straw/stalk in scenarios with mulching, composting and combustion, respectively.

Regarding total GHG emissions, an increasing efficiency on collection and utilization of cotton stalk/straw create subtle changes in scenarios with mulching. The emissions are slightly below 30 ktCO2e. As the efficiency increases, total GHG emissions in scenarios with composting increase apparently from about 50 ktCO2e to approximately 60 ktCO2e (nearly 0.25 ktCO2e increased per 1% efficiency of utilization on cotton residues increased). The uptrend for the scenarios with combustion is more remarkable from about 90 ktCO2e to approximately 110 ktCO2e (nearly 0.5 ktCO2e increased per 1% efficiency of utilization on cotton residues increased). This suggests the mulching practice being a more environmentally friendly method to managing, processing, and disposing crop residues in contrast to the other three scenarios.

7.1.4. Efficiency of energy recovery at facilities

In this study, the efficiency of energy recovery, or power generation, is the part of energy contained in crop residues convertible to usable electricity at the waste facilities. It is a coefficient of generated electricity from a theoretical lower heating value of crop residue determined by the capacity, techniques, and methods owned by the waste facilities (Ali et al. 2019; Jiang et al. 2019; Momayez et al. 2019; Siwal et al. 2021; Van Fan et al. 2021). In the regular combustion/incineration scenario, this efficiency for generating electricity by combustion is generally 30% (Remondis 2022).

According to the sensitivity analysis particularly on the combustion practice engaged model, this efficiency is more sensitive than (1) the costs of processing and disposing residues and (2) the conjunctive coefficient of collected and utilized cotton residues. Also, from the key results related to combustion scenarios in Chapter 6, the energy recovery strategy has worked with positive results in particularly performances of profits. It can concurrently be challenged against its intensive GHG emissions, which triples those from the other crop management/disposal strategies, due to the embedded techniques in the local waste facilities that considerably emit GHGs (ALCAS 2020; lifecycles. 2020). However, according to literature in Chapter 2, numerous studies have advocated for a better usage of crop residues as a good biomass/bioenergy source. In these regards, it is still worthwhile to further assess how increased efficiency of generating electricity at the waste facilities by combusting crop residues would impact the optimized outcomes. Here, three values of the efficiency are set in combustion: 30%, 50%, and 70%.

Key results show that while enhancing the efficiency of power generation by combusting crop residues (from 30% to 70%), the total profits increase from AU$36.97 million to AU$60.77 million (almost AU$0.6 million increased per 1% power efficiency increased). The total GHG emissions correspondingly decrease from 91.43 ktCO2e to 80.69 ktCO2e (about 2.3 ktCO2e decreased per 1% power efficiency increased). This reveals an increase in efficiency of power recovery during a combustion practice in disposing crop residues does significantly promote economic returns in the form of avoided energy costs, while it mitigates a certain amount of GHG emissions. When the efficiency is enhanced to a high level (70%), the total GHG emissions are nearly 30 ktCO2e greater than those caused by composting related scenarios. **Figure 7.4** presents the main impacts on the total profits and total GHG emissions in the combustion related scenarios (energy recovery), in comparison with the baseline scenario, the regular mulching related scenario and the regular composting related scenario.

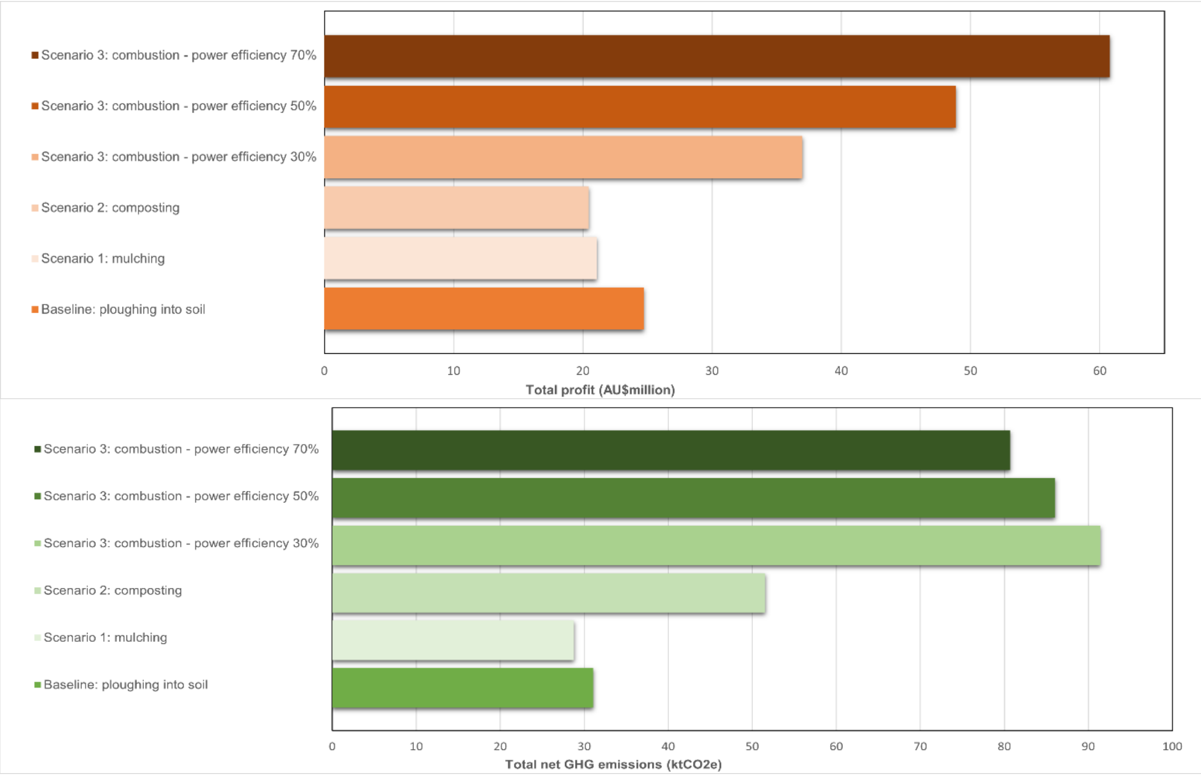


Figure 7.4. Total profits and total GHG emissions for different power generation efficiency in combustion at facilities in comparison with total profits and total GHG emissions from the baseline scenario, mulching scenario and composting scenario.

7.1.5. Feed-in tariffs of electricity

Electricity converted by solar power systems can be used in individual households of residential communities (Ergon Energy 2022a). Any unused electricity can be exported back to the electricity grid. Individuals may be eligible for a payment for the exported electricity, which is called a solar feed-in tariff and served as a dominant feed-in tariff policy in Queensland (Queensland Government 2022b). There has been a lack of pricing policies and regulations feed-in tariffs on other types of renewable energy in Queensland. Here in this thesis, the power feed-in tariff on the energy recovery involved in the combustion scenario model is designed to be identical to the regular tariff (AU$0.26/kWh) imposed on farming. This assumes that the generated power by combustion is returned to the farming areas to offset part of energy use. However, this energy recovery feed-in tariff (AU$0.26/kWh) is still a bit high in comparison with a regular level of solar feed-in tariff (as low as AU$0.09/kWh) (Ergon Energy 2022a). Thus, in this section lower levels of feed-in tariffs are attempted in scenarios to explore how different feed-in tariffs on recovered energy can affect the optimized outcomes with AU$0.06/kWh, AU$0.16/kWh, and AU$0.26/kWh.

When the power feed-in tariffs are lower than AU$0.16/kWh, the resource use performances for the cropping system are as below:

- Water application rates: cotton 7.74 ML/ha, wheat 2.02 ML/ha;
- Irrigated land: cotton 3,003 ha (28%), wheat 7,768 ha (72%);
- Total irrigated areas 10,770 ha (not reaching the maximal limit);
- Total water uses 38.92 GL (reaching the maximal water availability constraint).

When the power feed-in tariffs are higher than AU$0.16/kWh, the resource use performances for the cropping system will change, mainly in cotton growing, as below:

- Water application rates: cotton 5.99 ML/ha, wheat 2.02 ML/ha;
- Irrigated land: cotton 3,884 ha (33%), wheat 7,768 ha (67%);
- Total irrigated areas 11,652 ha (reaching the maximal limit);
- Total water uses 38.92 GL (reaching the maximal water availability constraint).

Figure 7.5 presents the impacts on the total profits and total GHG emissions in the combustion related model, in comparison with the other scenarios.

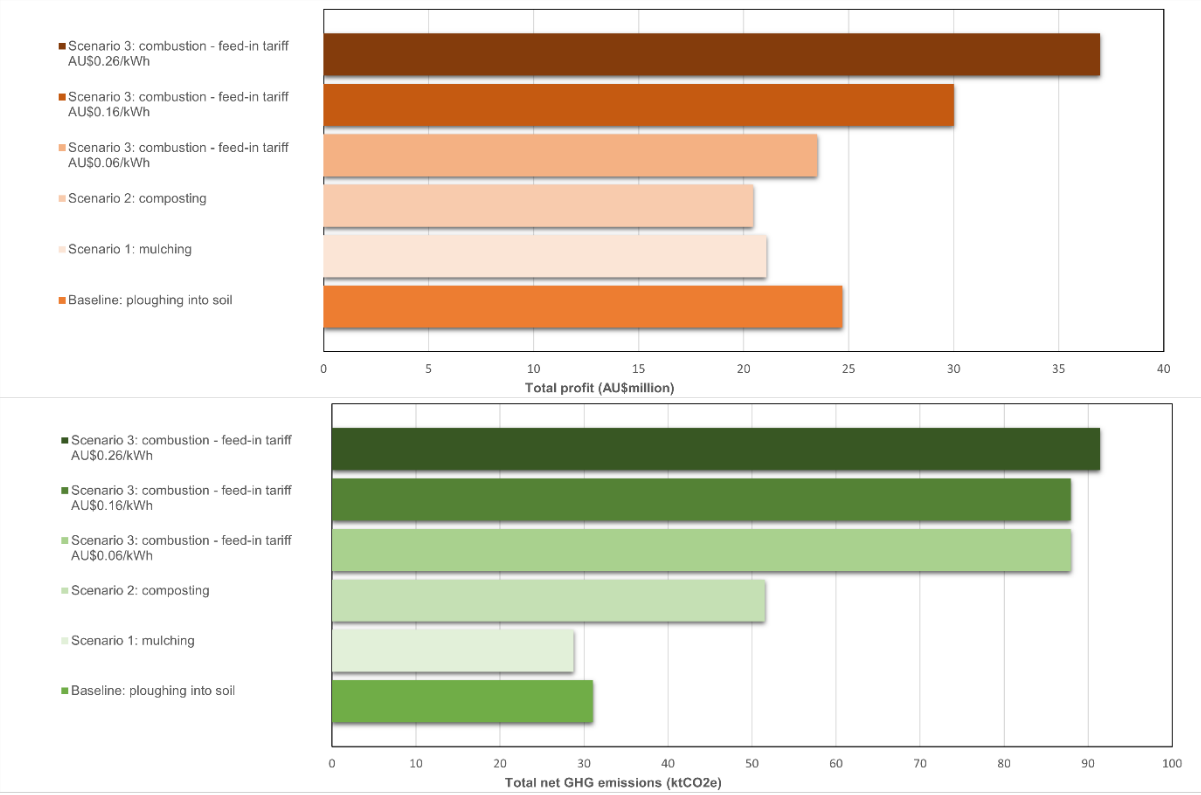


Figure 7.5. Total profits and total GHG emissions for different energy recovery feed-in tariffs in combustion at facilities in comparison with total profits and total GHG emissions from the baseline scenario, mulching scenario, and composting scenario.

When the feed-in tariff in the combustion related scenarios decreases from AU$0.26/kWh to AU$0.06/kWh, the total profits accordingly decrease from AU$36.97 million to AU$23.50 million (AU$67.37 million decreased per AU$1.0/kWh tariffs decreased). When it comes to around AU$0.08/kWh, the total profits are almost equal to the baseline scenario (AU$24.71 million). The total GHG emissions are 88 ktCO2e with a tariff lower than AU$0.16/kWh and 91 ktCO2e with a tariff greater than AU$0.16/kWh. It indicates that an increase in power recovery feed-in tariffs would enhance the overall economic performance and meanwhile not comprise the environmental performance. This can attribute to the role of feed-in tariffs played in positively impacting economic returns and meanwhile not impacting GHG emissions significantly. This parameter/factor can be perceived as univariate that imposes irregular/non-linear effects on the optimized outcomes of the cropping system particularly profits.

7.1.6. Implications for land and water uses

The key results and discussions in the previous chapters indicate that changes are seen in either resource use performances (total land use, total water use), economic performances (gross margins, profits) or environmental performances (mainly GHG emissions), when the two key independent variables, irrigated areas and water application rates, change.

The two key variables present the optimized solutions in pairs as they usually change interconnectedly. The more optimal solutions of the two variables are found under the impacts of a certain factor, the more essential and noteworthy this factor will be. For instance, crop prices, as an important factor investigated in Chapter 5, are remarkably influential as there are four pairs of optimal solutions on these two variables in cotton cultivation and two pairs of them in wheat cultivation. Contrastingly, for other factors like energy types, the optimal solutions for both cotton and wheat only have one certain pair. As such, the crop prices are regarded as a more influential factor than the energy types. The different pairs of optimal solutions on these two independent variables for the two crops are obtained from all scenarios including those in section 7.1 and listed in **Table 7.3** as below.

Table 7.3. A summary of optimized water application rates and irrigated areas.

Crops	Water application rate (ML/ha)	Irrigated land (ha)
Cotton	3.42	11,373
	5.99	3,884
	6.45	3,884
	7.74	3,003
	7.74	5,026
	7.77	2,823
	8.17	4,657
Wheat	0.00	278
	1.79	7,768
	2.02	7,768
	2.19	7,768
	3.11	278

The most frequently gained pairs of optimal water application rates and irrigated areas across all the scenarios are:

- Cotton: water application rate 7.74 ML/ha paired with irrigated land 3,003 ha;
- Wheat: water application rate 2.02 ML/ha paired with irrigated land 7,768 ha.

Most scenarios present such paired optimal solutions because they commonly feature a high level of wheat price (AU$400/t). The edge of cultivating cotton is not obvious from the point of economic returns with this high wheat price. This promotes the advantage of cultivating irrigated wheat relative to cultivating cotton considering maximization of the total profits for the cropping system.

The second most frequently gained paired optimal solutions are:

- Cotton: water application rate 5.99 ML/ha paired with irrigated land 3,884 ha;
- Wheat: water application rate 2.02 ML/ha paired with irrigated land 7,768 ha.

A much lower wheat price may also result in a big change in the optimal solutions, like wheat prices below AU$300/t, leading to:

- Cotton: water application rate 7.74 ML/ha paired with irrigated land 5,026 ha;
- Wheat: water application rate 0 ML/ha paired with irrigated land 278 ha.

When some factors/parameters change in scenarios, leading to a change of optimized results on the two key variables, the impacts of the factors are displayed in a non-linear pattern. For example, the optimal results of either gross margins, profits or GHG emissions towards different crop prices will be changing generally in a discontinuous/non-linear pattern, showing irregularity. Opposed to this, factors like energy costs will exert influences on the cropping system in a generally linear pattern. In such scenarios, the optimal water application rates and irrigated land are normally not changing. This is due to strictly constrained irrigated land availability and water application rates.

There has been deficit irrigation implemented in the cropping system, in which water application rates are supposed to not exceed the maximal crop water requirements for each crop. Under these restricted conditions, there will be a limited quantity of optimal solutions that can be found by model solving in maximizing the total profits of the cropping system. The unchanged water application rates and irrigated land will likely lead to a linear pattern of results on profits and/or GHG emissions. Therefore, the impacts of these factors will be like functions demonstrating a regular linearity, such as carbon price, transport distance on crop residues, costs of processing and disposing crop residues.

As mentioned above, the factors can be classified into univariate and multivariate ones, which contain single variable/parameter and multiple variables/parameters, respectively. **Table 7.4** summarizes factors in all scenarios in this study paired with their impacts on the cropping system.

Table 7.4. A summary of univariate and multivariate factors involved in all scenarios within this study as well as impacts imposed on the cropping system.

No.	Factors	Parameter type	Impact type	Major affected performances
1	Crop price	Univariate, economic	Non-linear	Resource (land and water), economic, environmental (GHG emissions)
2	Energy types	Multivariate, resource	Linear	Economic, environmental (GHG emissions)
3	Energy costs	Univariate, economic	Linear	Economic, environmental (GHG emissions)
4	Methods of crop residue management	Multivariate, integrated [a]	Non-linear	Resource (land and water), economic, environmental (GHG emissions)
5	Carbon costs	Univariate, integrated	Linear	Economic
6	Logistic distance in transporting residues	Univariate, technical [b]	Linear	Economic, environmental (GHG emissions)
7	Effective rainfall	Univariate, environmental	Non-linear	Resource (land and water), economic, environmental (GHG emissions)
8	Costs of processing & disposing crop residues	Univariate, economic	Linear	Economic
9	Conjunctive coefficient of collected & utilized cotton straw/stalk	Multivariate, technical	Linear	Economic, environmental (GHG emissions)
10	Efficiency of power generation by combustion (energy recovery)	Univariate, technical	Linear	Economic, environmental (GHG emissions)
11	Feed-tariff towards power generation	Univariate, economic	Non-linear	Resource (land and water), economic, environmental (GHG emissions)

[a] An integrated type of parameters is combined with more than one characteristics, such as methods of crop residue management including resource use, prices and/or costs, GHG emissions, techniques, etc, unlike a cost that only features an economic index.

[b] A technical type of parameters is referring to parameters with features other than those resource, economic or environmental related.

The four most essential factors are crop prices, effective rainfall (or rainfall), types of crop residue management practices, and power feed-in tariffs, as they all essentially influence the optimized resource use (land and water) and in turn change economic and environmental performances. They commonly feature a non-linear pattern of impacts on the cropping system and contribute to enhancing revenues. By contrast, if economic and/or environmental performances are changed, the factors may not have remarkable effects, such as alternative energy used in irrigation, costs associated with processing and disposing crop residues. Cost related factors usually have limited effects, mainly showing on economic performances (gross margins, profits), in a linear pattern. Crop residue management practices like mulching and composting involve avoided costs as well. However, the avoided costs or additionally achieved revenues are not influential to change the optimal water and land allocations.

7.2. Study limitations and possible solution

This section will outline and discuss all related limitations throughout this thesis which have potentially influenced the outcomes. Accordingly, viable solutions are to be proposed given adequate research conditions.

7.2.1. Crop water production function

7.2.1.1. Limitations

As stated in Chapter 3, the Stewart model (Doorenbos et al. 1979; Steduto et al. 2012) is selected as the main crop water production function (CWPF) to estimate responsive crop yields to different levels of water application rates. This crop yield model is primarily applied to a deficit irrigation practice, as it is essentially a linear mathematic function with local maximal crop yields and corresponding local maximal crop water demand as two key coefficients. The water application rate of one specific crop should not exceed the capped water application rate obtained by the difference between crop water demand and local average effective precipitation. Thus, responsive crop yields with water application rates higher than this capped value cannot properly be estimated. This little limitation is not technically affecting the work as this thesis aims at studying agricultural Water-Energy-Food (WEF) nexus of a single crop rotation system under a deficit irrigation practice mainly. But still it may be of vital importance for other peer researchers that would wish to conduct similar studies under a deficit and/or a full irrigation practice.

An indirect impact of this limitation may be limited optimal results derived in model running, as the intervals on one of the core independent variables, water application rate, are strictly constrained under the maximal crop water requirement and not many optimized solutions can be found. This can explain why optimal irrigated land use and water application rates do not change in some scenarios with varied conditions. Accordingly, the optimized outcomes of land and water resource uses, economic returns and GHG emissions will not vary significantly.

Another limitation about the CWPF selected for this study is the crop yield response factor and crop coefficients embedded in the model. The crop yield response factor represents the effect of a reduction in evapotranspiration on yield losses. The crop coefficients for each growth stage are mainly used to estimate evapotranspiration of that crop. Values for these two types of coefficients are derived from Steduto et al. (2012) and Brouwer et al. (1986a) respectively. Coefficients involved in a CWPF can only be accurately determined by experiments or software. It is rather time-consuming and cost-consuming and requires extensive precise crop growth data to simulate each crop growth stage, as stated in the literature review in Chapter 2. It is impossible to conduct either in-field experiments or software simulations due to restricted funding and time in our study.

The main issue that has been incurred and impacting the work is that the crop yields (cotton and wheat) may not have perfectly been determined as the coefficients are not locally contextualized. However, the values are based on the analysis of an extensive amount of the available literature on crop-yield and water relationships and deficit irrigation (Steduto et al. 2012). This is the only and best way to determine the crop yield response factor and the maximal crop water demand under a limited timeframe and funding of this study.

7.2.1.2. Potential solutions

Under sufficient research conditions, it will still be recommended to simulate crop growth and determine crop yield models by means of software for future studies. Classic software packages simulating crop growth include Aqua Crop (Steduto et al. 2009; Foster et al. 2017; FAO 2021a), Agricultural Systems Modelling and Simulation (APSIM) (Keating et al. 2003; APSIM 2021), Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al. 2004; DSSAT 2021) and CROPWAT (Smith et al. 2002; FAO 2021b). They are powerful in presenting detailed crop physiological responses to water deficits and enabled to predict natural crop-water production relationships in finer temporal scales (daily) than the above additive and multiplicative models (each growing stage lasting for dozens of days).

These software packages also embrace a broad array of functionalities determining associated environmental conditions and irrigation management practices, such as precipitation, evapotranspiration, temperature, CO2, soil profile, groundwater table, irrigation mode and scheduling, field practices. In this case, these programs can better serve to simulate the crop growing as realistic as possible on a daily basis in conjunction with all potential surroundings and climatic conditions as a whole cropping system, as well as to possibly predict the crop yields in an more accurate way (Foster et al. 2018).

In this way, a full functional model can be obtained involving both deficit irrigation and full irrigation conditions. These functions can be in either a generally cubic form (An-Vo et al. 2014; An-Vo et al. 2015; Maraseni et al. 2021) or a quadratic/parabola form (Peng et al. 2003; Zhang 2009). The crop yields are increasing as the water application rate increases; crop yields will peak when water application reaches the full irrigation point (or minimal crop water requirement); then yields will be declining as the water application rate increases.

If there are adequate datasets, coefficients of well-established crop models (namely Crop Coefficient Models) can be determined by curving fitting. Usually these functions are in a quadratic/parabola form (Peng et al. 2003; Zhang 2009). The data can be either primary or secondary. Primary datasets are usually derived by real in-field experiments that would take years. Secondary datasets are supposed to reflect crop yields responsive to both deficit and full irrigation conditions rather than to present crop yields responsive to only full irrigation practices throughout years.

Alternatively, a linear crop coefficient model can be used to simulate crop yields under deficit irrigation conditions, while the limitation is the inability to simulate the full irrigation part as discussed. The coefficients are expected to be curve fitted as well based on high data requirement like a quadratic/parabola model. One possible way to reduce the limitation of this linear function about the full irrigation part (beyond the point of maximal crop water demand) is simulating the coefficient of the function for the full irrigation part, as indicated in the dash lines below in **Figure 7.6**.

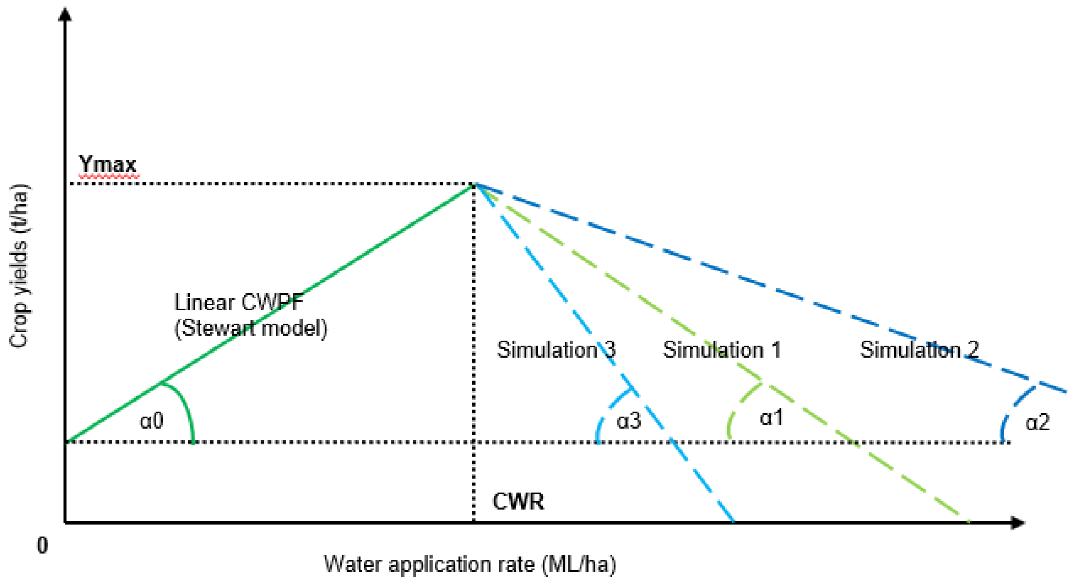


Figure 7.6. Linear crop water production function (CWPF) with supplementary part for full irrigation conditions. The left solid line in dark green is the Stewart model, while the dash lines are assumed/simulated models under full irrigation conditions, supplemented to the solid line. CWR refers to crop water requirement and responsively a maximal crop yield (Ymax) is gained. α0, α1, α2, α3 are values of slopes for these lines, where α0 and α1 have the same absolute values. These values are determined by native maximal crop yields, crop yield response coefficient, and native maximal crop water requirement.

As it is uncertain how the crop yields decline as the water application increases after the peak point, the slope of the simulated part (mainly the crop response coefficient) is still needed by curving fitting based on adequate datasets. An ideal CWPF is a quadratic/parabola which presents the relationship of crop yields and water use in a symmetrical pattern. Thus, Simulation 1 would be the theoretical supplementary to the Stewart model (deficit irrigation) for a full irrigation condition, when water application exceeds the crop water requirement and responsively crop yields begin to drop. This function is a discontinuous function, namely a piecewise mathematical function with two symmetrical linear functions on both sides, and hence α0 and α1 have the same absolute values of slopes. There will accordingly be two symmetrical functions to be established for further model solving. It should be noted that the results may be presented with slight deviations. So, during the model development, the peak point needs rectifying and validating when necessary.

7.2.2. Water allocation and rainfall

7.2.2.1. Limitations

As noted in Section 7.1.1, water allocation varies from year to year, depending on what year it is, namely wet year or dry year (Sunwater 2019b; MDBA 2022b). While studying impacts of rainfall on the cropping system, changes in rainfall will likely result in changes in total allocated water availability. However, there has not been a reliable model to establish a functional relationship between rainfall and water allocation, especially not on a high-resolution scale, such as local or farm. Estimation of water allocation is a complicated process with decision making considering many other factors, such as sustainable diversion limits and carryover, droughts (MDBA 2022b). Additionally, water entitlement and allocation are based on catchments, and thereby making it tough to estimate water allocation for a local governmental area scale. Moreover, agricultural sectors are usually defined as a medium priority for water use and divided into cropping, forestry, livestock, fishery, and so on. As such, an accurate amount of water that is specifically allocated to cropping is not possible to estimate.

7.2.2.2. Potential solutions

If conditions permit, it is still constructive to build up a functional relationship between water allocation and effective rainfall by referring to policies and regulations regarding water entitlement, allocation and trading, and by communicating with organizations like Murray Darling Basin Authority (MDBA) for data access and specific mechanisms on water allocation. Such organizations may be able to provide information about how allocations are calculated. In particular, access to water allocation to a small scale such as a local farm will facilitate model development under constrained conditions like water resource.

Particularly, data collection of water allocation to specific farms is very challenging. The total maximal water availability/allocation is one of the key resource constraints influencing optimal model outcomes. Effective communications or collaborations with farmers or any other stakeholders are supposed to be implemented throughout gathering essential information like exact water allocation. This will significantly contribute to WEF nexus research on a farm scale.

7.2.3. Solar energy use in irrigation

7.2.3.1. Limitations

As indicated in the sensitivity analysis and key results in 7.1.5, a power-by-combustion feed-in tariff rate is notably influential on the cropping system, particularly on energy use in irrigation. A solar feed-in tariff policy could change the economic performances by generating revenues or avoiding some energy costs and may further affect GHG emissions (Scobie et al. 2020).

The energy use for irrigation in this study is diesel fuel, on-grid electricity and solar photovoltaic (PV) power. However, the solar PV power used on irrigation driven by photovoltaic panels/modules have not been popularized in Toowoomba Region, so it is not practical to assume what is the commonly used type of solar PV systems. In this study, it is assumed that there would be enough solar PV facilities in the cropping areas, that the land occupied by the facilities would not be considered in the total land uses, and that farmers could receive premium prices for the irrigation practices with solar PV powers. So, it would not be feasible to conduct in-depth research into how solar PV power use impacts the optimal performances of cropping with further policy considerations in particular regarding a solar feed-in tariff. Moreover, solar feed-in tariff policies are usually designed for residential communities or small-scale businesses (Ergon Energy 2022a). This has added up more uncertainties in determining average tariffs that are applied to the whole Toowoomba Region.

7.2.3.2. Potential solutions

To quantify the annual capability of solar PV systems generating electricity, it has to be found out which is the most commonly or typically used system in the local area. This can be combined with considerations of climatic conditions from year to year: estimating rainfall, water allocation, and overall daylight lengths for the total capacity for generating solar power throughout a wet, moderate, and dry year, respectively. In this way, scenarios can be designed by correlating irrigation water with solar energy.

The optimal economic feasibility of solar energy occurs when the solar energy includes photovoltaic technology and remains eligible for a feed-in tariff. Such renewable energy is currently incentivized due to its capacity to reduce on-farm energy costs. Ergon has been evolving the solar feed-in tariff structures and the power generated, remained, and exported back to the grid is critical to a solar PV system investment (AgEcon 2019). Farmers are also encouraged to compare different solar feed-in tariffs with different providers to get the best quote for their farm businesses (QCA 2022). Regarding potential impacts of different feed-in tariffs, relevant studies can expect to design scenarios with different levels of the tariffs.

Otherwise, it would be easier to include this policy in a study on a farm scale, as feed-in tariff policies are usually designed for residential communities or small-scaled businesses and solar PV systems can be well fitted on farms. However, datasets can only be accessed by effective negotiations with farm owners, not only about the solar energy but also about the water allocation and use on the farms, provided that there is sufficient funding.

7.2.4. Projections of GHG emissions

7.2.4.1. Limitations

The Representative Concentration Pathways (RCPs) (Van Vuuren et al. 2011; Wayne 2013) scenarios are enabled to predict GHG emissions from various industries in the coming decades and centuries. They are basically environmental and climatic factors oriented scenario models and can supply reliable outputs relating to environmental changes in the future. However, the model developed in this study is based on an agronomic framework, involving a variety of economic parameters. This has made it impossible to project outputs of these parameters for the future decades or even centuries.

This study develops models incorporating a regular carbon price policy to see if a carbon price could impact the cropping system in a preliminary attempt. From the sensitivity analysis, the carbon price policy does not significantly influence optimal outcomes. The key results in crop residue disposal related scenarios with and without a carbon policy also indicate the carbon price policy has a limited effect on the cropping system in a linear trend, where profits are slowly decreasing while the carbon costs are increasing. Policies, programs, and activities such as GHG emissions reductions are not conducted as these will involve a broad variety of farm inputs reductions as well as their costs changes. How those inputs are reduced in proportion cannot be determined. Due to a limited timeframe, no further actions on carbon price policies or GHG emissions reductions targets are taken.

7.2.4.2. Potential solutions

One possible solution is to have in-depth designs of GHG emissions reductions related scenarios by dividing farming activities into several parts (agrochemicals and machinery, irrigation, crop residue management, and so on) and studying GHG emissions from each part.

Another way is akin to Li et al. (2021) who utilized the RCPs scenarios to project evapotranspiration of their cropping and forestry systems for future decades. The models they have developed are primarily about resource uses, environmental impacts and climatic changes. The series of studies by Li et al. (2015) since 2015 have often applied multi-objective modeling for optimization on WEF nexus in irrigated agriculture under uncertainties of modelling parameters (Li et al. 2016b; Li et al. 2017; Li et al. 2019b; Li et al. 2020; Li et al. 2021). This is a good way that the model development separates economic parameters based sub-models and environmental parameters based sub-models for different objective functions in a compatible and integrated model.

7.2.5. Crop residues

7.2.5.1. Limitations

Linking crop residues to the agricultural WEF nexus framework is the biggest research gap in this study, and it is challenging to overcome because of a severe lack of information and datasets. Disposal methods for processing, disposing and utilizing crop residues are very limited locally and there is no advanced technology such as anaerobic digestion, co-fermentation, co-fire, gasification. Local authorities like city councils or municipalities do not provide services on processing and disposing crop residues (Toowoomba Regional Council 2022a). It is not common for private businesses to deal with crop residues either. A small number of them may do but usually they take in crop residues as a generic category of green waste like other green waste (forestry residues, municipal green waste, and so forth). The costs between existing simple disposal methods have much difference. It is an arduous task to determine an average value of these costs for a local scale.

7.2.5.2. Potential solutions

In these regards, an entry point can be an attempt to conceptualize and contextualize the “Waste” component to be correlated to targeted agricultural WEF nexus. Besides crop residues, other types of agricultural residues or waste include forestry residues, livestock manure, which can be incorporated as well if the WEF nexus framework is to be expanded to include forestry (Guta et al. 2018; Melo et al. 2021), livestock or fishery (Vogeler et al. 2019; Li et al. 2020; de Castro Sobrosa Neto et al. 2021).

Challenges about availability and accessibility of relevant datasets and policies can be addressed possibly by referring to relevant research conducted in other nations particularly China, US, and India, which produce the highest quantity of such studies. Those studies involve advanced environmental technologies for disposing agricultural residues, such as anaerobic digestion, co-fermentation, co-digestion. It would further address the challenge to estimate economic parameters such as costs of these methods, as those studies mostly focus on environmental performances.

Methods such as gasification, pyrolysis, torrefaction, co-firing are usually related to bio-energy and/or bio-mass recovery that enhances performances of energy use and environment. Relevant information and data about these high-end methods are supposed to be accessed by collaborating with privately owned businesses/facilities or institutions.

7.3. Conclusion

Based on the key results and discussions in Chapter 4, 5 and 6, this chapter gives further discussions on other potential factors having effects on the cropping system and limitations coupled with possible solutions. These potential factors are selected from all the parameters ranked by importance in the sensitivity analysis on either the basic model or extended models. These include:

(1) Effective rainfall;
(2) Cost of processing and disposing crop residues involved in mulching, composting and combustion;
(3) Conjunctive coefficient of collected and utilized cotton straw/stalk;
(4) Efficiency of energy recovery at facilities;

(5) Power feed-in tariff rate.

It has been found that factors (1) and (5) demonstrate more complex impacts than the other factors, as they will change the original optimized water application rates (cotton: 7.74ML/ha; wheat: 2.02ML/ha) and irrigated land (cotton: 3,002.94 ha; wheat: 7,767.61 ha). In turn, economic performances (profits, gross margins, and so on) and environmental performances (total GHG emissions, GHG emission intensity, and so on) will be influenced and presenting a non-linear/discontinuous pattern. The other three factors have indicated limited effects on the optimized water application rates and irrigated land. Rather, they impose linear patterns of effects on the cropping system's economic performances and/or environmental performances.

Throughout all the scenarios, it is implied that the significant changes incurred are attributed to essential changes of the two independent variable, namely the resource uses of water application rates and irrigated areas on each crop. They are the core variates of the integrated models developed in this study, interrelating other parameters and thus impacting them correspondingly. The most gained optimums among all scenarios are:

- Cotton: water application rate 7.74 ML/ha paired with irrigated land 3,003 ha;
- Wheat: water application rate 2.02 ML/ha paired with irrigated land 7,768 ha.

It has been found that the most influential factors towards these core variates in the modelled single crop rotation systems are crop prices (cotton lint and wheat), effective rainfall (or rainfall), alternative crop residue management practices (particularly combustion/incineration with energy recovery), and power feed-in tariff policies. These factors essentially changed optimums of the core variates and performances of the cropping system show significant differences among scenarios.

Limitations of this study mainly include:

(1) Insufficient approaches to derive more robust crop water production models due to limited funding and timeframe;

(2) Lack of models and datasets to establish certain relationships between water allocation and rainfall;

(3) Unviability to determine common technical parameters of solar power systems and associated solar feed-in tariff policies applied to cropping on

a local scale;

(4) Unsuitability of GHG emission projections in economic models;

(5) Lack of datasets and policies about disposal methods/practices.

These limitations mostly restrict further development of methods and models in our study. Due to a lack of practical approaches to determine a crop water production function for full irrigation conditions, optimal outcomes of the models are derived under deficit irrigation practices. The most direct consequence is that there have been limited optimal solutions across all scenarios discussed throughout this study. In most scenarios, the optimal solutions of the core variates remain stable, unless there are key factors correlating revenues of the cropping system (such as crop prices, rainfall, native maximal crop yields) or significantly affecting the costs (such as different crop residue disposal practices, on-grid/solar power feed-in tariffs). Possibilities of achieving further optimal solutions are restricted, albeit the crop water production function adopted in this study satisfies our study goal to research cropping systems under strictly deficit irrigation conditions.

A lack of robust models and datasets to effectively develop the relevancy of water allocation and precipitation has limited further delve into potential impacts of rainfall, water availability and even water trading policies on cropping. It may make the models more complicated to take into consideration water resource and, in particular, trading policy.

Owing to the disparity of technical parameters among different solar power systems, it has been challenging to determine a certain type of solar system that can be applied to our study area, the Toowoomba Region, while popularity of solar power application is still underway. What is more, employing solar feed-in tariffs to solar energy use in cropping has been an arduous task because of varying climatic conditions leading to uncertain quantity of power generation by solar systems. Additionally, the varying climatic situations will most likely associate with rainfall and water allocations as mentioned above. This would complicate the process of model development.

The carbon prices in both sensitivity analysis and scenarios analysis reveal its limited effects on the models. Thus, no further actions have been taken to research GHG emissions and associated carbon policies. Many scholars have studied projections of GHG emissions in the future decades in response to global climate change. The predictions on these climatic parameters for the future would not be possible to be combined with economic parameter oriented models as the economic factors cannot be effectively determined for the future which are intertwined with many external factors and keep changing irregularly.

Application of disposal methods to crop residue management is the biggest research gap in this study. No studies have dived into an agricultural Water-Energy-Food nexus system linking crop waste in particular. There has been a severe lack of information and experience that can be supplied regarding disposal methods on crop residues. In the market, private companies commonly do not take over such businesses of coping with crop residues. Data is limited to better solve the models. Scenarios cannot be further designed as there are few feasible environmental solutions to crop disposals. The only three types of environmental practices found in Toowoomba Region are mulching, composting and combustion/incineration with energy recovery.

With all discussed above in this chapter as well as previous chapters, conclusions will be made in the next chapter in line with recommendations about potential directions and outlooks for future studies.

CHAPTER 8: CONCLUSIONS AND RECOMMENDATIONS

Due to the increased demand for water resources, energy and food production on a global level, Water-Energy-Food (WEF) nexus has been coined and studied to be effectively responsive to ensuing issues. Climate change caused by anthropogenic greenhouse gas (GHG) emissions and food waste are also two noteworthy aspects to be addressed aligned with multiple Sustainable Development Goals (SDGs). In agricultural industries in arid or semi-arid areas like most part of Australia particularly, water and energy use are often significant constraints. They are correlated and in turn affect and being affected by crop production. Research of agricultural WEF nexus can thus help to enhance typical Australian cropping systems' performances.

In relation to these factors, this thesis has developed an integrated optimization model, based on insights into Water-Energy-Food (WEF) nexus, for a single crop rotation system (cotton cultivation in summer and wheat cultivation in winter) in the Toowoomba Region, Queensland, Australia. The overall study goal is to achieve an optimal balancing of resource use (water and land), economic benefits, and associated environmental performances (GHG emissions).

8.1. WEF nexus: major research gaps

With that aim, major research gaps regarding WEF nexus have been found out through literature review, including:

- Difficulties in implementation due to complex contexts and policy background;
- Lack of all-round robust models - overly complicated methods for large scales while not integrated enough for small scales, such as local or farm;
- Limitations in nexus optimization;
- Lack of waste components.

The main research gaps pertaining to agricultural WEF nexus involve few numbers of WEF nexus studies engaging in agriculture compared with total number of WEF nexus studies, lack of research with depth in small scales like local or farm where the foci are on a dual Water-Energy nexus without "Food" component (crop yield or production) being robustly connected or highlighted. There have also been limited other components engaged in the nexus, particularly waste.

Accordingly, this study has developed an integrated model to optimize the total cropping profits with sub-models of crop yields, water costs, other variable costs, and associated carbon costs. The model developed employs mathematical programming and optimization under coordinated resource and technical constraints. It is applied to one of the common cropping systems in Australia. The study area is Toowoomba Region located in Southern Queensland of Australia. The selected crops are cotton grown in summer and wheat grown in winter, constituting a single-crop rotation system. The total irrigated study area is at maximum 11,651.59 ha.

With basic situations in Toowoomba Region as a baseline, a business-as-usual scenario involving common farm practices is first studied. Different scenarios are then designed by considering: (1) different crop prices (cotton lint and wheat), (2) alternative energy sources and associated costs involved in irrigation (diesel, on-grid electricity, and solar photovoltaic power), (3) alternative methods to process, dispose and utilize crop residues (mulching, composting, combustion/incineration with energy recovery). Other potentially influential factors are further considered to investigate how they would impact the optimized performances of the cropping system.

8.2. Key findings

In the baseline scenario with the assumed cost structure for cotton and wheat production in Toowoomba Region, it has been found that the optimized irrigated areas of wheat (72%; 7,768 ha) are remarkably higher than those of cotton (28%; 3,003 ha) under cotton irrigation application rate of 7.74 ML/ha and wheat irrigation application rate of 2.02 ML/ha. The gross margins per ha irrigated area are AU$4,132/ha in cotton cultivation, being higher than AU$1,584/ha in wheat cultivation. GHG emission intensities are also higher in cotton (3.25 tCO2e/ha and 0.52 tCO2e/t) than those in wheat (2.69 t CO2e/ha and 0.45 tCO2e/t).

Among scenarios with different crop prices, the scenario of cotton lint price AU$700/bale and wheat price AU$400/t generate the maximal total profits of the cropping system in the Toowoomba Region over the year, AU$31.72 million. Such outcomes will most likely occur when the cotton lint price is high and the wheat price is low with their price gap being more than AU$250 per unit in values. This implies crop price is one of the major factors influencing economic returns of cropping. The land use and GHG emissions are the highest as well, which are 11,651 ha and 33 ktCO2e, respectively. The scenario giving rise to the highest GHG emissions is the one with cotton price AU$650/bale and wheat price AU$400/t for 33 ktCO2e, slightly greater than the one with cotton price AU$700/bale and wheat price AU$400/t for 33 ktCO2e.

In contrast, impacts of alternative energy sources used in irrigation are less remarkable than those caused by crop prices. It has been found that optimized total profits in scenarios involving diesel and on-grid electricity are AU$24.71 million and AU$24.48 million, respectively. Solar photovoltaic (PV) power use can generate higher total profits than diesel or on-grid electricity, AU$25.61 million, and lower total GHG emissions, 27 ktCO2e. This can be achieved by cutting down costs of diesel or network electricity.

If there is no additional value chain considered in the cropping system, namely the life cycle of farming commencing from land preparation and ending at fallow, crop prices are the major factor influencing the trade-offs and synergies of resource uses, economic performances, and GHG emissions of the system. They affect it in two main ways: (1) the relative advantage of price for one crop over the other, and (2) the absolute price for crop. A higher cotton market price and a lower wheat market price will likely be the most profitable with identical levels of land and water consumption and GHG emissions. Such a scenario can achieve an optimal balancing of resource uses (water and land), economic benefits, and associated environmental performances (GHG emissions).

In scenarios on the further developed models for crop residue disposal, those with a combustion (energy recovery) practice for crop residue disposal reveal high total profits coupled with high GHG emissions at the same time. It has been found that the economic performances are the best in the combustion scenario (total profits around AU$38.44 million without carbon costs), followed by the ploughing-into-soil scenario (baseline) (total profits around AU$25.20 million without carbon costs). A composting scenario produces the lowest total profits (around AU$21.26 million without carbon costs). The best environmental performances are in a mulching scenario (28 ktCO2e), followed by the ploughing-into-soil scenario (31 ktCO2e). GHG emissions from composting and combustion almost double or triple as opposed to ploughing (51 ktCO2e and 91 ktCO2e, respectively). Carbon price policies (AU$15.99/tCO2e) or different logistic distances impose only a limited effect on the system performances. The scenario without carbon costs and with a short logistic distance has total profits of AU$38.98 million coupled with total GHG emissions of 90 ktCO2e. The total GHG emissions are 91 ktCO2e in the scenario without carbon costs and a long logistic distance, where the total profits are AU$38 million.

Regarding other potentially influential factors, it has been found that rainfall and power feed-in tariffs show more complex influences than the other factors, as they change the core variables, water application rates (cotton: 7.74ML/ha; wheat: 2.02ML/ha) and irrigated land (cotton: 3,003 ha; wheat: 7,768 ha). The other factors have shown only limited effects on the optimized performances. Across all scenarios, the maximal total profits (AU$60.77 million) are gained in the scenario involving combustion with an assumed efficiency of power generation being high (70%).

Among rainfall related scenarios, a wet year has a higher profitability than a moderate or a dry year, AU$27.29 million. Rainfall has notable but still limited impacts on each crop, as crop yields reach the maximum in most scenarios. More rainfall leads to more land allocation to cotton cultivation and in turn generates higher total revenues (increased by over AU$3 million).

If the costs of processing and disposing crop residues low (AU$30/t) in a combustion practice are lowered, the total profits will be AU$38.06 million with total GHG emissions of 91 ktCO2e. When enhancing the efficiency of utilizing cotton residues up to 90%, the total profits will be increased to AU$40.81 million with the highest GHG emissions of 109 kt CO2e. When increasing the efficiency of power generation in the combustion up to 70%, the total profits will be further increased to AU$60.77 million while the total GHG emissions are reduced to 81 ktCO2e. When keeping the power feed-in tariff for combustion energy recovery at a high level (AU$0.26/kWh), the total profits will be AU$36.97 million but the GHG emissions will still be high, 91 ktCO2e.

If the value chain is extended by replacing the conventional crop residue management practice (ploughing into soil) with an alternative disposal method, a practice with energy recovery can be the most impactful factor influencing the trade-offs and synergies of resource use, economic performances, and GHG emissions of the cropping system. In particular, increase in efficiency of power generation in this practice will significantly promote economic returns. Increasing efficiency of collection and utilization on crop residues will also increase economic returns and greatly increase GHG emissions. However, those scenarios involving a ploughing-in-soil or mulching practice for crop residue management manifest significantly lower total profits coupled with lower GHG emissions simultaneously.

8.3. Study limitations

Throughout this study, major limitations of this study include insufficient approaches to derive more robust crop water production models, lack of models and datasets to establish certain relationships between water allocation and rainfall, unviability to determine common technical parameters of solar power systems and associated solar feed-in tariff policies applied to cropping on a local scale, unsuitability of GHG emission projections in economic models, and lack of datasets and policies about agri-environmental crop residue management practices. In general, while the overall goal of this study is mostly achieved, these limitations primarily restrict further model development in this work.

In the first instance, the Crop Water Production Function (CWPF) adopted in this work is usually used for cropping under deficit irrigation conditions. This is aligned with our study goal as this work aims at researching an agricultural Water-Energy-Food (WEF) nexus system in strictly constrained water and land resources. This CWPF is technically a linear model, no more accurate than a quadratic/parabola or a cubic model in estimating crop yields particularly under full irrigation conditions. But a quadratic/parabola or a cubic model is challenging to derive as it would be very time consuming, no matter by means of real fieldwork or software simulations, and also highly data demanding (extensive and accurate datasets for each crop). Due to limited timeframe and research funding, it is not practical to carry out the work. If there is a need to study both deficit and full irrigation conditions in future research and research conditions allow, it is still highly recommended to use software packages and simulate the relationships between crop yields and water use.

Due to lack of models and datasets to establish certain relationships between water allocation and rainfall, no in-depth scenarios are further designed for evaluating more precise impacts of rainfall on the cropping system. Rainfall within a water year is linked with water entitlements and allocations. Allocations to a certain local area is however subject to many other considerations. Besides, it is not practical to do so without support from farm owners if the study is based on a farm scale. Collaboration with specific farm owners is not feasible in this study because of limited resources. If these issues can be resolved, however, scenarios regarding impacts of water trading policies can be further designed, integrated, and implemented.

Solar feed-in tariff policies are not applied to the cropping system in this work. The use of solar photovoltaic (PV) power in irrigation particularly is yet to be popularized and just used on a number of cotton farms but not for other crops except cotton and wheat (Scobie et al. 2020). There have been too many uncertainties to apply a solar feed-in tariff further to the cropping system. This work primarily explores how solar PV power influence the cropping system without solar feed-in tariff policies, but this can be a good prospect for future studies.

Likewise, pertaining to carbon price policies, this work mainly investigates how a regular carbon price imposed on the cropping activities would influence the optimal outcomes. The sensitivity analysis indicates the carbon price policies have limited impacts on the outcome. Moreover, future scenarios about GHG emission projections, Representative Concentration Pathways (RCPs), do not match with the agronomic model in this work. As such, no in-depth scenarios about carbon policies or GHG emissions are further designed. However, this can also be a good prospect for future studies, as cropping on a local or farm scale does not usually consider carbon policies or GHG emissions. In addition to indirect impacts due to changes in policies, programs, and activities addressing climate change issues, direct impacts due to changes in climate itself can be considered in scenarios with GHG emission projections for future studies.

Lack of information about environmentally technical disposal practices on crop residues is one cause resulting in the research gap of WEF nexus connecting with crop residues (Agricultural WEF-Waste nexus). Mulching, composting, and incineration/combustion with energy recovery are the three dominant disposal methods, with which local private waste facilities can provide services for commercial purposes. Data collected for these practices are limited and can be used for this work. But the data reveals uncertainties of parameters, like the costs/quotes showing much difference in different companies. On account of constrained fund and timeframe in this study, no further scenarios are designed for more insights into crop residue related parameters or more alternative crop residue disposal methods such as anaerobic digestion, co-digestion, or co-fermentation. However, this direction would be promising to narrow this research gap.

8.4. Recommendations for stakeholders

8.4.1. Practical recommendations for farmers

Crop prices are usually expected to be the most influential factor as crop prices directly affect the total revenues. In a typical single crop rotation system, there is need to be well aware of the price gap between the more profitable crop and the less one, like cotton and wheat in this thesis. Usually, summer crops have significantly higher water requirement and the responsive crop yields are higher than winter crops. Summer crops are sold at a higher price in the market and thus they are more profitable. It is recommended to improve crop yields and quality so as to make them more competitive in the market. If the price of summer crop higher enough than the winter crop, the most overall economic benefits will be generated. If the price gap is not large enough and both crops' prices are low, adjusting land allocation with a bit more to the winter crop will be better.

Under constrained water resources or deficit irrigation practices in particular, rainfall in wet years is supposed to be fully used. This would help to improve water use efficiency by reducing water application rates. Rainfall has particularly a notable effect on summer crops. While crop water need is partly met, more land can be assigned to summer crop cultivation.

Even though energy types and costs may have limited effects on cropping, it will still be worthwhile to take advantage of renewable energy sources like solar power, which is common in Queensland because of both the geo-climate advantage (abundant sunshine throughout years) and policy advantage (solar PV power being promoted by the government). It contributes to saving significant amount of traditional and non-renewable energy sources and associated costs, and avoiding associated GHG emissions, especially in irrigation activities which is one of the largest water and energy users in agriculture. In this way, the overall benefit can be maximized in contrast to that generated by use of conventional energy sources like diesel fuels or on-grid electricity. Furthermore, solar power use paired with feed-in tariffs are remarkably economically more viable than that without a tariff (AgEcon 2019; Currey et al. 2020). Thus, farmers should be encouraged to make full use of solar feed-in tariff policies for potentially extra economic returns by exporting remaining generated power to the network. They may be offered good prices of selling the electricity by selecting an appropriate energy service provider like Ergon Energy (2022a).

When it comes to considering environmental practices on crop residue disposals, farmers should be encouraged to select those involving bio-energy and/or bio-mass recovery as end products, which will generate additional revenues or avoided costs for cropping. In particular, combustion/incineration with energy recovery can be the most profitable. It produces electricity and/or heat that can be re-utilized in the upper stream value chain (such as back to farming) to avoid some costs or re-sold for extra economic returns. The electricity would also displace network electricity generated by coals, other fuel resources and even solar energy. The heat would likely produce hot water and so avoid the need to use natural gas to mitigate GHG emissions (Anshassi et al. 2021; Amulen et al. 2022). Likewise, anaerobic digestion would produce digestate, which displaces urea and ammonium nitrate used on farms, and biogas, which displaces natural gas (Anukam et al. 2019; Li et al. 2019d; Pramanik et al. 2019).

To avoid extra costs, businesses charging less for costs of processing and disposing crop residues should be chosen as a priority. Despite a wide range of costs/quotes offered by those private companies, the services may not differ much in the same type of service (such as mulching). The significantly different prices/quotes may be caused by undeveloped regulations on crop residue disposal in the markets. Regarding logistics on crop residues, it is recommended to improve efficiency on collecting and utilizing crop residues and have the residues disposed as near as possible to cropping/farming areas.

8.4.2. Recommendations for policy makers

Relevant policy rules and regulations are needed pertinent to water allocation, solar feed-in tariffs, carbon costs and GHG emissions, regulations on markets of crop residue disposal by businesses, and viable feed-in tariffs for power generated from combustion/incineration.

Access to specific water allocations to certain areas based on a Local Governmental Area standard is unpractical. Information for more precise allocations to specific farms are supposed to be available via effective communication and cooperation with farm owners. If these statistics are accessible through government databases websites, it will be beneficial to use the model to achieve more accurate outcomes. Or alternatively, it is recommended that relative authorities provide/disclose calculation methods on water allocations to specific local areas and farms.

The Murray Darling Basin Authority (MDBA) used to roll out Generation 2 Hydrological Models for Border Rivers, Condamine, Balonne and Moonie Valleys (Bewsher Consulting Pty Ltd 2019). These models provide a general relationship between rainfall and water entitlement. Similar hydrological models are expected to be released by authorities. It would facilitate further model development with potential functional relationships between effective rainfall and specific water allocation by jointly utilizing calculation methods on water allocations to specific local areas and farms. Then in-depth scenarios about water trading can be further designed. This will enhance accuracy of data and help to better examine the impacts of water trading.

In considering policy, network and retail within Australia in applying solar renewables, five ways should be considered: policy installation incentives; network contexts; feed-in tariffs and eligibility; connection to embedded generation, and avoided emissions (Powell et al. 2019). In particular, installation policies with network connections would incentivize both farmers and business owners to prompt advancement of solar energy applications to native farming communities. Queensland’s feed-in tariffs are restricted to very small scales like residential communities or small businesses (Ergon Energy 2022a; QCA 2022; Queensland Government 2022b). This may be more beneficial for small farm owners. But for a larger spatial scale like a local area, these policies are yet to be facilitated and made uniform throughout the whole local farming areas.

Neither farmers nor private businesses have good awareness of the importance of considering GHG emissions and associated carbon costs (Zhao et al. 2016; Graham 2022a; Scobie 2022) (Phoenix Power Recycles 2022; Remondis 2022; Cleanaway 2023; WestRex 2023; Zilch Waste Recycles 2023). This study indicates the carbon costs as a parameter in the models are limited influencing factors. Policy makers are encouraged to popularize carbon pricing policies (such as Australia’s Emissions Reduction Fund (ERF) scheme) and further GHG emissions reduction targets on small/higher-resolution scales of commercial activities like on farms or in local areas. This would not only be highly aligned with GHG emissions mitigation initiatives advocated worldwide today but also promote further development of relevant carbon policies including carbon trading.

Businesses providing services for managing crop residues should be regulated with policies particularly on commercial charges/quotes. The end products are expected to be further classified with standardized prices, as some generated bio-mass must be subject to specific legislations about waste and chemicals classification (Tursi 2019; Remondis 2022). These includes further developing and designing power feed-in tariffs for electricity generated by combustion/incineration in the waste facilities or power plant. The power feed-in tariffs have noteworthy impacts on cropping as indicated in this study. This policy resembles a solar feed-in tariff. They can be integrated into a more systematic policy framework regarding renewables feed-in tariffs. Then, it would be better to link them with other Renewable Energy Schemes (Ergon Energy 2022a) based on existing farming tariff policies (Ergon Energy 2022b).

8.4.3. Infrastructure related recommendations for businesses

Suggestions for businesses concerning improvement on infrastructure include solar photovoltaic (PV) systems, setting up facilities for on-site disposal, improve power generation facilities.

Cotton Australia (2018) has published a number of grid-connected solar irrigation case studies, concluding cotton growers have met a good opportunity to adopt renewable energy pumping systems for reducing both on-farm costs and GHG emissions. The commercial viability in solar will be highest at the time when solar energy produced can be employed throughout the year and variable electricity costs are high. In the first instance, a wider spread electricity network should be established for the sake of a better access to the grid and for further consideration of grid-connected solar installations. These will help to promote feed-in tariff policies as well as other possible renewables incentives promoted by authorities. Meanwhile, businesses should be encouraged to advance batteries technology for long-term pump use, as this is also a key factor for the consideration of grid-connected solar installations.

During crop residue management/disposals, the logistic distance plays a part in impacting economic viability and interest (Jiang et al. 2012; Qiu et al. 2014; Pastori et al. 2021). Longer distance in transporting and delivering crop residues will also cause greater GHG emissions due to fossil fuels being the primary energy sources in logistics. Commercial waste facilities would be recommended to establish their sites in proximity to farms. For larger scales, scattered on-site facilities within major cropping/farming areas can be a good idea. This can contribute to making crop residue management an economically viable option by reducing logistic costs. Also, this could increase the efficiency of crop residue collection and utilization that would have been lost during long logistic distances (waste loss avoidance). Furthermore, establishing waste facilities/power plants near major cropping areas would more practically return the power generated to the farms for re-use. This again highlights the importance of access to electricity network paired with grid-connected power installations as grid-connected solar installations.

In light of power recovery by combustion/incineration of crop residues, improvement of the efficiency of power generation would be another idea worthwhile considering. An increased efficiency of power generation would boost the economic benefits of cropping and simultaneously cut off GHG emissions during the processing and disposal of residues. This will encourage businesses/commercial activities in managing crop residues to meet the goal of GHG emissions mitigation and being carbon smart.

8.5. Recommendations for future studies

8.5.1. Multiple crop rotation

Crops may have a different market advantage between one another. This advantage can be reflected in crop quality, price, market share and so on. Like cotton and wheat in this study, irrigated wheat compared with rainfed wheat has significantly higher yields and market prices, indirectly narrowing the advantage gap between cotton and wheat. That explains why more land is allocated to irrigated wheat in a number of scenarios in this study. Given the factors of different crop characteristics (mainly water responsiveness and maximal yields), seasonality (mainly rainfall) and native crop market (crop prices), multiple crop rotations will be recommended by applying the integrated models developed in this study. It can be extended to a multi-crop rotation system with water demanding summer crops, exemplified by cotton, and winter crops, exemplified by winter wheat. Usually there will be 2-3 crops grown in summer and 2-3 crops grown in winter in a multi-crop rotation system. This would bring a greater diversity of paired optimal solutions achieved. A multiple crop rotation could offer a greater range of options and possibilities for better resilience of the agro-ecological system to resist potential risks such as drought. Thus, it would be of high significance to study WEF nexus in a multiple rotation system and explore more solutions.

8.5.2. Crop water production models

As discussed in the section 7.2.1, it is recommended to simulate crop growth and determine crop yield models by means of software such as AquaCrop or APSIM, if conditions allow, especially considering transferring to a multi-crop rotation system. Otherwise, if there are adequate datasets, coefficients of well-established crop models (namely Crop Coefficient Models) can be determined by curve fitting. The Stewart model adopted in this study cannot simulate cropping under full irrigation conditions.

8.5.3. Alternative irrigation systems

The most used irrigation system for cotton cultivation in the Toowoomba Region is surface irrigation (80% - 90%), followed by center pivot (10% - 20%). There is an increasing number of center pivot irrigation systems that have been installed particularly in the Toowoomba Region, but there are insufficient datasets of center pivot systems for wheat cultivation (Queensland Government 2022a) (Graham 2022). This has made it difficult to research impacts of different irrigation practices on the cropping system in this study. Irrigation systems show differences in various ways, including machinery designs, applicability for different purposes, irrigation efficiency. Different types of irrigation systems can be a complicated/multivariate factor notably for further scenario design and analysis.

8.5.4. Water trading policies and solar power

Water markets are a key mechanism by which Australia manages water scarcity while still supporting economic growth. Agricultural water use may be constrained by permanent entitlements to water and seasonal allocations of water (DAWE 2020a). Water trading – both in and out of a region - will likely have significant and diverse impacts on GHG emissions (Maraseni et al. 2020).

As abovementioned in the section 7.2.2 and 7.2.3, rainfall is related to water allocation in a certain water year. The time length of sunshine throughout that year impacts solar systems’ capacity for power generation and further solar feed-in tariff policies. Our developed models can be made more comprehensive by establishing a more definite relationship between rainfall and water allocation and integrating water trading policies alongside interactions with additional solar power availability and a solar feed-in tariff policy. This will naturally interlink more water related factors with energy related factors, contributing to a more robust water-energy-food nexus.

8.5.5. Agri-voltaic systems for all farming activities

During the past few years, agrivoltaic systems have gained attention for their applications in farming (Toledo et al. 2021; Trommsdorff et al. 2021; Zainol Abidin et al. 2021; Al Mamun et al. 2022). One major concern is considerable land occupation by these systems. This could possibly be addressed by utilising the Water-Energy-Food (WEF) nexus. The land occupation could be incorporated into total land use to investigate synergies and trade-offs between the land use and energy productivity and to further explore optimal agricultural land use for energy production (Willockx et al. 2022). This would relate to solar radiation (Pulido-Mancebo et al. 2022) and cooling provided by shading (Williams et al. 2023), which, in turn, is impactful to crop yields. This is a promising direction as these solar systems combine food, energy and land, aligned with WEF nexus framework (Perederii 2021; Trommsdorff et al. 2021). Compared with individual on-farm solar irrigation systems, agrivoltaic systems are well suited to larger geographical scales, like local areas or large farms. They have the capacity to generate a greater amount of energy and suffice the need of a broader range of farming activities including irrigation. Their grid-connected installations would be more economically viable with solar feed-in tariffs.

8.5.6. Carbon pricing and trading, and GHG emission projections

As one step above and beyond for the future, the Australia-European Union (EU) Emissions Trading System (ETS) linking negotiations are a successful bilateral cooperation in August 2012, which agreed to link the EU ETS and the Australian Carbon Pricing Mechanism. Similar carbon trading systems have been rolled out in other nations, including the Switzerland ETS and the EU ETS (Welfens et al. 2017), ETSs in the United States (Murray et al. 2015), South Korea (Choi et al. 2017) and Vietnam (Nong et al. 2020), and the Carbon Emissions Trading Scheme (CETS) in China (Jiang et al. 2016; Yang et al. 2020). They have been built up with the main purpose of managing, regulating and governing businesses and industries within each nation to limit their carbon emissions based on pricing mechanisms (Lin et al.

2017; Hu et al. 2020). For future scenarios about carbon trading, similar policies could likewise be advocated and promoted. Apart from linking current carbon pricing policies with carbon trading mechanisms, GHG emissions reduction targets can also be set and designed in future studies. It would be promising for researchers to further integrate future scenarios regarding predictions on GHG emissions into the targets, as GHG emissions mitigation in response to global climate change is a long-term and arduous task that must be tackled in the long run.

8.5.7. Crop residue disposal methods

To make the best use of crop residues, Waste Hierarchy (Waste Classification Processing) (Pires et al. 2019; Zhang et al. 2022) can be employed to systematically investigate impacts of various environmental methods from disposing crop residues. The conventional practice, ploughing crop residues into soil, can be classified as "Prevention" in the hierarchy. Valorization (feeding to livestock) (De Menna et al. 2020), as a "Reuse" stage of the Waste Hierarchy, could also be advised to replace animal feeds like soybean meal, corn gluten meal (Pinotti et al. 2021). Combustion/incineration with energy recovery and anaerobic digestion fall into the "Recovery" category. Composting and most other bio-mass production methods belong to "Recycling".

Notably, landfilling, as part of the "Disposal" stage, is commonly adopted by regional councils or municipalities throughout Australia to deal with green waste from native residential communities. The commercial charges are regulated and standardized, but these councils/municipalities do not apply this service to crop residues. It would also be worthwhile to compare landfilling with other types of disposal methods in scenarios about managing crop residues for their economic and environmental performances.

8.5.8. Forestry residues

Apart from crop residue, forestry residue can also be productively used for medium-to-large-scale bioenergy production (power recovery) (Iye et al. 2013b; ALCAS 2020). Forestry being incorporated into cropping systems would likely be a promising direction towards a more integrated and systematic agricultural WEF nexus (Li et al. 2021). A forestry system can also facilitate a sustainable cropping system such as carbon sequestration of GHG emissions from cropping by forestry, and conservation on soils and farming land by forestry's ecological featuring services. This will likely address challenges in relation to the high rate of deforestation continually downsizing forest areas (Iye et al. 2013b), including re-afforestation preventing further forest land transitioning to farming land.

8.6. Contribution of this thesis

To sum up, the major contributions of this thesis are:

- An integrated optimization model is developed to investigate the agricultural WEF nexus by means of constrained non-linear programming.
- Basing the study on a local geographical scale with common and existing situations in Toowoomba Region, the model is applied, and the outcomes can also be applied to a farm scale.
- Maximization on profitability of a typical single crop rotation system (cotton and wheat) located in the Toowoomba Region is achieved for optimal performances of water and land resource uses, economic benefits, and GHG emissions.
- The interactions are identified between different components/sectors, in particular definite functional relationships between crop yields and water applications, relationships between crop yields and crop residues, relationships between water use, energy use and associated GHG emissions, and so on. This has reinforced dual connections between each sector as references for future studies especially utilizing mathematical programming for optimization.
- The waste component/sector (crop residues) are incorporated into the WEF nexus system to reduce the research gap in this realm as references for future research.
- Recommendations are developed for stakeholders (farmers, policy makers, and potential businesses) and future research based on the key findings throughout this thesis.

8.7. Significance of the thesis

In a nutshell, the abovementioned key findings and recommendations are targeted at stakeholders including farmers, policy makers, infrastructure related businesses, and also researchers. The significance can be specified from the angles of all stakeholders, as below:

(1) Farmers:

- The outcomes of this study indicate crop prices, other than water application and land use, are the most influential factor for farmers as crop prices directly affect the total revenues.
- The results show that integrating rainfed mode into the cropping system would help to improve water use efficiency by reducing water application rates. In particular, rainfall is usually expected to have a more notable effect on summer crops.
- According to the key findings, it is worthwhile to make more use of renewable energy sources like solar power, which is common in Queensland that has both a geo-climate advantage (abundant sunshine throughout years) and a policy advantage (solar PV power being promoted within the state). It contributes to saving significant amount of traditional and non-renewable energy sources and associated costs, and avoiding associated GHG emissions, especially because irrigation is one of the largest water and energy users in agriculture. Solar power use paired with feed-in tariffs are economically more viable than that without a tariff. This will generate additional revenues or can reduce costs for cropping.
- From the outcomes of crop residue disposal scenarios, alternative disposal methods such as combustion/incineration with energy recovery can be the most profitable option. It produces electricity and/or heat that can be re-utilized in the upper stream value chain (such as back to farming) to avoid some costs or re-sold for extra economic returns. The electricity would displace network electricity generated by coals, other fuel resources and even solar energy. The heat would likely produce hot water and so avoid the need to use natural gas to mitigate GHG emissions. It is significant to help farmers in exploring different financially viable, economically rewarding and environmentally beneficial crop residue disposal ways by collaborating with infrastructure related businesses.
- The major barriers for farmers to uptake such findings/recommendations are related to climate change (GHG emissions and carbon price policies)

and crop residue disposal. Farmers usually do not consider GHG emissions and associated carbon costs incurred by farming activities. However, this study presents outcomes implying that GHG emissions and associated carbon costs could potentially impose some influences. This can increase farmers awareness for environmental protection while in the meantime decreasing their concerns about profitability. It can apply to the crop residue disposal as well. The key findings of this study show a cost-effective disposal method can not only generate considerable revenues but also mitigate GHG emissions.

(2) Policy makers:

- Statistics accessible government databases/websites will be beneficial in attaining more accurate model outcomes.
- Models providing a better relationship between rainfall and water entitlement would facilitate further model development with potential functional relationships between effective rainfall and specific water allocation by jointly utilizing calculation methods on water allocations to specific local areas and farms. This will enhance accuracy of data and develop better models to evaluate the impacts by water trading.
- In terms of power network establishment, installation policies with network connections would incentivize both farmers and business owners to promote solar energy applications to native farming communities. This would not only be highly aligned with GHG emissions mitigation initiatives advocated worldwide today but also promote further development of relevant carbon policies for the future.

(3) Businesses:

- Building up and developing power networks with solar power facilities will promote feed-in tariff policies as well as other possible renewables incentives promoted by authorities.
- Establishment of waste facilities in the proximity to major farming areas can contribute to making crop residue management an economically viable option by reducing logistic costs. Also, this could increase the efficiency of crop residue collection and utilization that would have been lost during long logistic distances (waste loss avoidance). Furthermore,

establishing waste facilities/power plants near major cropping areas would more practically return the power generated to the farms for re-use. This in turn highlights the importance of access to electricity network paired with grid-connected power installations as grid-connected solar installations and will simultaneously align businesses/commercial activities in managing crop residues to meet the goal of GHG emissions mitigation and carbon smart.

(4) Researchers:

- A multiple crop rotation could offer a greater range of options and possibilities for better resilience of the agro-ecological system to resist potential risks such as drought.
- Developing agri-voltaic systems is a promising direction as these solar systems combine food, energy and land, aligned with the overall WEF nexus framework. Compared with individual on-farm solar irrigation systems, agrivoltaic systems are well suited to larger geographical scales, like local areas or large farms. They have the capacity to generate a greater amount of energy and suffice the need of a broader range of farming activities including irrigation. Their grid-connected installations would be more economically viable with solar feed-in tariffs.
- Associated with alternative waste disposal methods, the Waste Hierarchy would be of high significance in designing and developing those methods. It would be worthwhile to compare different types of disposal methods in scenarios about managing crop residues for their economic and environmental performances.
- Forestry being incorporated into cropping systems would likely be a promising direction towards a more integrated agricultural WEF nexus. A forestry system can also facilitate a sustainable cropping system such as carbon sequestration of GHG emissions from cropping by forestry, and conservation on soils and farming land by forestry’s ecological featuring services. This will likely address challenges in relation to the high rate of deforestation continually downsizing forest areas, like re-afforestation preventing further forest land transitioning to farming land.

REFERENCES

ABARES 2020, *Australian crop report,* Australian Bureau of Agricultural and Resource Economics and Sciences, Canberra, DOI: CC BY 4.0.

ABARES 2022a, *Australian Crop Report*, viewed 02/03/2022, <https://www.agriculture.gov.au/abares/research-topics/agricultural-outlook/australian-crop-report#download-report>.

ABARES 2022b, *About my region*, viewed 15/05/2022, <https://public.tableau.com/app/profile/australian.bureau.of.agricultural.and.resource.economics.and.sci/viz/AMR_v9_A3L/Dashboard1>.

ABARES 2022c, *Agricultural commodities and trade data*, ABARES, viewed 31/05/2022, <https://www.agriculture.gov.au/abares/research-topics/agricultural-outlook/data#agricultural-commodities>.

Abdul Salam, P, Shrestha, S, Pandey, VP & Anal, A 2017, *Water-energy-food Nexus : principles and practices*, AGU, Hoboken, NJ.

ABS 2011, *Crop Residue*, Australian Bureau of Statistics, viewed 15/12/2020, <https://www.abs.gov.au/ausstats/abs@.nsf/Products/4627.0~2009-10~Main+Features~Crop+residue?OpenDocument>.

ABS 2019, *Water Use on Australian Farms, 2017-18. Document 4618.0. Canberra ACT, Australia: Australian Bureau of Statistics (ABS)*, viewed 09/11/2020, <https://www.abs.gov.au/ausstats/abs@.nsf/mf/4618.0.>.

ABS 2020, *Water Use on Australian Farms*, Australian Bureau of Statistics (ABS), viewed 29/01/2021, <https://www.abs.gov.au/statistics/industry/agriculture/water-use-australian-farms/latest-release>.

ABS 2021, *Digital boundary files*, viewed 06/05/2022, <https://www.abs.gov.au/statistics/standards/australian-statistical-geography-standard-asgs-edition-3/jul2021-jun2026/access-and-downloads/digital-boundary-files>.

ABS 2022a, *Region summary: Toowoomba*, viewed 11/12/2022, <https://dbr.abs.gov.au/region.html?lyr=lga&rgn=36910#top>.

ABS 2022b, *Water Use on Australian Farms*, viewed 18/08/2022, <https://www.abs.gov.au/statistics/industry/agriculture/water-use-australian-farms/2020-21>.

ABS 2022c, *Agricultural Commodities, Australia*, viewed 31/05/2022, <https://www.abs.gov.au/statistics/industry/agriculture/agricultural-commodities-australia/2019-20#content>.

AgEcon 2019, 'Integrating alternative energy solutions: irrigated cane', viewed 10/11/2021,<https://sugarresearch.com.au/sugar_files/2019/03/AgEconEnergyStudyFactSheet.pdf>.

Agency, IE 2017, 'Delivering Sustainable Bioenergy', Iea.

Akkoli, KM, Gangavati, PB, Ingalagi, MR & Chitgopkar, RK 2018, 'Assessment and Characterization of Agricultural Residues', *Materials Today: Proceedings*, vol. 5, no. 9, Part 3, pp. 17548-52.

Al-Ansari, T, Korre, A, Nie, Z & Shah, N 2015a, 'Development of a life cycle assessment tool for the assessment of food production systems within the energy, water and food nexus'.

Al-Ansari, T, Korre, A, Nie, Z & Shah, N 2015b, 'Development of a life cycle assessment tool for the assessment of food production systems within the energy, water and food nexus', *Sustainable production and consumption*, vol. 2, pp. 52-66.

Al-Ansari, T, Korre, A, Nie, Z & Shah, N 2017, 'Integration of greenhouse gas control technologies within the energy, water and food nexus to enhance the environmental performance of food production systems', *Journal of Cleaner Production*, vol. 162, pp. 1592-606.

Al-Kaisi, M 2000, 'Crop water use or evapotranspiration', *Integrated Crop Management*, vol. 484, pp. 84-5.

Al-Kaisi, MM & Broner, I 2009, *Crop water use and growth stages*, Colorado State University Extension Fort Collins, CO, USA.

Al-Saidi, M & Hussein, H 2021, 'The water-energy-food nexus and COVID-19: Towards a systematization of impacts and responses', *Science of the total environment*, vol. 779, p. 146529.

Al Mamun, MA, Dargusch, P, Wadley, D, Zulkarnain, NA & Aziz, AA 2022, 'A review of research on agrivoltaic systems', *Renewable and Sustainable Energy Reviews*, vol. 161, p. 112351.

Albrecht, TR, Crootof, A & Scott, CA 2018, 'The Water-Energy-Food Nexus: A systematic review of methods for nexus assessment', *Environmental Research Letters*, vol. 13, no. 4, p. 043002.

Alcamo, J 2008, *Environmental futures: the practice of environmental scenario analysis*, Elsevier.

ALCAS 2020, *AusLCI datasets*, Australian Life Cycle Assessment Society (ALCAS), viewed 02/02/2021, <http://www.auslci.com.au/index.php/Datasets>.

Alexandratos, N & Bruinsma, J 2012, 'World agriculture towards 2030/2050: the 2012 revision'.

Alfonso, S, Gesto, M & Sadoul, B 2021, 'Temperature increase and its effects on fish stress physiology in the context of global warming', *Journal of Fish Biology*, vol. 98, no. 6, pp. 1496-508.

Ali, M & Mubarak, S 2017, 'Effective rainfall calculation methods for field crops: an overview, analysis and new formulation', *Asian Research Journal of Agriculture*, vol. 7, no. 1, pp. 1-12.

Ali, M, Saleem, M, Khan, Z & Watson, IA 2019, 'The use of crop residues for biofuel production', in D Verma, et al. (eds), *Biomass, Biopolymer-Based Materials, and Bioenergy*, Woodhead Publishing, pp. 369-95.

Allen, R, Pereira, LS, Raes, D & Smith, M 1998a, 'Chapter 1. Introduction to evapotranspiration', *Crop evapotranspiration–Guidelines for computing crop water requirements [online]. Food and Agriculture Organization of the United Nations (FAO). Irrigation and Drainage Paper*, vol. 56.

Allen, RG, Pereira, LS, Raes, D & Smith, M 1998b, 'Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56', *Fao, Rome*, vol. 300, no. 9, p. D05109.

Allouche, J, Middleton, C & Gyawali, D 2019, *The water–food–energy nexus: power, politics, and justice*, Routledge.

Amulen, J, Kasedde, H, Serugunda, J & Lwanyaga, JD 2022, 'The potential of energy recovery from municipal solid waste in Kampala City, Uganda by incineration', *Energy Conversion and Management: X*, vol. 14, p. 100204.

An-Vo, D-A, Mushtaq, S & Reardon-Smith, K 2014, 'Estimating the value of conjunctive water use at a system-level using nonlinear programming model', *Journal of Economic and Social Policy*, vol. 17, no. 2, pp. 1-20.

An-Vo, D-A, Mushtaq, S, Nguyen-Ky, T, Bundschuh, J, Tran-Cong, T, Maraseni, T & Reardon-Smith, K 2015, 'Nonlinear optimisation using production functions to estimate economic benefit of conjunctive water use for multicrop production', *Water Resources Management*, vol. 29, no. 7, pp. 2153-70.

Anshassi, M, Sackles, H & Townsend, TG 2021, 'A review of LCA assumptions impacting whether landfilling or incineration results in less greenhouse gas emissions', *Resources, Conservation and Recycling*, vol. 174, p. 105810.

Anukam, A, Mohammadi, A, Naqvi, M & Granström, K 2019, 'A review of the chemistry of anaerobic digestion: Methods of accelerating and optimizing process efficiency', *Processes*, vol. 7, no. 8, p. 504.

Anwar, MR, Li Liu, D, Macadam, I & Kelly, G 2013, 'Adapting agriculture to climate change: a review', *Theoretical and applied climatology*, vol. 113, no. 1-2, pp. 225-45.

APSIM 2021, *APSIM: The Leading Software Framework for Agricultural Systems Modelling and Simulation*, viewed 30/06/2021, <https://www.apsim.info/>.

Archer, DW & Johnson, JM 2012, 'Evaluating local crop residue biomass supply: economic and environmental impacts', *BioEnergy Research*, vol. 5, pp. 699-712.

Australian Government 2021, *Auction April 2021*, viewed 03/10/2021, <https://www.cleanenergyregulator.gov.au/ERF/auctions-results/april-2021>.

Australian Government 2022a, *How allocations work in the Murray–Darling Basin*, viewed 03/06/2022, <https://www.mdba.gov.au/water-management/allocations-states-mdba/guide-allocations>.

Australian Government 2022b, *About the National Greenhouse and Energy Reporting scheme*, viewed 30/08/2022, <https://www.cleanenergyregulator.gov.au/NGER/About-the-National-Greenhouse-and-Energy-Reporting-scheme>.

Australian Government 2022c, *Global warming potentials*, viewed 07/06/2022, <https://www.cleanenergyregulator.gov.au/NGER/About-the-National-Greenhouse-and-Energy-Reporting-scheme/global-warming-potentials>.

Australian Government 2023, *Auction March 2023*, viewed 07/06/2023, <https://www.cleanenergyregulator.gov.au/ERF/auctions-results/march-2023>.

Ayers, RS & Westcot, DW 1985, *Water quality for agriculture*, vol. 29, Food and Agriculture Organization of the United Nations Rome.

Baffes, J 2021, 'Distortions to Cotton Sector Incentives in West and Central Africa'.

Bardi, U 2019, 'Peak oil, 20 years later: Failed prediction or useful insight?', *Energy research & social science*, vol. 48, pp. 257-61.

Batlle-Bayer, L, Aldaco, R, Bala, A & Fullana-i-Palmer, P 2020, 'Toward sustainable dietary patterns under a water–energy–food nexus life cycle thinking approach', *Current Opinion in Environmental Science & Health*, vol. 13, pp. 61-7.

Bazilian, M, Rogner, H, Howells, M, Hermann, S, Arent, D, Gielen, D, Steduto, P, Mueller, A, Komor, P & Tol, RS 2011, 'Considering the energy, water and food nexus: Towards an integrated modelling approach', *Energy Policy*, vol. 39, no. 12, pp. 7896-906.

Belinskij, A 2015, 'Water-energy-food nexus within the framework of international water law', *Water*, vol. 7, no. 10, pp. 5396-415.

Bellezoni, RA, Sharma, D, Villela, AA & Junior, AOP 2018, 'Water-energy-food nexus of sugarcane ethanol production in the state of Goiás, Brazil: An analysis with regional input-output matrix', *Biomass and Bioenergy*, vol. 115, pp. 108-19.

Belmonte, BA, Benjamin, MFD & Tan, RR 2017, 'Biochar systems in the water-energy-food nexus: the emerging role of process systems engineering', *Current Opinion in Chemical Engineering*, vol. 18, pp. 32-7.

Bentsen, NS, Nilsson, D & Larsen, S 2018, 'Agricultural residues for energy-A case study on the influence of resource availability, economy and policy on the use of straw for energy in Denmark and Sweden', *Biomass and Bioenergy*, vol. 108, pp. 278-88.

Bewsher Consulting Pty Ltd 2019, *Independent Review of Generation 2 Hydrological Models for: Border Rivers, CondamineBalonne and Moonie Valleys*, DoEa Science, viewed 09/06/2022, <https://www.mdba.gov.au/sites/default/files/pubs/Review-QMDB-models-April2019.pdf>.

Bhaduri, A, Ringler, C, Dombrowski, I, Mohtar, R & Scheumann, W 2015, *Sustainability in the water–energy–food nexus*, 5-6, Taylor & Francis, 0250-8060.

Bian, Z & Liu, D 2021, 'A Comprehensive Review on Types, Methods and Different Regions Related to Water–Energy–Food Nexus', *International Journal of Environmental Research and Public Health*, vol. 18, no. 16, p. 8276.

Biggs, EM, Bruce, E, Boruff, B, Duncan, JMA, Horsley, J, Pauli, N, McNeill, K, Neef, A, Van Ogtrop, F, Curnow, J, Haworth, B, Duce, S & Imanari, Y 2015, 'Sustainable development and the water–energy–food nexus: A perspective on livelihoods', *Environmental Science and Policy*, vol. 54, no. C, pp. 389-97.

BOM 2022, *Climate statistics for Australian locations*, viewed 03/05/2022, <http://www.bom.gov.au/climate/averages/tables/cw_041529.shtml>.

BoM 2024, *National Water Account 2016*, viewed 04/06/2024, <http://www.bom.gov.au/water/nwa/2016/seq/regiondescription/waterrights.shtml>.

Boote, KJ, Jones, JW & Pickering, NB 1996, 'Potential uses and limitations of crop models', *Agronomy journal*, vol. 88, no. 5, pp. 704-16.

Boretti, A & Rosa, L 2019, 'Reassessing the projections of the World Water Development Report', *npj Clean Water*, vol. 2, no. 1, p. 15.

Borrelli, P, Robinson, DA, Panagos, P, Lugato, E, Yang, JE, Alewell, C, Wuepper, D, Montanarella, L & Ballabio, C 2020, 'Land use and climate change impacts on global soil erosion by water (2015-2070)', *Proceedings of the National Academy of Sciences*, vol. 117, no. 36, pp. 21994-2001.

Brouwer, C & Heibloem, M 1986a, 'Irrigation water management: irrigation water needs', *Training manual*, vol. 3.

Brouwer, C & Heibloem, M 1986b, 'Irrigation water management: irrigation water needs', *Training manual*, vol. 3, pp. 1-5.

Bruinsma, J 2009, 'The resource outlook to 2050: by how much do land, water and crop yields need to increase by 2050', *Expert meeting on how to feed the world in*, pp. 24-6.

Cameron, H & Amanda, K 2019, 'GOVERNING THE ENERGY-WATER-FOOD NEXUS: REGULATING UNCONVENTIONAL GAS DEVELOPMENT IN QUEENSLAND, AUSTRALIA', *JURIMETRICS*, vol. 59, no. 2, pp. 233-66.

Campolongo, F & Braddock, R 1999, 'The use of graph theory in the sensitivity analysis of the model output: a second order screening method', *Reliability Engineering & System Safety*, vol. 64, no. 1, pp. 1-12.

Campolongo, F, Cariboni, J & Saltelli, A 2007, 'An effective screening design for sensitivity analysis of large models', *Environmental modelling & software*, vol. 22, no. 10, pp. 1509-18.

Cansino-Loeza, B, Tovar-Facio, J & Ponce-Ortega, JM 2021, 'Stochastic optimization of the water-energy-food nexus in disadvantaged rural communities to achieve the sustainable development goals', *Sustainable production and consumption*, vol. 28, pp. 1249-61.

CER 2019, *The safeguard mechanism*, viewed 11/01/2022, <https://www.cleanenergyregulator.gov.au/ERF/About-the-Emissions-Reduction-Fund/the-safeguard-mechanism>.

CER 2022a, *Buying ACCUs*, viewed 11/01/2022, <https://www.cleanenergyregulator.gov.au/Infohub/Markets/Pages/Buying-ACCUs.aspx>.

CER 2022b, *About the Emissions Reduction Fund*, viewed 11/01/2022, <https://www.cleanenergyregulator.gov.au/ERF/About-the-Emissions-Reduction-Fund>.

Challinor, AJ, Watson, J, Lobell, DB, Howden, S, Smith, D & Chhetri, N 2014, 'A meta-analysis of crop yield under climate change and adaptation', *Nature Climate Change*, vol. 4, no. 4, pp. 287-91.

Chang, Y, Li, G, Yao, Y, Zhang, L & Yu, C 2016, 'Quantifying the water-energy-food nexus: Current status and trends', *Energies*, vol. 9, no. 2, p. 65.

Chen, G, Maraseni, T & Yang, Z 2010, 'Life cycle energy and carbon footprint assessments: agricultural and food products'.

Chen, G, Maraseni, T, Banhazi, T & Bundschuh, J 2015a, 'Benchmarking energy use on farm', *Rural Industries Research and Development Corporation (RIRDC) Publication*, no. 15/059.

Chen, G, Maraseni, T, Bundschuh, J & Zare, D 2015b, 'Agriculture: alternative energy sources'.

Chen, J, Gong, Y, Wang, S, Guan, B, Balkovic, J & Kraxner, F 2019, 'To burn or retain crop residues on croplands? An integrated analysis of crop residue management in China', *Science of the total environment*, vol. 662, pp. 141-50.

Chen, W-P, Tu, H-Z, Peng, C & Hou, Y 2017, 'Comment on sensitivity analysis methods for environmental models', *Huan jing ke xue= Huanjing kexue*, vol. 38, no. 11, pp. 4889-97.

Chen, X 2016, 'Economic potential of biomass supply from crop residues in China', *Applied Energy*, vol. 166, pp. 141-9.

Cherubin, MR, Oliveira, DMdS, Feigl, BJ, Pimentel, LG, Lisboa, IP, Gmach, MR, Varanda, LL, Morais, MC, Satiro, LS & Popin, GV 2018, 'Crop residue harvest for bioenergy production and its implications on soil functioning and plant growth: A review', *Scientia Agricola*, vol. 75, pp. 255-72.

Choi, Y, Liu, Y & Lee, H 2017, 'The economy impacts of Korean ETS with an emphasis on sectoral coverage based on a CGE approach', *Energy Policy*, vol. 109, pp. 835-44.

Choudhury, A & Jones, J 2014, 'Crop yield prediction using time series models', *Journal of Economics and Economic Education Research*, vol. 15, no. 3, p. 53.

Cleanaway 2023, *Request for a free quote*, 19/01/2023, <https://www.cleanaway.com.au/>.

Cotton Australia 2018, *Grid connected solar – Irrigation case studies*, viewed 06/05/2022, <https://www.cottoninfo.com.au/publications/grid-connected-solar-irrigation-case-studies>.

Cotton Australia 2022a, *Cotton's Water Use*, viewed 06/09/2022, <https://cottonaustralia.com.au/cottons-water-use>.

Cotton Australia 2022b, *Cotton Growing Regions*, viewed 09/06/2022, <https://cottonaustralia.com.au/where-is-cotton-grown>.

Cotton Australia 2022c, *Where Is Cotton Grown?*, viewed 16/07/2022, <https://cottonaustralia.com.au/where-is-cotton-grown>.

CottonInfo 2017, 'ENERGY: Diesel vs electric vs solar', *Energy Efficiency*, viewed 26/06/2022,<https://www.cottoninfo.com.au/index.php/publications/energy-diesel-vs-electric-vs-solar>.

Coyle, RG 1997, 'System dynamics modelling: a practical approach', *Journal of the Operational Research Society*, vol. 48, no. 5, pp. 544-.

Cristiano, E, Deidda, R & Viola, F 2021, 'The role of green roofs in urban Water-Energy-Food-Ecosystem nexus: A review', *Science of the total environment*, vol. 756, p. 143876.

Crooks, AT & Heppenstall, AJ 2011, 'Introduction to agent-based modelling', in *Agent-based models of geographical systems*, Springer, pp. 85-105.

Cropping, P 2005, 'Crop residue management for nutrient cycling and improving soil productivity in rice-based cropping systems in the tropics', *Adv Agron*, vol. 85, p. 269.

CSIRO 2021, *What are the sources of Australia's greenhouse gases?*, viewed 16/07/2021, <https://www.csiro.au/en/research/environmental-impacts/climate-change/climate-change-qa/sources-of-ghg-gases>.

CSIRO & BOM 2012, *State of the Climate e 2012*, viewed 09/11/2020, <http://www.bom.gov.au/climate/annual_sum/2012/AnClimSum2012_HR1.0.pdf.>.

Cukier, R, Fortuin, C, Shuler, KE, Petschek, A & Schaibly, J 1973, 'Study of the sensitivity of coupled reaction systems to uncertainties in rate coefficients. I Theory', *The Journal of chemical physics*, vol. 59, no. 8, pp. 3873-8.

Currey, A & Pitcher, C 2020, 'Technology: Rural-Solar system cuts pump cost to zero', *Irrigation Australia: The Official Journal of Irrigation Australia*, vol. 36, no. 3, pp. 8-9.

DAF 2018, *Queensland agriculture snapshot 2018*, viewed 01/12/2020, <https://www.daf.qld.gov.au/__data/assets/pdf_file/0007/1383928/State-of-Agriculture-Report.pdf>.

DAF, USQ, RDA & FLA 2015, *Agricultural Opportunities in Southern Queensland*, <https://www.rda-ddsw.org.au/fileadmin/user_upload/Southern_Qld_-Opportunities_in_Agriculture_MEDIUM.pdf>.

DAFF 2021, *Wheat*, viewed 09/11/2021, <https://www.agriculture.gov.au/agriculture-land/farm-food-drought/crops/wheat>.

DAFF 2022a, *Climate and drought*, viewed 11/11/2022, <https://www.agriculture.gov.au/abares/research-topics/climate>.

DAFF 2022b, *Australian Agricultural Productivity - Broadacre and Dairy Estimates*, viewed 11/11/2022, <https://www.agriculture.gov.au/abares/research-topics/productivity/agricultural-productivity-estimates#references>.

Daher, BT & Mohtar, RH 2015, 'Water–energy–food (WEF) Nexus Tool 2.0: guiding integrative resource planning and decision-making', *Water International*, vol. 40, no. 5-6, pp. 748-71.

Daher, BT & Mohtar, RH 2018, 'Water–energy–food (WEF) Nexus Tool 2.0: guiding integrative resource planning and decision-making', in *Sustainability in the Water Energy Food Nexus*, Routledge, pp. 36-59.

Dahikar, SS & Rode, SV 2014, 'Agricultural crop yield prediction using artificial neural network approach', *International journal of innovative research in electrical, electronics, instrumentation and control engineering*, vol. 2, no. 1, pp. 683-6.

Dai, J, Wu, S, Han, G, Weinberg, J, Xie, X, Wu, X, Song, X, Jia, B, Xue, W & Yang, Q 2018, 'Water-energy nexus: A review of methods and tools for macro-assessment', *Applied Energy*, vol. 210, pp. 393-408.

DAWE 2019a, *Cotton*, viewed 29/01/2021, <https://www.agriculture.gov.au/ag-farm-food/crops/cotton>.

DAWE 2019b, *Energy and agriculture support*, Department of Agriculture Water and the Environment, viewed 31/10/2020, <https://www.agriculture.gov.au/ag-farm-food/climatechange/energy-and-agriculture-support>.

DAWE 2020a, *Australian water markets*, viewed 06/02/2021, <https://www.agriculture.gov.au/water/markets>.

DAWE 2020b, *Sugar*, Department of Agriculture Water and the Environment, viewed 05/01/2021, <https://www.agriculture.gov.au/ag-farm-food/crops/sugar>.

DCCEEW 2021, *Agriculture*, viewed 09/11/2021, <https://www.energy.gov.au/business/industry-sector-guides/agriculture#toc-anchor-case-studies>.

DCCEEW 2022a, *Electricity generation*, viewed 15/07/2021, <https://www.energy.gov.au/data/electricity-generation>.

DCCEEW 2022b, *Energy productivity*, viewed 07/07/2022, <https://www.energy.gov.au/data/energy-productivity>.

DCCEEW 2022c, *Energy production*, viewed 07/07/2022, <https://www.energy.gov.au/data/energy-production>.

DCCEEW 2022d, *Energy consumption*, viewed 07/07/2022, <https://www.energy.gov.au/data/energy-consumption>.

DCCEEW 2022e, *Tracking and reporting greenhouse gas emissions*, viewed 11/10/2022, <https://www.dcceew.gov.au/climate-change/emissions-reporting/tracking-reporting-emissions#toc_0>.

de Castro Sobrosa Neto, R, da Silva, AL, Maia, JS, Nunes, NA, Casagrande, JL & de Andrade Guerra, JBSO 2021, 'The Use of Biodigesters in the Treatment of Swine Manure in Southern Brazil: An Analysis of an R&D Project from the Perspective of the WEF Nexus', *The Water–Energy–Food Nexus: Concept and Assessments*, pp. 97-126.

De Menna, F, Davis, J, Östergren, K, Unger, N, Loubiere, M & Vittuari, M 2020, 'A combined framework for the life cycle assessment and costing of food waste prevention and valorization: an application to school canteens', *Agricultural and Food Economics*, vol. 8, no. 1, pp. 1-11.

De Roo, A, Trichakis, I, Bisselink, B, Gelati, E, Pistocchi, A & Gawlik, B 2021, 'The Water-Energy-Food-Ecosystem Nexus in the Mediterranean: Current Issues and Future Challenges', *Frontiers in Climate*, vol. 3, p. 782553.

de Vito, R, Portoghese, I, Pagano, A, Fratino, U & Vurro, M 2017, 'An index-based approach for the sustainability assessment of irrigation practice based on the water-energy-food nexus framework', *Advances in Water Resources*, vol. 110, pp. 423-36.

Del Borghi, A, Moreschi, L & Gallo, M 2020, 'Circular economy approach to reduce water–energy–food nexus', *Current Opinion in Environmental Science & Health*, vol. 13, pp. 23-8.

Delannoy, L, Longaretti, P-Y, Murphy, DJ & Prados, E 2021, 'Peak oil and the low-carbon energy transition: A net-energy perspective', *Applied Energy*, vol. 304, p. 117843.

DES 2019, *Climate change in the Eastern Downs region,* DoEa Science, Department of Environment and Science, viewed 01/02/2022, <https://www.qld.gov.au/__data/assets/pdf_file/0027/68337/eastern-downs-climate-change-impact-summary.pdf>.

Dhaubanjar, S, Davidsen, C & Bauer-Gottwein, P 2017, 'Multi-objective optimization for analysis of changing trade-offs in the Nepalese water–energy–food nexus with hydropower development', *Water*, vol. 9, no. 3, p. 162.

Díaz de los Ríos, M & Hernández Ramos, E 2020, 'Determination of the Hansen solubility parameters and the Hansen sphere radius with the aid of the solver add-in of Microsoft Excel', *SN Applied Sciences*, vol. 2, pp. 1-7.

Doorenbos, J, Doorenbos, J & Akassam, A 1979, *Yield Reponse to Water FAO Irrigation and Drainage Paper No. 33*, FAO.

Dosdogru, F, Kalin, L, Wang, R & Yen, H 2020, 'Potential impacts of land use/cover and climate changes on ecologically relevant flows', *Journal of Hydrology*, vol. 584, p. 124654.

DSSAT 2021, *What is DSSAT?*, viewed 30/06/2021, <https://dssat.net/>.

Du, S, Zhu, Y, Zhu, Y & Tang, W 2020, 'Allocation policy considering firm's time-varying emission reduction in a cap-and-trade system', *Annals of Operations Research*, vol. 290, pp. 543-65.

Duinker, PN & Greig, LA 2007, 'Scenario analysis in environmental impact assessment: Improving explorations of the future', *Environmental impact assessment review*, vol. 27, no. 3, pp. 206-19.

Duque-Acevedo, M, Belmonte-Urena, LJ, Cortés-García, FJ & Camacho-Ferre, F 2020, 'Agricultural waste: Review of the evolution, approaches and perspectives on alternative uses', *Global Ecology and Conservation*, vol. 22, p. e00902.

Ekonomou, A & Eckard, RJ 2022a, *Tools - Greenhouse Accounting Frameworks (GAF) for Australian Primary Industries*, viewed 10/10/2022, <https://piccc.org.au/resources/Tools>.

Ekonomou, A & Eckard, RJ 2022b, *A Greenhouse Accounting Framework for cotton farms (C-GAF) based on the Australian National Greenhouse Gas Inventory methodology.*, http://www.piccc.org.au/resources/Tools>.

El-Gafy, I 2017, 'Water–food–energy nexus index: analysis of water–energy–food nexus of crop's production system applying the indicators approach', *Applied Water Science*, vol. 7, no. 6, pp. 2857-68.

El Gafy, I, Grigg, N & Reagan, W 2017, 'Dynamic behaviour of the water–food–energy Nexus: focus on crop production and consumption', *Irrigation and Drainage*, vol. 66, no. 1, pp. 19-33.

Elliott, J, Deryng, D, Müller, C, Frieler, K, Konzmann, M, Gerten, D, Glotter, M, Flörke, M, Wada, Y & Best, N 2014, 'Constraints and potentials of future irrigation water availability on agricultural production under climate change', *Proceedings of the National Academy of Sciences*, vol. 111, no. 9, pp. 3239-44.

Endo, A, Tsurita, I, Burnett, K & Orencio, PM 2017, 'A review of the current state of research on the water, energy, and food nexus', *Journal of Hydrology: Regional Studies*, vol. 11, pp. 20-30.

Endo, A, Burnett, K, Orencio, PM, Kumazawa, T, Wada, CA, Ishii, A, Tsurita, I & Taniguchi, M 2015, 'Methods of the water-energy-food nexus', *Water*, vol. 7, no. 10, pp. 5806-30.

Endo, A, Yamada, M, Miyashita, Y, Sugimoto, R, Ishii, A, Nishijima, J, Fujii, M, Kato, T, Hamamoto, H & Kimura, M 2020, 'Dynamics of water–energy–food nexus methodology, methods, and tools', *Current Opinion in Environmental Science & Health*, vol. 13, pp. 46-60.

EngineerExcel 2022, *Excel Solver: Which solover method should I choose?*, viewed 06/05/2022, <https://engineerexcel.com/excel-solver-solving-method-choose/>.

Ergon Energy 2022a, *Solar feed-in tariffs*, viewed 04/05/2022, <https://www.ergon.com.au/retail/residential/tariffs-and-prices/solar-feed-in-tariff>.

Ergon Energy 2022b, *Farming tariffs*, viewed 07/07/2022, <https://www.ergon.com.au/retail/business/support-for-farmers/farming-tariffs>.

Ermolieva, TY, Ermoliev, YM, Havlik, P, Mosnier, A, Leclere, D, Kraksner, F, Khabarov, N & Obersteiner, M 2015, 'Systems analysis of robust strategic decisions to plan secure food, energy, and water provision based on the stochastic GLOBIOM model', *Cybernetics and Systems Analysis*, vol. 51, no. 1, pp. 125-33.

Europe, UNECf 2018, 'Methodology for assessing the water-food-energy-ecosystems nexus in transboundary basins and experiences from its application: synthesis', *(No Title)*.

Fabiani, S, Vanino, S, Napoli, R & Nino, P 2020, 'Water energy food nexus approach for sustainability assessment at farm level: An experience from an intensive agricultural area in central Italy', *Environmental Science & Policy*, vol. 104, pp. 1-12.

Falconer, RE, Haltas, I, Varga, L, Forbes, PJ, Abdel-Aal, M & Panayotov, N 2020, 'Anaerobic Digestion of food waste: Eliciting sustainable water-energy-food nexus practices with Agent Based Modelling and visual analytics', *Journal of Cleaner Production*, vol. 255, p. 120060.

FAO 2009, *Global Agriculture 2050 — How to Feed the World 2050.*, Food and Agriculture Organization of the United Nations, Rome.

FAO 2014a, *The water-energy-food nexus: A new approach in support of food security and sustainable agriculture*, FAO Rome, Italy.

FAO 2014b, *Walking the nexus talk: Assessing the water-energy-food nexus in the context of the sustainable energy for all initiative, Alessandro Flammini, Manas Puri, Lucie Pluschke, Olivier Dubois,* EaNRWPN 58, FAO, Rome, viewed 11 April 2020, <www.fao.org/3/a - i3959e.pdf>.

FAO 2018, 'Water-Energy-Food Nexus for the Review of SDG 7'.

FAO 2021a, *AquaCrop*, viewed 30/06/2021, <https://www.fao.org/aquacrop/overview/whatisaquacrop/en/>.

FAO 2021b, *CropWat*, viewed 30/06/2021, <https://www.fao.org/land-water/databases-and-software/cropwat/en/>.

FAO 2022, *Three principles of Conservation Agriculture*, viewed 11/10/2022, <https://www.fao.org/conservation-agriculture/en/>.

FAO & EARTHSCAN 2011, *The state of the world's land and water resources for food and agriculture (SOLAW)–Managing systems at risk*, Food and Agruculture Organization of the United Nations, Rome and Earthscan ….

Feng, B, van Dam, KH, Guo, M, Shah, N, Passmore, S & Wang, X 2020, 'Planning of Food-Energy-Water-Waste (FEW2) nexus for sustainable development', *BMC Chemical Engineering*, vol. 2, no. 1, pp. 1-19.

Ferroukhi, R, Nagpal, D, Lopez-Peña, A, Hodges, T, Mohtar, RH, Daher, B, Mohtar, S & Keulertz, M 2015, 'Renewable energy in the water, energy & food nexus', *IRENA, Abu Dhabi*, pp. 1-125.

Findlater, KM, Kandlikar, M & Satterfield, T 2019, 'Misunderstanding conservation agriculture: Challenges in promoting, monitoring and evaluating sustainable farming', *Environmental Science & Policy*, vol. 100, pp. 47-54.

Flammini, A, Puri, M, Pluschke, L & Dubois, O 2014, *Walking the nexus talk: assessing the water-energy-food nexus in the context of the sustainable energy for all initiative*, Fao.

Flower, K, Dang, Y & Ward, P 2020, 'Advances in crop residue management', *Australian agriculture in*.

Flower, KC, Ward, PR, Passaris, N & Cordingley, N 2022, 'Uneven crop residue distribution influences soil chemical composition and crop yield under long-term no-tillage', *Soil and Tillage Research*, vol. 223, p. 105498.

Foster, T & Brozović, N 2018, 'Simulating crop-water production functions using crop growth models to support water policy assessments', *Ecological Economics*, vol. 152, pp. 9-21.

Foster, T, Brozović, N, Butler, A, Neale, C, Raes, D, Steduto, P, Fereres, E & Hsiao, TC 2017, 'AquaCrop-OS: An open source version of FAO's crop water productivity model', *Agricultural Water Management*, vol. 181, pp. 18-22.

Franczyk, A 2019, 'Using the Morris sensitivity analysis method to assess the importance of input variables on time-reversal imaging of seismic sources', *Acta Geophysica*, vol. 67, no. 6, pp. 1525-33.

FRL 2007, *National Greenhouse and Energy Reporting Act 2007*, Australian Government, viewed 11/07/2022, <https://www.legislation.gov.au/Series/C2007A00175>.

Fu, B, Chen, L, Huang, H, Qu, P & Wei, Z 2021, 'Impacts of crop residues on soil health: A review', *Environmental Pollutants and Bioavailability*, vol. 33, no. 1, pp. 164-73.

Gaddam, SJ & Sampath, PV 2022, 'Are multiscale water–energy–land–food nexus studies effective in assessing agricultural sustainability?', *Environmental Research Letters*, vol. 17, no. 1, p. 014034.

Galaitsi, S, Veysey, J & Huber-Lee, A 2018, 'Where is the added value? A review of the water-energy-food nexus literature'.

Garcia-Tejero, I, Arriaga, J, Durán-Zuazo, V & Muriel-Fernández, J 2013, 'Predicting crop-water production functions for long-term effects of deficit irrigation on citrus productivity (SW Spain)', *Archives of Agronomy and Soil Science*, vol. 59, no. 12, pp. 1591-606.

García, AM, Gallagher, J, McNabola, A, Poyato, EC, Barrios, PM & Díaz, JR 2019, 'Comparing the environmental and economic impacts of on-or off-grid solar photovoltaics with traditional energy sources for rural irrigation systems', *Renewable energy*, vol. 140, pp. 895-904.

Garcia, D & You, F 2017, 'Systems engineering opportunities for agricultural and organic waste management in the food–water–energy nexus', *Current Opinion in Chemical Engineering*, vol. 18, pp. 23-31.

Garcia, DJ & You, F 2016, 'The water-energy-food nexus and process systems engineering: A new focus', *Computers & Chemical Engineering*, vol. 91, pp. 49-67.

Geressu, R, Siderius, C, Harou, JJ, Kashaigili, J, Pettinotti, L & Conway, D 2020, 'Assessing river basin development given water - energy - food - environment interdependencies', *Earth's Future*, vol. 8, no. 8, p. e2019EF001464.

Giampietro, M, Mayumi, K & Ramos-Martin, J 2009, 'Multi-scale integrated analysis of societal and ecosystem metabolism (MuSIASEM): Theoretical concepts and basic rationale', *Energy*, vol. 34, no. 3, pp. 313-22.

Giller, KE, Andersson, JA, Corbeels, M, Kirkegaard, J, Mortensen, D, Erenstein, O & Vanlauwe, B 2015, 'Beyond conservation agriculture', *Frontiers in plant science*, vol. 6, p. 870.

Go, AW, Conag, AT, Igdon, RMB, Toledo, AS & Malila, JS 2019, 'Potentials of agricultural and agro-industrial crop residues for the displacement of fossil fuels: A Philippine context', *Energy Strategy Reviews*, vol. 23, pp. 100-13.

Gondhalekar, D & Ramsauer, T 2017, 'Nexus city: operationalizing the urban water-energy-food nexus for climate change adaptation in Munich, Germany', *Urban Climate*, vol. 19, pp. 28-40.

Goswami, SB, Mondal, R & Mandi, SK 2020, 'Crop residue management options in rice–rice system: a review', *Archives of Agronomy and Soil Science*, vol. 66, no. 9, pp. 1218-34.

Goulder, LH & Schein, AR 2013, 'Carbon taxes versus cap and trade: a critical review', *Climate Change Economics*, vol. 4, no. 03, p. 1350010.

Graham, H 2022a, *AgTrends Spatial*, 19/10/2022.

Graham, H 2022b, *AgMargins Update - Transitioning existing gross margins from old version*.

Granero de Melo, T, Lacerra de Souza, B & Scopinho, RA 2020, 'Peri-urban territories and WEF nexus: the challenges of Brazilian agrarian reform areas for social justice', *Journal of Integrative Environmental Sciences*, vol. 17, no. 2, pp. 45-67.

Green, TR, Ahuja, LR & Benjamin, JG 2003, 'Advances and challenges in predicting agricultural management effects on soil hydraulic properties', *Geoderma*, vol. 116, no. 1-2, pp. 3-27.

Gregg, JS & Smith, SJ 2010, 'Global and regional potential for bioenergy from agricultural and forestry residue biomass', *Mitigation and Adaptation Strategies for Global Change*, vol. 15, pp. 241-62.

Guo, Y, Fang, G, Xu, Y-P, Tian, X & Xie, J 2020, 'Identifying how future climate and land use/cover changes impact streamflow in Xinanjiang Basin, East China', *Science of the total environment*, vol. 710, p. 136275.

Guta, DD & Thiam, DR 2018, 'Challenges and opportunities associated with the role of forestry in promoting water-energy and food security nexus in Ethiopia', *International Journal of Global Environmental Issues*, vol. 17, no. 2-3, pp. 214-29.

Guta, DD, Jara, J, Adhikari, NP, Chen, Q, Gaur, V & Mirzabaev, A 2017, 'Assessment of the successes and failures of decentralized energy solutions and implications for the water–energy–food security nexus: Case studies from developing countries', *Resources*, vol. 6, no. 3, p. 24.

Hafeez, M, Bundschuh, J & Mushtaq, S 2014, 'Exploring synergies and tradeoffs: Energy, water, and economic implications of water reuse in rice-based irrigation systems', *Applied Energy*, vol. 114, pp. 889-900.

Hajkowicz, S, Cook, H & Littleboy, A 2012, *Our future world: Global megatrends that will change the way we live*, CSIRO.

Hajkowicz, S, Cook, H & Littleboy, A 2014, 'Our future world', no. 37, pp. 14-5.

Hamidov, A & Helming, K 2020, 'Sustainability considerations in water–energy–food nexus research in irrigated agriculture', *Sustainability*, vol. 12, no. 15, p. 6274.

Hang, MYLP, Martinez-Hernandez, E, Leach, M & Yang, A 2016, 'Designing integrated local production systems: a study on the food-energy-water nexus', *Journal of Cleaner Production*, vol. 135, pp. 1065-84.

Hara, T 2020, *An essay on the principle of sustainable population*, Springer.

Heard, BR, Miller, SA, Liang, S & Xu, M 2017, 'Emerging challenges and opportunities for the food–energy–water nexus in urban systems', *Current Opinion in Chemical Engineering*, vol. 17, pp. 48-53.

Herman, J, Usher, W & Others 2019, *SALib - Sensitivity Analysis Library in Python*, viewed 07/01/2021, <https://salib.readthedocs.io/en/latest/>.

Hiel, M-P, Barbieux, S, Pierreux, J, Olivier, C, Lobet, G, Roisin, C, Garré, S, Colinet, G, Bodson, B & Dumont, B 2018, 'Impact of crop residue management on crop production and soil chemistry after seven years of crop rotation in temperate climate, loamy soils', *PeerJ*, vol. 6, p. e4836.

Hiloidhari, M, Das, D & Baruah, D 2014, 'Bioenergy potential from crop residue biomass in India', *Renewable and Sustainable Energy Reviews*, vol. 32, pp. 504-12.

Hoff, H 2011a, 'The Water, Energy, and Food Security Nexus; Solutions for the Green Economy', *Proc. Bonn2011 Conf*, pp. 1-52.

Hoff, H 2011b, 'Understanding the nexus'.

Holt, N, Shukla, S, Hochmuth, G, Muñoz-Carpena, R & Ozores-Hampton, M 2017, 'Transforming the food-water-energy-land-economic nexus of plasticulture production through compact bed geometries', *Advances in Water Resources*, vol. 110, pp. 515-27.

Honorato-Salazar, JA & Sadhukhan, J 2020, 'Annual biomass variation of agriculture crops and forestry residues, and seasonality of crop residues for energy production in Mexico', *Food and Bioproducts Processing*, vol. 119, pp. 1-19.

Hoogenboom, G, Jones, J, Wilkens, P, Porter, C, Batchelor, W, Hunt, L, Boote, K, Singh, U, Uryasev, O & Bowen, W 2004, 'Decision support system for agrotechnology transfer version 4.0', *University of Hawaii, Honolulu, HI (CD-ROM)*.

Howells, M, Hermann, S, Welsch, M, Bazilian, M, Segerström, R, Alfstad, T, Gielen, D, Rogner, H, Fischer, G & Van Velthuizen, H 2013, 'Integrated analysis of climate change, land-use, energy and water strategies', *Nature Climate Change*, vol. 3, no. 7, pp. 621-6.

Hu, Y, Ren, S, Wang, Y & Chen, X 2020, 'Can carbon emission trading scheme achieve energy conservation and emission reduction? Evidence from the industrial sector in China', *Energy Economics*, vol. 85, p. 104590.

Hung, C-LJ, James, LA, Carbone, GJ & Williams, JM 2020, 'Impacts of combined land-use and climate change on streamflow in two nested catchments in the Southeastern United States', *Ecological Engineering*, vol. 143, p. 105665.

Hunter, MC, Smith, RG, Schipanski, ME, Atwood, LW & Mortensen, DA 2017, 'Agriculture in 2050: Recalibrating Targets for Sustainable Intensification', *Bioscience*, vol. 67, no. 4, pp. 386-91.

Ibrahim, MD, Ferreira, DC, Daneshvar, S & Marques, RC 2019, 'Transnational resource generativity: Efficiency analysis and target setting of water, energy, land, and food nexus for OECD countries', *Science of the total environment*, vol. 697, p. 134017.

Irabien, A & Darton, R 2016, 'Energy–water–food nexus in the Spanish greenhouse tomato production', *Clean technologies and environmental policy*, vol. 18, pp. 1307-16.

Irrigation Australia 2020, *Irrigation methods in Australia*, viewed 01/12/2020, <https://www.irrigationaustralia.com.au/about-us/types-of-irrigation/types-of-irrigation>.

Iye, E & Bilsborrow, P 2013a, 'Cellulosic ethanol production from agricultural residues in Nigeria', *Energy Policy*, vol. 63, pp. 207-14.

Iye, EL & Bilsborrow, PE 2013b, 'Assessment of the availability of agricultural residues on a zonal basis for medium-to large-scale bioenergy production in Nigeria', *Biomass and Bioenergy*, vol. 48, pp. 66-74.

Jacobson, M & Pekarcik, G 2022, 'Water-energy-food nexus approaches and initiatives in Africa', *Handbook on the Water-Energy-Food Nexus*, pp. 211-30.

Jamal, T, Shoeb, MA, Shafiullah, GM, Carter, CE & Urmee, T 2016, 'A design consideration for solar PV-diesel remote electricity network: Australia perspective', *2016 IEEE Innovative Smart Grid Technologies - Asia (ISGT-Asia)*, pp. 821-6.

Jamali, M, Soufizadeh, S, Yeganeh, B & Emam, Y 2021, 'A comparative study of irrigation techniques for energy flow and greenhouse gas (GHG) emissions in wheat agroecosystems under contrasting environments in south of Iran', *Renewable and Sustainable Energy Reviews*, vol. 139, p. 110704.

Janssen, MA 2005, 'Agent-based modelling', *Modelling in ecological economics*, vol. 155, no. 1, pp. 172-81.

Jeswani, HK, Burkinshaw, R & Azapagic, A 2015, 'Environmental sustainability issues in the food–energy–water nexus: Breakfast cereals and snacks', *Sustainable production and consumption*, vol. 2, pp. 17-28.

Ji, C, Cheng, K, Nayak, D & Pan, G 2018, 'Environmental and economic assessment of crop residue competitive utilization for biochar, briquette fuel and combined heat and power generation', *Journal of Cleaner Production*, vol. 192, pp. 916-23.

Ji, L, Zheng, Z, Wu, T, Xie, Y, Liu, Z, Huang, G & Niu, D 2020, 'Synergetic optimization management of crop-biomass coproduction with food-energy-water nexus under uncertainties', *Journal of Cleaner Production*, vol. 258, p. 120645.

Jiang, D, Zhuang, D, Fu, J, Huang, Y & Wen, K 2012, 'Bioenergy potential from crop residues in China: Availability and distribution', *Renewable and Sustainable Energy Reviews*, vol. 16, no. 3, pp. 1377-82.

Jiang, J, Xie, D, Ye, B, Shen, B & Chen, Z 2016, 'Research on China's cap-and-trade carbon emission trading scheme: Overview and outlook', *Applied Energy*, vol. 178, pp. 902-17.

Jiang, Y, Havrysh, V, Klymchuk, O, Nitsenko, V, Balezentis, T & Streimikiene, D 2019, 'Utilization of crop residue for power generation: The case of Ukraine', *Sustainability*, vol. 11, no. 24, p. 7004.

Jubb, I, Canadell, P & Dix, M 2013, 'Representative concentration pathways (RCPs)', *Australian Government, Department of the Environment*.

Jusakulvijit, P, Bezama, A & Thrän, D 2021, 'The availability and assessment of potential agricultural residues for the regional development of second-generation bioethanol in Thailand', *Waste and Biomass Valorization*, pp. 1-28.

Kaddoura, S & El Khatib, S 2017, 'Review of water-energy-food Nexus tools to improve the Nexus modelling approach for integrated policy making', *Environmental Science & Policy*, vol. 77, pp. 114-21.

Kahan, A 2019, *EIA projects nearly 50% increase in world energy usage by 2050, led by growth in Asia*, U.S. Energy Information Administration, viewed 09/01/2021, <https://www.eia.gov/todayinenergy/detail.php?id=41433>.

Kang, Y, Yang, Q, Bartocci, P, Wei, H, Liu, SS, Wu, Z, Zhou, H, Yang, H, Fantozzi, F & Chen, H 2020, 'Bioenergy in China: Evaluation of domestic biomass resources and the associated greenhouse gas mitigation potentials', *Renewable and Sustainable Energy Reviews*, vol. 127, p. 109842.

Karabulut, AA, Crenna, E, Sala, S & Udias, A 2018, 'A proposal for integration of the ecosystem-water-food-land-energy (EWFLE) nexus concept into life cycle assessment: A synthesis matrix system for food security', *Journal of Cleaner Production*, vol. 172, pp. 3874-89.

Karamian, F, Mirakzadeh, AA & Azari, A 2021, 'The water-energy-food nexus in farming: Managerial insights for a more efficient consumption of agricultural inputs', *Sustainable production and consumption*, vol. 27, pp. 1357-71.

Karan, E, Asadi, S, Mohtar, R & Baawain, M 2018, 'Towards the optimization of sustainable food-energy-water systems: A stochastic approach', *Journal of Cleaner Production*, vol. 171, pp. 662-74.

Karnib, A 2017, 'A quantitative assessment framework for water, energy and food nexus', *Computational Water, Energy, and Environmental Engineering*, vol. 6, no. 01, p. 11.

Karnib, A 2018, 'Bridging science and policy in water-energy-food nexus: using the Q-Nexus model for informing policy making', *Water Resources Management*, vol. 32, no. 15, pp. 4895-909.

Kaur, K, Kaur, P & Sharma, S 2019, 'Management of crop residue through various techniques', *Journal of Pharmacognosy and Phytochemistry*, vol. 8, no. 1S, pp. 618-20.

Keating, BA, Carberry, PS, Hammer, GL, Probert, ME, Robertson, MJ, Holzworth, D, Huth, NI, Hargreaves, JN, Meinke, H & Hochman, Z 2003, 'An overview of APSIM, a model designed for farming systems simulation', *European Journal of Agronomy*, vol. 18, no. 3-4, pp. 267-88.

Ken Flower, Yash Dang & Ward, P 2019, 'Advances in crop residue management', in Jim Pratley & J Kirkegaard (eds), *Australian agriculture in 2020: from conservation to automation*, Agronomy Australia and Charles Sturt University: Wagga Wagga, Graham Centre for Agricultural Innovation, Charles Sturt University, Wagga Wagga NSW, Australia 2678, vol. pp 137-149.

Khacheba, R, Cherfaoui, M, Hartani, T & Drouiche, N 2018, 'The nexus approach to water-energy-food security: an option for adaptation to climate change in Algeria', *Desalination and Water Treatment*, vol. 131, pp. 30-3.

Khaki, S & Wang, L 2019, 'Crop yield prediction using deep neural networks', *Frontiers in plant science*, vol. 10, p. 621.

Khan, MA, Wahid, A, Ahmad, M, Tahir, MT, Ahmed, M, Ahmad, S & Hasanuzzaman, M 2020, 'World cotton production and consumption: An overview', *Cotton production and uses: Agronomy, crop protection, and postharvest technologies*, pp. 1-7.

Kibler, KM, Reinhart, D, Hawkins, C, Motlagh, AM & Wright, J 2018, 'Food waste and the food-energy-water nexus: A review of food waste management alternatives', *Waste Management*, vol. 74, pp. 52-62.

Kipkorir, E, Raes, D & Massawe, B 2002, 'Seasonal water production functions and yield response factors for maize and onion in Perkerra, Kenya', *Agricultural Water Management*, vol. 56, no. 3, pp. 229-40.

Kirkegaard, JA, Conyers, MK, Hunt, JR, Kirkby, CA, Watt, M & Rebetzke, GJ 2014, 'Sense and nonsense in conservation agriculture: principles, pragmatism and productivity in Australian mixed farming systems', *Agriculture, Ecosystems & Environment*, vol. 187, pp. 133-45.

Kitonyo, OM, Zhou, Y, Coventry, DR & Denton, MD 2018, 'Canopy development and grain yield of dryland wheat is modified by strategic nitrogen supply and stubble management', *European Journal of Agronomy*, vol. 99, pp. 195-205.

Klöpffer, W 2006, 'The Hitch Hiker´s Guide to LCA - An orientation in LCA methodology and application', *The international journal of life cycle assessment*, vol. 11, no. 2, pp. 142-.

Koul, B, Yakoob, M & Shah, MP 2022, 'Agricultural waste management strategies for environmental sustainability', *Environmental Research*, vol. 206, p. 112285.

Kraucunas, I, Clarke, L, Dirks, J, Hathaway, J, Hejazi, M, Hibbard, K, Huang, M, Jin, C, Kintner-Meyer, M & van Dam, KK 2015, 'Investigating the nexus of climate, energy, water, and land at decision-relevant scales: the Platform for Regional Integrated Modeling and Analysis (PRIMA)', *Climatic Change*, vol. 129, no. 3-4, pp. 573-88.

Kruidhof, HM, Bastiaans, L & Kropff, MJ 2009, 'Cover crop residue management for optimizing weed control', *Plant and soil*, vol. 318, pp. 169-84.

Kumar, K & Goh, K 1999, 'Crop residues and management practices: effects on soil quality, soil nitrogen dynamics, crop yield, and nitrogen recovery', *Advances in agronomy*, vol. 68, pp. 197-319.

Laso, J, Margallo, M, García-Herrero, I, Fullana, P, Bala, A, Gazulla, C, Polettini, A, Kahhat, R, Vázquez-Rowe, I & Irabien, A 2018, 'Combined application of life cycle assessment and linear programming to evaluate food waste-to-food strategies: Seeking for answers in the nexus approach', *Waste Management*, vol. 80, pp. 186-97.

Laspidou, CS, Mellios, N & Kofinas, D 2019, 'Towards ranking the water–energy–food–land use–climate nexus interlinkages for building a nexus conceptual model with a heuristic algorithm', *Water*, vol. 11, no. 2, p. 306.

Lawford, R, Bogardi, J, Marx, S, Jain, S, Wostl, CP, Knüppe, K, Ringler, C, Lansigan, F & Meza, F 2013, 'Basin perspectives on the water–energy–food security nexus', *Current Opinion in Environmental Sustainability*, vol. 5, no. 6, pp. 607-16.

Lawford, RG 2019, 'A design for a data and information service to address the knowledge needs of the Water-Energy-Food (WEF) Nexus and strategies to facilitate its implementation', *Frontiers in Environmental Science*, vol. 7, p. 56.

Leck, H, Conway, D, Bradshaw, M & Rees, J 2015, 'Tracing the water–energy–food nexus: Description, theory and practice', *Geography Compass*, vol. 9, no. 8, pp. 445-60.

Lee, S-H, Choi, J-Y, Hur, S-O, Taniguchi, M, Masuhara, N, Kim, KS, Hyun, S, Choi, E, Sung, J-h & Yoo, S-H 2020, 'Food-centric interlinkages in agricultural food-energy-water nexus under climate change and irrigation management', *Resources, Conservation and Recycling*, vol. 163, p. 105099.

Leese, M & Meisch, S 2015, 'Securitising sustainability? Questioning the 'water, energy and food-security nexus'', *Water Alternatives*, vol. 8, no. 1, pp. 695-709.

Lele, U, Klousia-Marquis, M & Goswami, S 2013, 'Good governance for food, water and energy security', *Aquatic procedia*, vol. 1, pp. 44-63.

Li, G, Huang, D & Li, Y 2016a, 'China’s input-output efficiency of water-energy-food nexus based on the data envelopment analysis (DEA) model', *Sustainability*, vol. 8, no. 9, p. 927.

Li, G, Wang, Y & Li, Y 2019a, 'Synergies within the water-energy-food nexus to support the integrated urban resources governance', *Water*, vol. 11, no. 11, p. 2365.

Li, K, Song, J, Duan, H & Wang, S 2018, 'Integrated assessment of straw utilization for energy production from views of regional energy, environmental and socioeconomic benefits', *Journal of Cleaner Production*, vol. 190, pp. 787-98.

Li, M & Guo, P 2015, 'A coupled random fuzzy two-stage programming model for crop area optimization—A case study of the middle Heihe River basin, China', *Agricultural Water Management*, vol. 155, pp. 53-66.

Li, M, Guo, P, Singh, VP & Yang, G 2016b, 'An uncertainty-based framework for agricultural water-land resources allocation and risk evaluation', *Agricultural Water Management*, vol. 177, pp. 10-23.

Li, M, Guo, P, Singh, VP & Zhao, J 2016c, 'Irrigation Water Allocation Using an Inexact Two‐Stage Quadratic Programming with Fuzzy Input under Climate Change', *JAWRA Journal of the American Water Resources Association*, vol. 52, no. 3, pp. 667-84.

Li, M, Fu, Q, Singh, VP, Ma, M & Liu, X 2017, 'An intuitionistic fuzzy multi-objective non-linear programming model for sustainable irrigation water allocation under the combination of dry and wet conditions', *Journal of Hydrology*, vol. 555, pp. 80-94.

Li, M, Fu, Q, Singh, VP, Liu, D & Li, T 2019b, 'Stochastic multi-objective modeling for optimization of water-food-energy nexus of irrigated agriculture', *Advances in Water Resources*, vol. 127, pp. 209-24.

Li, M, Fu, Q, Singh, VP, Liu, D & Li, J 2020, 'Optimization of sustainable bioenergy production considering energy-food-water-land nexus and livestock manure under uncertainty', *Agricultural Systems*, vol. 184, p. 102900.

Li, M, Li, H, Fu, Q, Liu, D, Yu, L & Li, T 2021, 'Approach for optimizing the water-land-food-energy nexus in agroforestry systems under climate change', *Agricultural Systems*, vol. 192, p. 103201.

Li, M, Fu, Q, Singh, VP, Ji, Y, Liu, D, Zhang, C & Li, T 2019c, 'An optimal modelling approach for managing agricultural water-energy-food nexus under uncertainty', *Science of the total environment*, vol. 651, pp. 1416-34.

Li, Y, Chen, Y & Wu, J 2019d, 'Enhancement of methane production in anaerobic digestion process: A review', *Applied Energy*, vol. 240, pp. 120-37.

lifecycles. 2020, *AusLCI database*, Life Cycle Strategies,, viewed 01/02/2021, <https://www.lifecycles.com.au/auslci-database>.

Lin, B & Jia, Z 2017, 'The impact of Emission Trading Scheme (ETS) and the choice of coverage industry in ETS: A case study in China', *Applied Energy*, vol. 205, pp. 1512-27.

Liu, J, Li, Y & Li, X 2020, 'Identifying optimal security management policy for water–energy–food nexus system under stochastic and fuzzy conditions', *Water*, vol. 12, no. 11, p. 3268.

Liu, J, Hull, V, Godfray, HCJ, Tilman, D, Gleick, P, Hoff, H, Pahl-Wostl, C, Xu, Z, Chung, MG, Sun, J & Li, S 2018, 'Nexus approaches to global sustainable development', *Nature Sustainability*, vol. 1, no. 9, pp. 466-76.

Looss, B & Lemaître, P 2015, 'A review on global sensitivity analysis methods', in *Uncertainty management in simulation-optimization of complex systems*, Springer, pp. 101-22.

López-Díaz, DC, Lira-Barragán, LF, Rubio-Castro, E, Serna-González, M, El-Halwagi, MM & Ponce-Ortega, JM 2018, 'Optimization of biofuels production via a water–energy–food nexus framework', *Clean technologies and environmental policy*, vol. 20, pp. 1443-66.

Lu, F, Chi, B-j & Dong, H-z 2022, 'Cotton cultivation technology with Chinese characteristics has driven the 70-year development of cotton production in China', *Journal of Integrative Agriculture*, vol. 21, no. 3, pp. 597-609.

Luo, W, Chen, M, Kang, Y, Li, W, Li, D, Cui, Y, Khan, S & Luo, Y 2022, 'Analysis of crop water requirements and irrigation demands for rice: Implications for increasing effective rainfall', *Agricultural Water Management*, vol. 260, p. 107285.

Makarichi, L, Jutidamrongphan, W & Techato, K-a 2018, 'The evolution of waste-to-energy incineration: A review', *Renewable and Sustainable Energy Reviews*, vol. 91, pp. 812-21.

Malav, LC, Yadav, KK, Gupta, N, Kumar, S, Sharma, GK, Krishnan, S, Rezania, S, Kamyab, H, Pham, QB & Yadav, S 2020, 'A review on municipal solid waste as a renewable source for waste-to-energy project in India: Current practices, challenges, and future opportunities', *Journal of Cleaner Production*, vol. 277, p. 123227.

Mannan, M, Al-Ansari, T, Mackey, HR & Al-Ghamdi, SG 2018, 'Quantifying the energy, water and food nexus: A review of the latest developments based on life-cycle assessment', *Journal of Cleaner Production*, vol. 193, pp. 300-14.

Maraseni, T & Cockfield, G 2012, 'Including the costs of water and greenhouse gas emissions in a reassessment of the profitability of irrigation', *Agricultural Water Management*, vol. 103, pp. 25-32.

Maraseni, T, An-Vo, D-A, Mushtaq, S & Smith, KR 2020, 'Carbon smart agriculture: an integrated regional approach offers significant potential to increase profit and resource use efficiency, and reduce emissions', *Journal of Cleaner Production*, p. 124555.

Maraseni, T, An-Vo, D-A, Mushtaq, S & Reardon-Smith, K 2021, 'Carbon smart agriculture: An integrated regional approach offers significant potential to increase profit and resource use efficiency, and reduce emissions', *Journal of Cleaner Production*, vol. 282, p. 124555.

Maraseni, TN, Deo, RC, Qu, J, Gentle, P & Neupane, PR 2018, 'An international comparison of rice consumption behaviours and greenhouse gas emissions from rice production', *Journal of Cleaner Production*, vol. 172, pp. 2288-300.

Maraveas, C 2020, 'Production of sustainable and biodegradable polymers from agricultural waste', *Polymers*, vol. 12, no. 5, p. 1127.

Martinez-Hernandez, E & Samsatli, S 2017a, 'Biorefineries and the food, energy, water nexus—towards a whole systems approach to design and planning', *Current Opinion in Chemical Engineering*, vol. 18, pp. 16-22.

Martinez-Hernandez, E, Leach, M & Yang, A 2017b, 'Understanding water-energy-food and ecosystem interactions using the nexus simulation tool NexSym', *Applied Energy*, vol. 206, pp. 1009-21.

Martinez, P, Blanco, M & Castro-Campos, B 2018, 'The water–energy–food nexus: A fuzzy-cognitive mapping approach to support nexus-compliant policies in Andalusia (Spain)', *Water*, vol. 10, no. 5, p. 664.

Masud, M, Ananno, AA, Arefin, AM, Ahamed, R, Das, P & Joardder, MU 2019, 'Perspective of biomass energy conversion in Bangladesh', *Clean technologies and environmental policy*, vol. 21, pp. 719-31.

Mayor Rodríguez, B 2016, 'The Water-Energy-Food nexus: trends, trade-offs and implications for strategic energies'.

McGrane, S, Acuto, M, Artioli, F, Chen, PY, Comber, R, Cottee, J, Farr-Wharton, G, Green, N, Helfgott, A, Larcom, S, McCann, J, O'Reilly, P, Salmoral, G, Scott, M, Todman, L, van Gevelt, T & Yan, X 2018, 'Scaling the nexus: towards integrated frameworks for analysing water, energy and food', *Geogr J*, pp. 1-13.

MDBA 2022a, *Water entitlements in Basin states*, viewed 10/05/2022, <https://www.mdba.gov.au/water-use/allocations/water-entitlements-basin-states>.

MDBA 2022b, *How allocations work in the Murray–Darling Basin*, viewed 08/09/2022, <https://www.mdba.gov.au/water-management/allocations-states-mdba/guide-allocations>.

Mehran, A, Aghakouchak, A, Nakhjiri, N, Stewardson, MJ, Peel, MC, Phillips, TJ, Wada, Y & Ravalico, JK 2017, 'Compounding Impacts of Human-Induced Water Stress and Climate Change on Water Availability', *Scientific Reports*, vol. 7, no. 1.

Melikoglu, M & Cinel, AM 2020, 'Food waste-water-energy nexus: Scrutinising sustainability of biodiesel production from sunflower oil consumption wastes in Turkey till 2030', *Environmental Technology & Innovation*, vol. 17, p. 100628.

Melo, FP, Parry, L, Brancalion, PH, Pinto, SR, Freitas, J, Manhães, AP, Meli, P, Ganade, G & Chazdon, RL 2021, 'Adding forests to the water–energy–food nexus', *Nature Sustainability*, vol. 4, no. 2, pp. 85-92.

Mohtar, RH & Daher, B 2016, 'Water-energy-food nexus framework for facilitating multi-stakeholder dialogue', *Water International*, vol. 41, no. 5, pp. 655-61.

Momayez, F, Karimi, K & Taherzadeh, MJ 2019, 'Energy recovery from industrial crop wastes by dry anaerobic digestion: A review', *Industrial Crops and Products*, vol. 129, pp. 673-87.

Monforti, F, Bódis, K, Scarlat, N & Dallemand, J-F 2013, 'The possible contribution of agricultural crop residues to renewable energy targets in Europe: A spatially explicit study', *Renewable and Sustainable Energy Reviews*, vol. 19, pp. 666-77.

Monteith, JL 1996, 'The quest for balance in crop modeling', *Agronomy journal*, vol. 88, no. 5, pp. 695-7.

Morris, MD 1991, 'Factorial sampling plans for preliminary computational experiments', *Technometrics*, vol. 33, no. 2, pp. 161-74.

Murray, BC & Maniloff, PT 2015, 'Why have greenhouse emissions in RGGI states declined? An econometric attribution to economic, energy market, and policy factors', *Energy Economics*, vol. 51, pp. 581-9.

Murray, M 2022, *Cotton Datasets*, 24/08/2022.

Mushtaq, S, Maraseni, T & Reardon-Smith, K 2013, 'Climate change and water security: estimating the greenhouse gas costs of achieving water security through investments in modern irrigation technology', *Agricultural Systems*, vol. 117, pp. 78-89.

Naidoo, D, Nhamo, L, Mpandeli, S, Sobratee, N, Senzanje, A, Liphadzi, S, Slotow, R, Jacobson, M, Modi, AT & Mabhaudhi, T 2021, 'Operationalising the water-energy-food nexus through the theory of change', *Renewable and Sustainable Energy Reviews*, vol. 149, p. 111416.

Nasrollahi, H, Shirazizadeh, R, Shirmohammadi, R, Pourali, O & Amidpour, M 2021, 'Unraveling the water-energy-food-environment nexus for climate change adaptation in Iran: Urmia Lake Basin case-study', *Water*, vol. 13, no. 9, p. 1282.

Nathan, SS 1971, 'Estimating agricultural production functions from experimental data for different crops in relation to irrigation, fertilization and soil management in northern Utah'.

Neupane Bhandari, S, Schlüter, S, Kuckshinrichs, W, Schlör, H, Adamou, R & Bhandari, R 2021, 'Economic feasibility of agrivoltaic systems in food-energy nexus context: modelling and a case study in Niger', *Agronomy*, vol. 11, no. 10, p. 1906.

Newell, JP, Goldstein, B & Foster, A 2019, 'A 40-year review of food–energy–water nexus literature and its application to the urban scale', *Environmental Research Letters*, vol. 14, no. 7, p. 073003.

Nhamo, L, Ndlela, B, Nhemachena, C, Mabhaudhi, T, Mpandeli, S & Matchaya, G 2018, 'The water-energy-food nexus: Climate risks and opportunities in southern Africa', *Water*, vol. 10, no. 5, p. 567.

Nhamo, L, Mabhaudhi, T, Mpandeli, S, Nhemachena, C, Senzanje, A, Naidoo, D, Liphadzi, S & Modi, AT 2019, 'Sustainability indicators and indices for the water-energy-food nexus for performance assessment: WEF nexus in practice–South Africa case study'.

Nie, Y, Avraamidou, S, Xiao, X, Pistikopoulos, EN, Li, J, Zeng, Y, Song, F, Yu, J & Zhu, M 2019, 'A Food-Energy-Water Nexus approach for land use optimization', *Science of the total environment*, vol. 659, pp. 7-19.

Nong, D, Nguyen, TH, Wang, C & Van Khuc, Q 2020, 'The environmental and economic impact of the emissions trading scheme (ETS) in Vietnam', *Energy Policy*, vol. 140, p. 111362.

Oakleaf, JR, Kennedy, CM, Baruch-Mordo, S, Gerber, JS, West, PC, Johnson, JA & Kiesecker, J 2019, 'Mapping global development potential for renewable energy, fossil fuels, mining and agriculture sectors', *Scientific data*, vol. 6, no. 1, p. 101.

Okello, C, Pindozzi, S, Faugno, S & Boccia, L 2013, 'Bioenergy potential of agricultural and forest residues in Uganda', *Biomass and Bioenergy*, vol. 56, pp. 515-25.

Ozturk, I 2017, 'The dynamic relationship between agricultural sustainability and food-energy-water poverty in a panel of selected Sub-Saharan African Countries', *Energy Policy*, vol. 107, pp. 289-99.

Panchasara, H, Samrat, NH & Islam, N 2021, 'Greenhouse gas emissions trends and mitigation measures in australian agriculture sector—a review', *Agriculture*, vol. 11, no. 2, p. 85.

Pastori, M, Udias, A, Cattaneo, L, Moner-Girona, M, Niang, A & Carmona-Moreno, C 2021, 'Bioenergy Potential of Crop Residues in the Senegal River Basin: A Cropland–Energy–Water-Environment Nexus Approach', *Sustainability*, vol. 13, no. 19, p. 11065.

Patwardhan, AS, Nieber, JL & Johns, EL 1990, 'Effective rainfall estimation methods', *Journal of irrigation and Drainage Engineering*, vol. 116, no. 2, pp. 182-93.

Paul, AS, Panwar, NL, Salvi, BL, Jain, S & Sharma, D 2020, 'Experimental investigation on the production of bio-oil from wheat straw', *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, pp. 1-16.

Peña-Torres, D, Boix, M & Montastruc, L 2022, 'Optimization approaches to design water-energy-food nexus: A litterature review', *Computers & Chemical Engineering*, p. 108025.

Peng, Y & Su, L 2003, 'The Establishment of Water-production Functions during Crops' Full-bearing Period', *Journal of Arid Land Resources and Environment*, vol. 17, no. 4, pp. 122-4.

Perea-Moreno, M-A, Samerón-Manzano, E & Perea-Moreno, A-J 2019, 'Biomass as renewable energy: Worldwide research trends', *Sustainability*, vol. 11, no. 3, p. 863.

Perederii, T 2021, 'Agrivoltaics as a promising direction of land use for for ensuring global energy and food security'.

Perera, A, Nik, VM, Chen, D, Scartezzini, J-L & Hong, T 2020, 'Quantifying the impacts of climate change and extreme climate events on energy systems', *Nature Energy*, vol. 5, no. 2, pp. 150-9.

Petrariu, R, Constantin, M, Dinu, M, Pătărlăgeanu, SR & Deaconu, ME 2021, 'Water, energy, food, waste nexus: Between synergy and trade-offs in Romania based on entrepreneurship and economic performance', *Energies*, vol. 14, no. 16, p. 5172.

Phoenix Power Recycles 2022, *Request for a quote*, 16/11/2022, <https://www.phoenixpower.com.au/organic-products/organic-compost/pc100-prescription-compost.htm>.

Pinotti, L, Luciano, A, Ottoboni, M, Manoni, M, Ferrari, L, Marchis, D & Tretola, M 2021, 'Recycling food leftovers in feed as opportunity to increase the sustainability of livestock production', *Journal of Cleaner Production*, vol. 294, p. 126290.

Pires, A & Martinho, G 2019, 'Waste hierarchy index for circular economy in waste management', *Waste Management*, vol. 95, pp. 298-305.

Postma, TJ & Liebl, F 2005, 'How to improve scenario analysis as a strategic management tool?', *Technological Forecasting and Social Change*, vol. 72, no. 2, pp. 161-73.

Powell, JW, Welsh, JM & Freebairn, J 2019, 'The economics of integrating alternative energy: A farm case study at Emerald, Queensland', *Australian Farm Business Management Journal*, vol. 16, pp. 1-16.

Pramanik, SK, Suja, FB, Zain, SM & Pramanik, BK 2019, 'The anaerobic digestion process of biogas production from food waste: Prospects and constraints', *Bioresource Technology Reports*, vol. 8, p. 100310.

Prasad, S, Singh, A, Korres, NE, Rathore, D, Sevda, S & Pant, D 2020, 'Sustainable utilization of crop residues for energy generation: A life cycle assessment (LCA) perspective', *Bioresource Technology*, vol. 303, p. 122964.

Pratley, J & Kirkegaard, J 2019, 'Australian agriculture in 2020: from conservation to automation', *Agronomy Australia and Charles Sturt University, Wagga Wagga*.

Praveen, JP, Donthi, R, Prasad, SV, Mahaboob, B & Venkateswarlu, B 2019, 'A glance on the estimation of Cobb-Douglas production functional model', *AIP Conference Proceedings*, AIP Publishing LLC, p. 020067.

Pulido-Mancebo, JS, López-Luque, R, Fernández-Ahumada, LM, Ramírez-Faz, JC, Gómez-Uceda, FJ & Varo-Martínez, M 2022, 'Spatial Distribution Model of Solar Radiation for Agrivoltaic Land Use in Fixed PV Plants', *Agronomy*, vol. 12, no. 11, p. 2799.

Purwanto, A, Sušnik, J, Suryadi, FX & de Fraiture, C 2021, 'Water-energy-food nexus: Critical review, practical applications, and prospects for future research', *Sustainability*, vol. 13, no. 4, p. 1919.

Pushpalatha, R, Sarojini Amma, S, George, J, Rajan, S & Gangadharan, B 2020, 'Development of optimal irrigation schedules and crop water production function for cassava: study over three major growing areas in India', *Irrigation Science*, vol. 38, no. 3, pp. 251-61.

QCA 2022, *Solar feed-in tariffs*, viewed 05/06/2022, <http://www.qca.org.au/project/customers/solar-feed-in-tariffs/>.

QFF 2022, *Cotton*, viewed 23/05/2022, <https://www.qff.org.au/farming-in-qld/cotton/>.

Qin, Y & Horvath, A 2020, 'Use of alternative water sources in irrigation: potential scales, costs, and environmental impacts in California', *Environmental Research Communications*, vol. 2, no. 5, p. 055003.

Qiu, H, Sun, L, Xu, X, Cai, Y & Bai, J 2014, 'Potentials of crop residues for commercial energy production in China: A geographic and economic analysis', *Biomass and Bioenergy*, vol. 64, pp. 110-23.

Queensland Government 2022a, *Queensland Murray-Darling Basin*.

Queensland Government 2022b, *How feed-in tariffs work*, viewed 04/05/2022, <https://www.qld.gov.au/housing/buying-owning-home/energy-water-home/solar/feed-in-tariffs/how-feed-in-tariffs-work>.

Queensland Government 2022c, *Queensland Spatial Catalogue - QSpatial*, Department of Resources, viewed 11/09/2022, <https://qldspatial.information.qld.gov.au/catalogue/custom/index.page>.

Queensland Government 2022d, *Agricultural Gross Margin Calculator Servicing Queensland Agricultural Industries*, 2014, 31/05/2022, <https://agmargins.net.au/>.

Queensland Government 2022e, *SILO - Australian climate data from 1889 to yesterday*, https://www.longpaddock.qld.gov.au/silo/point-data/>.

Rai, PK 2021, 'Heavy metals and arsenic phytoremediation potential of invasive alien wetland plants Phragmites karka and Arundo donax: Water-Energy-Food (WEF) Nexus linked sustainability implications', *Bioresource Technology Reports*, vol. 15, p. 100741.

Rajput, G & Singh, J 1986, 'Water production functions for wheat under different environmental conditions', *Agricultural Water Management*, vol. 11, no. 3-4, pp. 319-32.

Ramamurthi, PV, Fernandes, MC, Nielsen, PS & Nunes, CP 2014, 'Logistics cost analysis of rice residues for second generation bioenergy production in Ghana', *Bioresource Technology*, vol. 173, pp. 429-38.

Ramesh, D & Vardhan, BV 2015, 'Analysis of crop yield prediction using data mining techniques', *International Journal of research in engineering and technology*, vol. 4, no. 1, pp. 47-473.

Rao, A & Chandran, MS 1977, 'Crop water requirements', *Agrometeorol Data Collect Anal Manag*, vol. 51.

Rasul, G & Sharma, B 2016, 'The nexus approach to water–energy–food security: an option for adaptation to climate change', *Climate Policy*, vol. 16, no. 6, pp. 682-702.

Remondis 2022, *Discuss options for organic waste*, 22/11/2022, <https://www.remondis.com.au/en/home/>.

Ringler, C, Bhaduri, A & Lawford, R 2013, 'The nexus across water, energy, land and food (WELF): potential for improved resource use efficiency?', *Current Opinion in Environmental Sustainability*, vol. 5, no. 6, pp. 617-24.

Rizwan, M, Zaheer, J, Tahir, MN, Ansar, M & Ali, M 2023, 'Benefits of Research and Development on Cotton Crop: Lessons from China', *Dinkum Journal of Natural & Scientific Innovations*, vol. 2, no. 09, pp. 509-13.

Rodriguez, D, Cox, H, deVoil, P & Power, B 2014, 'A participatory whole farm modelling approach to understand impacts and increase preparedness to climate change in Australia', *Agricultural Systems*, vol. 126, pp. 50-61.

Roidt, M & Avellán, T 2019, 'Learning from integrated management approaches to implement the Nexus', *Journal of environmental management*, vol. 237, pp. 609-16.

Rosillo-Calle, F, De Groot, P, Hemstock, S & Woods, J 2007, 'Non-woody biomass and secondary fuels', *The biomass assesement handbook: Bioenergy for a sustainable environment. Sterling, VA: Earthscan*.

Sachs, I & Silk, D 1990, *Food and energy: strategies for sustainable development*, United Nations University Press.

Sadeghi, SH, Moghadam, ES, Delavar, M & Zarghami, M 2020, 'Application of water-energy-food nexus approach for designating optimal agricultural management pattern at a watershed scale', *Agricultural Water Management*, vol. 233, p. 106071.

Saladini, F, Betti, G, Ferragina, E, Bouraoui, F, Cupertino, S, Canitano, G, Gigliotti, M, Autino, A, Pulselli, F & Riccaboni, A 2018, 'Linking the water-energy-food nexus and sustainable development indicators for the Mediterranean region', *Ecological Indicators*, vol. 91, pp. 689-97.

Saltelli, A 2002, 'Making best use of model evaluations to compute sensitivity indices', *Computer physics communications*, vol. 145, no. 2, pp. 280-97.

Saltelli, A, Tarantola, S & Chan, K-S 1999, 'A quantitative model-independent method for global sensitivity analysis of model output', *Technometrics*, vol. 41, no. 1, pp. 39-56.

Saltelli, A, Annoni, P, Azzini, I, Campolongo, F, Ratto, M & Tarantola, S 2010, 'Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index', *Computer physics communications*, vol. 181, no. 2, pp. 259-70.

Saltelli, A, Aleksankina, K, Becker, W, Fennell, P, Ferretti, F, Holst, N, Li, S & Wu, Q 2019, 'Why so many published sensitivity analyses are false: A systematic review of sensitivity analysis practices', *Environmental modelling & software*, vol. 114, pp. 29-39.

Samadi, SH, Ghobadian, B & Nosrati, M 2020, 'Prediction and estimation of biomass energy from agricultural residues using air gasification technology in Iran', *Renewable energy*, vol. 149, pp. 1077-91.

Santeramo, FG & Lamonaca, E 2021, 'Food loss–food waste–food security: a new research agenda', *Sustainability*, vol. 13, no. 9, p. 4642.

Santy, S, Mujumdar, P & Bala, G 2020, 'Potential impacts of climate and land use change on the water quality of Ganga River around the industrialized Kanpur region', *Scientific Reports*, vol. 10, no. 1, pp. 1-13.

Sargentis, G-F, Siamparina, P, Sakki, G-K, Efstratiadis, A, Chiotinis, M & Koutsoyiannis, D 2021, 'Agricultural land or photovoltaic parks? The water–energy–food nexus and land development perspectives in the thessaly plain, Greece', *Sustainability*, vol. 13, no. 16, p. 8935.

Sarker, T, Kibler, K & Reinhart, D 2016, 'Concept mapping of food waste management alternatives within the food-energy-water nexus', *World Environmental and Water Resources Congress 2016*, pp. 155-63.

Satpute, S, Singh, MC & Garg, S 2021, 'Assessment of irrigation water requirements for different crops in central Punjab, India', *Journal of Agrometeorology*, vol. 23, no. 4, pp. 481-4.

Saunders, CM, Barber, A & Taylor, GJ 2006, 'Food miles-comparative energy/emissions performance of New Zealand's agriculture industry'.

Scardigno, A 2020, 'New solutions to reduce water and energy consumption in crop production: A water–energy–food nexus perspective', *Current Opinion in Environmental Science & Health*, vol. 13, pp. 11-5.

Scarlat, N, Martinov, M & Dallemand, J-F 2010, 'Assessment of the availability of agricultural crop residues in the European Union: Potential and limitations for bioenergy use', *Waste Management*, vol. 30, no. 10, pp. 1889-97.

Scarlat, N, Fahl, F, Lugato, E, Monforti-Ferrario, F & Dallemand, J 2019a, 'Integrated and spatially explicit assessment of sustainable crop residues potential in Europe', *Biomass and Bioenergy*, vol. 122, pp. 257-69.

Scarlat, N, Fahl, F, Lugato, E, Monforti-Ferrario, F & Dallemand, J-F 2019b, 'Integrated and spatially explicit assessment of sustainable crop residues potential in Europe', *Biomass and Bioenergy*, vol. 122, pp. 257-69.

Scobie, M 2022, *Cotton and wheat in Darling Downs*, 03/08/2022.

Scobie, M, Schmidt, E, Bowtell, L, Hill, A & Garmendia, A 2020, 'Feasibility of Solar PV Irrigation in Queensland
Report 1 Solar Power and Solar Irrigation Systems', p. 33.

Scott, B, Eberbach, P, Evans, J & Wade, L 2010, 'Stubble retention in cropping systems in Southern Australia: benefits and challenges', *Stubble retention in cropping systems in Southern Australia: benefits and challenges.*

Scott, B, Podmore, C, Burns, H, Bowden, P & McMaster, C 2013, *Developments in stubble retention in cropping systems in southern Australia. Report to GRDC on Project DAN 00170.(Ed. C Nicholls and EC (Ted) Wolfe). Department of Primary Industries, Orange NSW pp 103*.

Scott, CA, Kurian, M & Wescoat, JL 2015, 'The Water-Energy-Food Nexus: Enhancing Adaptive Capacity to Complex Global Challenges', in M Kurian & R Ardakanian (eds), *Governing the Nexus: Water, Soil and Waste Resources Considering Global Change*, Springer International Publishing, Cham, pp. 15-38.

Searle, S & Bitnere, K 2017, 'Review of the impact of crop residue management on soil organic carbon in Europe', *The International Council on Clean Transportation, Working Paper*, vol. 15.

Segovia-Hernández, JG, Contreras-Zarazúa, G & Ramírez-Márquez, C 2023, 'Sustainable design of water-energy-food nexus: A literature review', *RSC Sustainability*.

Sen, A 2020, 'APPLICATION OF MICROSOFT EXCEL SOLVER TECHNIQUES TO COMPUTE CLUSTER SIZE IN CELLULAR WIRELESS NETWORK', *Issues in Information Systems*, vol. 21, no. 1.

Shah, E, Liebrand, J, Vos, J, Veldwisch, GJ & Boelens, R 2018, 'The UN World Water Development Report 2016, Water and Jobs: A Critical Review', *Development and Change*, vol. 49, no. 2, pp. 678-91.

Shani, U, Tsur, Y, Zemel, A & Zilberman, D 2009, 'Irrigation production functions with water ‐ capital substitution', *Agricultural Economics*, vol. 40, no. 1, pp. 55-66.

Sherwood, J, Clabeaux, R & Carbajales-Dale, M 2017, 'An extended environmental input–output lifecycle assessment model to study the urban food–energy–water nexus', *Environmental Research Letters*, vol. 12, no. 10, p. 105003.

Si, Y, Li, X, Yin, D, Li, T, Cai, X, Wei, J & Wang, G 2019, 'Revealing the water-energy-food nexus in the Upper Yellow River Basin through multi-objective optimization for reservoir system', *Science of the total environment*, vol. 682, pp. 1-18.

Siciliano, G, Rulli, MC & D'odorico, P 2017, 'European large-scale farmland investments and the land-water-energy-food nexus', *Advances in Water Resources*, vol. 110, pp. 579-90.

Sieber, J 2006, 'WEAP water evaluation and planning system'.

Simon, D, Tyner, WE & Jacquet, F 2010, 'Economic analysis of the potential of cellulosic biomass available in France from agricultural residue and energy crops', *BioEnergy Research*, vol. 3, pp. 183-93.

Simpson, GB & Jewitt, GPW 2019a, 'The water-energy-food nexus in the anthropocene: moving from 'nexus thinking' to 'nexus action'', *Current Opinion in Environmental Sustainability*, vol. 40, pp. 117-23.

Simpson, GB, Badenhorst, J, Jewitt, GP, Berchner, M & Davies, E 2019b, 'Competition for land: the water-energy-food nexus and coal mining in Mpumalanga Province, South Africa', *Frontiers in Environmental Science*, vol. 7, p. 86.

Simpson, GJ, García-López, V, Daniel Boese, A, Tour, JM & Grill, L 2019c, *Nature Commun*, vol. 10, p. 1.

Singh, BP, Noack, SR, Fang, Y, Mehra, P, Page, K & Dang, YP 2020, 'Crop Residue Management for Improving Soil Carbon Storage, Nutrient Availability, and Fertilizer Use Efficiency', in *Soil and Fertilizers*, CRC Press, pp. 29-65.

Siwal, SS, Zhang, Q, Devi, N, Saini, AK, Saini, V, Pareek, B, Gaidukovs, S & Thakur, VK 2021, 'Recovery processes of sustainable energy using different biomass and wastes', *Renewable and Sustainable Energy Reviews*, vol. 150, p. 111483.

Skawińska, E & Zalewski, RI 2022, 'Combining the Water–Energy–Food and Food Waste–Food Loss–Food Security Nexuses to Reduce Resource Waste', *Energies*, vol. 15, no. 16, p. 5866.

Slorach, PC, Jeswani, HK, Cuéllar-Franca, R & Azapagic, A 2020, 'Environmental sustainability in the food-energy-water-health nexus: a new methodology and an application to food waste in a circular economy', *Waste Management*, vol. 113, pp. 359-68.

Can 'nexus thinking' alleviate global water, food and energy pressures? 2013, Created by Smedley, T, <https://www.theguardian.com/sustainable-business/nexus-thinking-global-water-food-energy>.

Smeets, E, Faaij, A, Lewandowski, I & Turkenburg, WC 2004, 'A quickscan of global bio-energy potentials to 2050', *Bio-EnergyTrade, March*.

Smidt, SJ, Haacker, EM, Kendall, AD, Deines, JM, Pei, L, Cotterman, KA, Li, H, Liu, X, Basso, B & Hyndman, DW 2016, 'Complex water management in modern agriculture: Trends in the water-energy-food nexus over the High Plains Aquifer', *Science of the total environment*, vol. 566, pp. 988-1001.

Smilovic, M, Gleeson, T & Adamowski, J 2016, 'Crop kites: determining crop-water production functions using crop coefficients and sensitivity indices', *Advances in Water Resources*, vol. 97, pp. 193-204.

Smirnov, RG & Wang, K 2019, 'The Cobb-Douglas production function revisited', *International Conference on Applied Mathematics, Modeling and Computational Science*, Springer, pp. 725-34.

Smith, M, Kivumbi, D & Heng, L 2002, 'Use of the FAO CROPWAT model in deficit irrigation studies', in *Deficit irrigation practices*.

Sobol, IM 2001, 'Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates', *Mathematics and computers in simulation*, vol. 55, no. 1-3, pp. 271-80.

SoilWealth 2017, *What is compost worth? Using compost in Australian vegetable systems*, https://www.soilwealth.com.au/resources/articles-publications-and-case-studies/what-is-compost-worth-using-compost-in-australian-vegetable-systems/>.

Song, S, Govindan, K, Xu, L, Du, P & Qiao, X 2017, 'Capacity and production planning with carbon emission constraints', *Transportation Research Part E: Logistics and Transportation Review*, vol. 97, pp. 132-50.

Song, X, Zhang, S, Wu, Y & Cao, Z 2020, 'Investigation on the properties of the bio-briquette fuel prepared from hydrothermal pretreated cotton stalk and wood sawdust', *Renewable energy*, vol. 151, pp. 184-91.

Sridharan, V, Pereira Ramos, E, Zepeda, E, Boehlert, B, Shivakumar, A, Taliotis, C & Howells, M 2019, 'The impact of climate change on crop production in Uganda—an integrated systems assessment with water and energy implications', *Water*, vol. 11, no. 9, p. 1805.

Steduto, P, Hsiao, TC, Raes, D & Fereres, E 2009, 'AquaCrop—The FAO crop model to simulate yield response to water: I. Concepts and underlying principles', *Agronomy journal*, vol. 101, no. 3, pp. 426-37.

Steduto, P, Hsiao, TC, Fereres, E & Raes, D 2012, *Crop yield response to water*, vol. 1028, Food and Agriculture Organization of the United Nations Rome.

Stephan, RM, Mohtar, RH, Daher, B, Embid Irujo, A, Hillers, A, Ganter, JC, Karlberg, L, Martin, L, Nairizi, S & Rodriguez, DJ 2018, 'Water–energy–food nexus: a platform for implementing the Sustainable Development Goals', *Water International*, vol. 43, no. 3, pp. 472-9.

Stokes, C & Howden, M 2010, *Adapting agriculture to climate change: preparing Australian agriculture, forestry and fisheries for the future*, CSIRO publishing.

Suardi, A, Bergonzoli, S, Alfano, V, Scarfone, A & Pari, L 2019, 'Economic distance to gather agricultural residues from the field to the integrated biomass logistic centre: A Spanish case-study', *Energies*, vol. 12, no. 16, p. 3086.

Subramanian, K, Chopra, SS, Wharton, CM, Yonge, W, Allen, J, Stevens, R, Fahy, S & Milindi, PS 2021, 'Mapping the food waste-energy-water-emissions nexus at commercial kitchens: A systems approach for a more sustainable food service sector', *Journal of Cleaner Production*, vol. 301, p. 126856.

Sukhwani, V, Shaw, R, Mitra, BK & Yan, W 2019, 'Optimizing Food-Energy-Water (FEW) nexus to foster collective resilience in urban-rural systems', *Progress in Disaster Science*, vol. 1, p. 100005.

Sumberg, J & Giller, KE 2022, 'What is ‘conventional’agriculture?', *Global Food Security*, vol. 32, p. 100617.

Sun, M, Zhang, X, Huo, Z, Feng, S, Huang, G & Mao, X 2016, 'Uncertainty and sensitivity assessments of an agricultural–hydrological model (RZWQM2) using the GLUE method', *Journal of Hydrology*, vol. 534, pp. 19-30.

Sun, Q, Miao, C, Hanel, M, Borthwick, AG, Duan, Q, Ji, D & Li, H 2019, 'Global heat stress on health, wildfires, and agricultural crops under different levels of climate warming', *Environment international*, vol. 128, pp. 125-36.

Sunwater 2019a, *Announced Allocations*, viewed 08/09/2022, <https://www.sunwater.com.au/customer/announced-allocations/>.

Sunwater 2019b, *Fees and Charges*, viewed 19/07/2022, <https://www.sunwater.com.au/customer/fees-and-charges/>.

Tian, H, Lu, C, Pan, S, Yang, J, Miao, R, Ren, W, Yu, Q, Fu, B, Jin, F-F & Lu, Y 2018, 'Optimizing resource use efficiencies in the food–energy–water nexus for sustainable agriculture: From conceptual model to decision support system', *Current Opinion in Environmental Sustainability*, vol. 33, pp. 104-13.

Toledo, C & Scognamiglio, A 2021, 'Agrivoltaic systems design and assessment: A critical review, and a descriptive model towards a sustainable landscape vision (three-dimensional agrivoltaic patterns)', *Sustainability*, vol. 13, no. 12, p. 6871.

Toowoomba Regional Council 2022a, *Enquiry about farm crop residue*, 17/11/2022.

Toowoomba Regional Council 2022b, *Register of Fees & Charges - 2022/2023*, viewed 17/11/2022, <https://www.tr.qld.gov.au/otherApps/feescharges/all/index.html?category=WASTE%20FACILITIES%20-%20COMMERCIAL%20CHARGES>.

Toptal, A, Özlü, H & Konur, D 2014, 'Joint decisions on inventory replenishment and emission reduction investment under different emission regulations', *International journal of production research*, vol. 52, no. 1, pp. 243-69.

Torres, CJF, Peixoto de Lima, CH, Suzart de Almeida Goodwin, B, Rebello de Aguiar Junior, T, Sousa Fontes, A, Veras Ribeiro, D, Saldanha Xavier da Silva, R & Dantas Pinto Medeiros, Y 2019, 'A Literature Review to Propose a Systematic Procedure to Develop “Nexus Thinking” Considering the Water–Energy–Food Nexus', *Sustainability*, vol. 11, no. 24, p. 7205.

Trommsdorff, M, Kang, J, Reise, C, Schindele, S, Bopp, G, Ehmann, A, Weselek, A, Högy, P & Obergfell, T 2021, 'Combining food and energy production: Design of an agrivoltaic system applied in arable and vegetable farming in Germany', *Renewable and Sustainable Energy Reviews*, vol. 140, p. 110694.

Tubiello, FN, Salvatore, M, Rossi, S, Ferrara, A, Fitton, N & Smith, P 2013, 'The FAOSTAT database of greenhouse gas emissions from agriculture', *Environmental Research Letters*, vol. 8, no. 1, p. 015009.

Turmel, M-S, Speratti, A, Baudron, F, Verhulst, N & Govaerts, B 2015, 'Crop residue management and soil health: A systems analysis', *Agricultural Systems*, vol. 134, pp. 6-16.

Tursi, A 2019, 'A review on biomass: importance, chemistry, classification, and conversion', *Biofuel Research Journal*, vol. 6, no. 2, pp. 962-79.

Udugama, IA, Petersen, LA, Falco, FC, Junicke, H, Mitic, A, Alsina, XF, Mansouri, SS & Gernaey, KV 2020, 'Resource recovery from waste streams in a water-energy-food nexus perspective: Toward more sustainable food processing', *Food and Bioproducts Processing*, vol. 119, pp. 133-47.

Uen, T-S, Chang, F-J, Zhou, Y & Tsai, W-P 2018, 'Exploring synergistic benefits of Water-Food-Energy Nexus through multi-objective reservoir optimization schemes', *Science of the total environment*, vol. 633, pp. 341-51.

Ulanowicz, RE 2004, 'Quantitative methods for ecological network analysis', *Computational biology and chemistry*, vol. 28, no. 5-6, pp. 321-39.

Umbers, A, Watson, P & Watson, D 2017, 'GRDC farm practices survey report 2016', *GRDC www. grdc. com. au/FarmPracticesSurveyReport*.

UNDP 2021, *The SDGs in Action*, viewed 12/11/2021, <https://www.undp.org/sustainable-development-goals?gclid=EAIaIQobChMIqe6_hcr4_gIVjQ4rCh1WWgRzEAAYASAAEgJYZPD_BwE>.

UNEP 2019, *The Emissions Gap Report. United Nations Environment Programme (UNEP),* Nairobi, Kenya, viewed 09/11/2020, <https://www.unenvironment.org/resources/emissions-gap-report-2019>.

Unkovich, M, Baldock, J & Forbes, M 2010, 'Variability in harvest index of grain crops and potential significance for carbon accounting: examples from Australian agriculture', *Advances in agronomy*, vol. 105, pp. 173-219.

Vakilifard, N, Anda, M, Bahri, PA & Ho, G 2018, 'The role of water-energy nexus in optimising water supply systems–review of techniques and approaches', *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 1424-32.

Van Fan, Y, Romanenko, S, Gai, L, Kupressova, E, Varbanov, PS & Klemeš, JJ 2021, 'Biomass integration for energy recovery and efficient use of resources: Tomsk Region', *Energy*, vol. 235, p. 121378.

van Gevelt, T 2020, 'The water–energy–food nexus: bridging the science–policy divide', *Current Opinion in Environmental Science & Health*, vol. 13, pp. 6-10.

Varzi, MM 2016, 'Crop water production functions—A review of available mathematical method', *J. Agric. Sci*, vol. 8, no. 4, pp. 76-83.

Veldhuis, AJ & Yang, A 2017, 'Integrated approaches to the optimisation of regional and local food–energy–water systems', *Current Opinion in Chemical Engineering*, vol. 18, pp. 38-44.

Venghaus, S & Hake, J-F 2018, 'Nexus thinking in current EU policies–The interdependencies among food, energy and water resources', *Environmental Science & Policy*, vol. 90, pp. 183-92.

Vermeulen, SJ, Campbell, BM & Ingram, JS 2012, 'Climate change and food systems', *Annual review of environment and resources*, vol. 37.

Vogeler, CS, Möck, M, Bandelow, NC & Schröder, B 2019, 'Livestock Farming at the Expense of Water Resources? The Water–Energy–Food Nexus in Regions with Intensive Livestock Farming', *Water*, vol. 11, no. 11, p. 2330.

Wagener, T & Gupta, HV 2005, 'Model identification for hydrological forecasting under uncertainty', *Stochastic Environmental Research and Risk Assessment*, vol. 19, no. 6, pp. 378-87.

Walker, RV, Beck, MB, Hall, JW, Dawson, RJ & Heidrich, O 2014, 'The energy-water-food nexus: Strategic analysis of technologies for transforming the urban metabolism', *Journal of environmental management*, vol. 141, pp. 104-15.

Wang, H, Zhang, L, Dawes, W & Liu, C 2001, 'Improving water use efficiency of irrigated crops in the North China Plain—measurements and modelling', *Agricultural Water Management*, vol. 48, no. 2, pp. 151-67.

Wang, Q, Li, S, He, G, Li, R & Wang, X 2018, 'Evaluating sustainability of water-energy-food (WEF) nexus using an improved matter-element extension model: A case study of China', *Journal of Cleaner Production*, vol. 202, pp. 1097-106.

Wang, S, Huang, X, Yin, C & Richel, A 2021, 'A critical review on the key issues and optimization of agricultural residue transportation', *Biomass and Bioenergy*, vol. 146, p. 105979.

Welfens, PJJ, Yu, N, Hanrahan, D & Geng, Y 2017, 'The ETS in China and Europe: dynamics, policy options and global sustainability perspectives', *International Economics and Economic Policy*, vol. 14, no. 3, pp. 517-35.

WestRex 2023, *Westrex Contact Form*, 18/01/2023, <https://www.westrex.com.au/>.

Wheat Quality Australia 2021, *Classification decisions apply to wheat grown in specified geographic areas, referred to as classification zones.*, viewed 18/03/2021, <https://wheatquality.com.au/classification/how-it-works/zones/>.

Wicaksono, A, Jeong, G & Kang, D 2017, 'Water, energy, and food nexus: review of global implementation and simulation model development', *Water Policy*, vol. 19, no. 3, pp. 440-62.

Wichelns, D 2017, 'The water-energy-food nexus: Is the increasing attention warranted, from either a research or policy perspective?', *Environmental Science & Policy*, vol. 69, pp. 113-23.

Williams, HJ, Hashad, K, Wang, H & Zhang, KM 2023, 'The potential for agrivoltaics to enhance solar farm cooling', *Applied Energy*, vol. 332, p. 120478.

Willockx, B, Lavaert, C & Cappelle, J 2022, 'Geospatial assessment of elevated agrivoltaics on arable land in Europe to highlight the implications on design, land use and economic level', *Energy reports*, vol. 8, pp. 8736-51.

Wolde, Z, Wei, W, Likessa, D, Omari, R & Ketema, H 2021, 'Understanding the impact of land use and land cover change on Water–Energy–Food Nexus in the Gidabo Watershed, East African Rift Valley', *Natural Resources Research*, vol. 30, pp. 2687-702.

Woods, B 2017, *Agricultural Gross Margin Calculator*, viewed 11/04/2021, <https://agmargins.net.au/>.

World Economic Forum 2011, *Water Security: The Water-Energy-Food-Climate Nexus*, https://www.weforum.org/reports/water-security-water-energy-food-climate-nexus/>.

Xiao, Z, Yao, M, Tang, X & Sun, L 2019, 'Identifying critical supply chains: an input-output analysis for Food-Energy-Water Nexus in China', *Ecological Modelling*, vol. 392, pp. 31-7.

Xu, X, Yu, Y, Dou, G & Ruan, X 2021, 'The choice of cap-and-trade and carbon tax regulations in a cap-dependent carbon trading price setting', *Kybernetes*, vol. 51, no. 8, pp. 2554-77.

Yang, M, Hou, Y, Fang, C & Duan, H 2020, 'Constructing energy-consuming right trading system for China's manufacturing industry in 2025', *Energy Policy*, vol. 144, p. 111602.

Yang, YE, Ringler, C, Brown, C & Mondal, MAH 2016, 'Modeling the agricultural water–energy–food nexus in the Indus River Basin, Pakistan', *Journal of Water Resources Planning and Management*, vol. 142, no. 12, p. 04016062.

Yates, D, Sieber, J, Purkey, D, Huber-Lee, A & WEAP21, À 2005, 'A demand, priority, and preference driven water planning model: Part 1, model characteristics', *Water Int*, vol. 30, no. 4, pp. 487-500.

Yillia, PT 2016, 'Water-Energy-Food nexus: framing the opportunities, challenges and synergies for implementing the SDGs', *Österreichische Wasser-und Abfallwirtschaft*, vol. 68, no. 3-4, pp. 86-98.

Yong, KJ & Wu, TY 2022, 'Second-generation bioenergy from oilseed crop residues: Recent technologies, techno-economic assessments and policies', *Energy conversion and Management*, vol. 267, p. 115869.

Yoon, J, Sun, Y & Rogers, JA 2010, 'Flexible Solar Cells Made of Nanowires/Microwires', in *Semiconductor Nanomaterials for Flexible Technologies*, Elsevier, pp. 159-96.

Yoro, KO & Daramola, MO 2020, 'CO2 emission sources, greenhouse gases, and the global warming effect', in *Advances in carbon capture*, Elsevier, pp. 3-28.

Yuan, K-Y, Lin, Y-C, Chiueh, P-T & Lo, S-L 2018, 'Spatial optimization of the food, energy, and water nexus: A life cycle assessment-based approach', *Energy Policy*, vol. 119, pp. 502-14.

Yue, Q & Guo, P 2021a, 'Managing agricultural water-energy-food-environment nexus considering water footprint and carbon footprint under uncertainty', *Agricultural Water Management*, vol. 252, p. 106899.

Yue, Q, Zhang, F, Wang, Y, Zhang, X & Guo, P 2021b, 'Fuzzy multi-objective modelling for managing water-food-energy-climate change-land nexus towards sustainability', *Journal of Hydrology*, vol. 596, p. 125704.

Yusaf, T, Goh, S & Borserio, J 2011, 'Potential of renewable energy alternatives in Australia', *Renewable and Sustainable Energy Reviews*, vol. 15, no. 5, pp. 2214-21.

Zainol Abidin, MA, Mahyuddin, MN & Mohd Zainuri, MAA 2021, 'Solar photovoltaic architecture and agronomic management in agrivoltaic system: A review', *Sustainability*, vol. 13, no. 14, p. 7846.

Zakwan, M 2022, 'Application of Excel optimisation tool in solving and teaching water resource problems', *International Journal of Hydrology Science and Technology*, vol. 14, no. 1, pp. 63-74.

Zarei, S, Bozorg-Haddad, O, Kheirinejad, S & Loáiciga, HA 2021, 'Environmental sustainability: A review of the water–energy–food nexus', *Journal of Water Supply: Research and Technology-Aqua*, vol. 70, no. 2, pp. 138-54.

Zhang, C, Chen, X, Li, Y, Ding, W & Fu, G 2018, 'Water-energy-food nexus: Concepts, questions and methodologies', *Journal of Cleaner Production*, vol. 195, pp. 625-39.

Zhang, C, Hu, M, Di Maio, F, Sprecher, B, Yang, X & Tukker, A 2022, 'An overview of the waste hierarchy framework for analyzing the circularity in construction and demolition waste management in Europe', *Science of the total environment*, vol. 803, p. 149892.

Zhang, F, Cai, Y, Tan, Q, Engel, BA & Wang, X 2021a, 'An optimal modeling approach for reducing carbon footprint in agricultural water-energy-food nexus system', *Journal of Cleaner Production*, vol. 316, p. 128325.

Zhang, H 2009, 'Field crop water-yield models and their applications', *Zhongguo Shengtai Nongye Xuebao/Chinese Journal of Eco-Agriculture*, vol. 17, no. 5, pp. 997-1001.

Zhang, P, Zhang, L, Chang, Y, Xu, M, Hao, Y, Liang, S, Liu, G, Yang, Z & Wang, C 2019, 'Food-energy-water (FEW) nexus for urban sustainability: A comprehensive review', *Resources, Conservation and Recycling*, vol. 142, pp. 215-24.

Zhang, W & Zhou, T 2020a, 'Increasing impacts from extreme precipitation on population over China with global warming', *Science Bulletin*, vol. 65, no. 3, pp. 243-52.

Zhang, X & Vesselinov, VV 2017, 'Integrated modeling approach for optimal management of water, energy and food security nexus', *Advances in Water Resources*, vol. 101, pp. 1-10.

Zhang, Y, Li, J, Liu, H, Zhao, G, Tian, Y & Xie, K 2020b, 'Environmental, social, and economic assessment of energy utilization of crop residue in China', *Frontiers in Energy*, pp. 1-12.

Zhang, Y, Li, J, Liu, H, Zhao, G, Tian, Y & Xie, K 2021b, 'Environmental, social, and economic assessment of energy utilization of crop residue in China', *Frontiers in Energy*, vol. 15, pp. 308-19.

Zhao, N & You, F 2021, 'Food-energy-water-waste nexus systems optimization for New York State under the COVID-19 pandemic to alleviate health and environmental concerns', *Applied Energy*, vol. 282, p. 116181.

Zhao, X-g & Li, A 2016, 'A multi-objective sustainable location model for biomass power plants: Case of China', *Energy*, vol. 112, pp. 1184-93.

Zhao, X, Liu, BY, Liu, SL, Qi, JY, Wang, X, Pu, C, Li, SS, Zhang, XZ, Yang, XG & Lal, R 2020, 'Sustaining crop production in China's cropland by crop residue retention: A meta - analysis', *Land Degradation & Development*, vol. 31, no. 6, pp. 694-709.

Zilch Waste Recycles 2023, *Request for a free quote*, 19/01/2023, <https://zilchwaste.com.au/>.

Zou, X, Li, Ye, Li, K, Cremades, R, Gao, Q, Wan, Y & Qin, X 2015, 'Greenhouse gas emissions from agricultural irrigation in China', *Mitigation and Adaptation Strategies for Global Change*, vol. 20, pp. 295-315.

APPENDIX A

Table A.1. Comparative analysis of existing multi-sectoral nexus models and tools in chronological order in publication.

Model	Spatial Scale	Model Type	Functions	References
MuSIASEM	National, regional	Integrated	Assess metabolic pattern of energy, food and water related to socio-economic and ecological variables.	Giampietro et al. (2009)
CLEWS	Multi-scales	Integrated	Assess climate impacts on resources and supply help in policies evaluation.	Howells et al. (2013)
Nexus Assessment 1.0	National, regional	Quantitative	Qualitative and quantitative assessment of Nexus.	FAO (2014b)
Nexus Assessment 2.0	National	Simulation	Quantitative assessment and forecast of WEFN.	Daher et al. (2015)
GLOBIOM	Global	Integrated	Long-term land use planning under risk conditions.	Ermolieva et al. (2015)
PRIMA	Regional	Simulation	Simulate interactions among natural and human systems for integrated regional modelling.	Kraucunas et al. (2015)
DEA	Local, urban	Quantitative	Evaluate regional input-output efficiency holistically.	Li et al. (2016a)
WEFO	Multi-scales	Integrated	Quantitatively assess the interconnections and trade-offs in resource systems and environmental effects.	Zhang et al. (2017)
NexSym	Local	Simulation	Explicit dynamic modelling of local techno-ecological interactions relevant to WEF operations.	Martinez-Hernandez et al. (2017b)
EIO-LCA	National, regional	Quantitative	Characterize WEF usage and intensities of every economic sector.	Sherwood et al. (2017)
Q-Nexus	Multi-scales	Quantitative	Integrated quantitative assessments on inter-sectoral linkages and competing demand for WEF resources.	Karnib (2017, 2018)

Model	Spatial Scale	Model Type	Functions	References
Extended Matter Element Model	Multi-scales	Quantitative	Quantitatively evaluate the sustainability of WEF nexus.	Wang et al. (2018)
IOA	Multi-scales	Quantitative	Evaluate the interactions between economic factors and natural resources, investigate both the physical flows and monetary flows through economic trade networks, and detect the driving force of resources consumption from an economic structure perspective.	Xiao et al. (2019)
AWEFSM	Regional	Integrated	Sustainable management of limited water-energy-food resource in an agricultural system by incorporating multi-objective programming, nonlinear programming, and intuitionistic fuzzy numbers into a general framework.	Li et al. (2019c)

APPENDIX B

Table B.1. Seasonal K_y values for various crops (Steduto et al. 2012).

Crop	K_y	Crop	K_y
Alfalfa	1.1	Safflower	0.8
Banana	1.2 – 1.35	Sorghum	0.9
Beans	1.15	Soybean	0.85
Cabbage	0.95	Spring wheat	1.15
Cotton	0.85	Sugar beet	1.0
Groundnuts	0.70	Sugarcane	1.2
Maize	1.25	Sunflower	0.95
Onion	1.1	Tomato	1.05
Peas	1.15	Watermelon	1.1
Pepper	1.1	Winter wheat	1.05
Potato	1.1		

APPENDIX C

Table C.1. Values of crop factors (K_c) for cotton and winter wheat and growth stages (Brouwer et al. 1986a).

Crop	Initial	Crop development	Mid-season	Late-season
Barley/Oats/Wheat	0.35	0.75	1.15	0.45
Bean, green	0.35	0.70	1.10	0.90
Bean, dry	0.35	0.70	1.10	0.30
Cabbage/Carrot	0.45	0.75	1.05	0.90
Cotton/Flax	0.45	0.75	1.15	0.75
Cucumber/Squash	0.45	0.70	0.90	0.75
Eggplant/Tomato	0.45	0.75	1.15	0.80
Grain/small	0.35	0.75	1.10	0.65
Lentil/Pulses	0.45	0.75	1.10	0.50
Lettuce/Spinach	0.45	0.60	1.00	0.90
Maize, sweet	0.40	0.80	1.15	1.00
Maize, grain	0.40	0.80	1.15	0.70
Melon	0.45	0.75	1.00	0.75
Millet	0.35	0.70	1.10	0.65
Onion, green	0.50	0.70	1.00	1.00
Onion, dry	0.50	0.75	1.05	0.85
Peanut/Groundnut	0.45	0.75	1.05	0.70
Pea, fresh	0.45	0.80	1.15	1.05
Pepper, fresh	0.35	0.70	1.05	0.90
Potato	0.45	0.75	1.15	0.85
Radish	0.45	0.60	0.90	0.90
Sorghum	0.35	0.75	1.10	0.65
Soybean	0.35	0.75	1.10	0.60
Sugar beet	0.45	0.80	1.15	0.80
Sunflower	0.35	0.75	1.15	0.55
Tobacco	0.35	0.75	1.10	0.90

This table gives average Kc values for the various crops and growth stages. The Kc is also dependent on the climate and, in particular, on the relative humidity and the windspeed. The values indicated above should be reduced by 0.05 if the relative humidity is high (RH > 80%) and the windspeed is low (u < 2 m/sec), such as Kc = 1.15 turns Kc = 1.10. The values should be increased by 0.05 if the relative humidity is low (RH < 50%) and the windspeed is high (u > 5 m/sec), such as Kc = 1.05 becomes Kc = 1.10.

APPENDIX D

Table D.1. Climate stations for irrigated cropping areas of Toowoomba Region by alphabetical order.

No.	Station Name	Station ID	Latitude	Longitude	Altitude (m)
1	Bon Accord	41153	-27.6000	151.2000	351.0
2	Bowenville	41008	-27.3033	151.4931	383.0
3	Brookstead Post Office	41314	-27.7578	151.4483	388.3
4	Cambooya Post Office	41011	-27.7072	151.8650	476.0
5	Cecil Plains Homestead	41016	-27.5331	151.2025	340.0
6	Condamine Pains	41019	-27.7233	151.2869	370.0
7	Ellangowan	41404	-27.9583	151.6636	403.0
8	Glen Royal	41504	-27.7358	151.4117	377.0
9	Gunbower	41270	-27.8242	151.5803	408.0
10	Jondarayan Station	41147	-27.4000	151.5667	379.0
11	Mirrabrooka	41225	-27.8393	152.0615	506.0
12	Mount Irving	41072	-27.4831	151.6003	396.0
13	Nobby Tooth St	41075	-27.8530	151.9023	483.0
14	Oakey Aero	41359	-27.4034	151.7413	405.7
15	Oakey Post Office	41077	-27.4500	151.7167	402.0
16	Pampas	41250	-27.7894	151.4133	390.0

APPENDIX E

Table E.1. Emission factors (in kg CO2e/kWh) for on-grid electricity use in Scope 2 and Scope 3 from different states and across Australia (Ekonomou et al. 2022b).

State or Territory	Scope 2 Emission Factor	Scope 3 Emission factor
NSW	0.81	0.09
ACT	0.81	0.09
Vic	1.02	0.1
QLD	0.81	0.12
SA	0.44	0.1
SW WA	0.69	0.04
NW WA	0.59	0
TAS	0.15	0.02
NT	0.63	0.08
Australia	0.73	0.09

Table E.2. Global Warming Potential and Conversion Factors (Ekonomou et al. 2022b).

Gas	CO2e	Conversion Factor
CO2	1	3.67
CH4	28	1.33
N2O	265	1.57
CF4	6,630	
C2F6	12,200	
SF6	22,800	
NF3	17,200	
NOx		3.29
CO		2.33
CO2 Lime		3.67
NMVOC		1.17

APPENDIX F

Table F.1. Summary of sensitivity analysis methods (Chen et al. 2017; Saltelli et al. 2019).

Method	Strength	Weakness	Application
One-at-a-time (OAT)	Simple, low computational cost, easy for application	Not applicable for non-linear models, incapable to calculate higher-order sensitivity	Ranking by importance of parameters and parameter correction in empirical or semi-empirical models
Differential Analysis (DA)	Applicable for screening potentially important parameters	Not applicable for non-linear models, incapable to calculate higher-order sensitivity, demand for use of specific software, high computational cost	Ranking by importance of parameters, identification for potentially important parameters, parameter correction
Regression Analysis (RA)	Relatively simple and low computational cost	Not applicable for non-linear models; The outcomes will be poor for models with highly interactive parameters; The results for analysis may be a bit poor with too narrow sampling ranges for parameters.	Ranking by importance of parameters, model correction, uncertainty analysis
Morris	Applicable for non-linear models, relatively low computational cost, easy for application, and suitable for screening potentially important parameters	Incapable to quantify sensitivity	Screening potentially important parameters among multiple parameters, model correction, uncertainty analysis
Sobol	Applicable for non-linear models, capable to quantify first-order/higher-order sensitivity; The results will be eminent for models with highly interactive parameters.	High requirements for quality of samples, high computational cost, not considering relevance of parameters	Ranking by importance of parameters in complex models, studies of influence by parameter interactions on models, parameter correction, uncertainty analysis
Fourier Amplitude Sensitivity Test (FAST)	Applicable for monotone/non-monotone models, relatively low computational cost, capable to quantify first-order sensitivity	Not applicable for calculating higher-order sensitivity, not suitable for discrete parameters, not considering relevance of parameters	Ranking by importance of parameters in complex models, studies of influence by parameter interactions on models,

Method	Strength	Weakness	Application
			parameter correction, uncertainty analysis
Regional Sensitivity Analysis (RSA)	Fewer assumption requirements, no need to modify models, visualized results for analysis, suitable for screening important parameters	Incapable to calculate higher-order sensitivity, incapable of quantifying sensitivity, weak in the ability to identify parameters of general sensitivity, results for analysis affected by sampling space	Identification on parameter sensitivity in complex models, parameter correction, uncertainty analysis

APPENDIX G

(1) Python codes for sensitivity tests on the basic model:

```
import numpy as np
from SALib.analyze import morris
from SALib.sample.morris import sample
from SALib.plotting.morris import (
    horizontal_bar_plot,
    covariance_plot
)
import matplotlib.pyplot as plt

# Define the model function
def BaselineRainfall(x):
    x1, x2, x3, x4, x5, x6, x7, x8, x9, x10, x11, x12, x13 = x
    y = (0.42*4.4*x3+0.58*x4)*(0.85*6.21*(x1+x5)/(9.4542)+0.9315)*x2-x6*x1*x2-x7*x2-
x8*0.1*x1*x2-x8*2.48*x2+x11*(1.05*6.00*(x9+x12)/(3.2640)-0.3)*x10-x6*x9*x10-x13*x10-
x8*0.1*x9*x10-x8*2.49*x10
    return y

# Define the bounds and levels for the input parameters
problem = {
    'num_vars': 13,
    'names': ['Irrigation Water of Cotton (ML/ha)', 'Irrigated Area of Cotton (ha)', 'Price of Cotton
Lint (AU$/bale)', 'Price of Cotton Seed (AU$/t)', 'Effective Rainfall of Cotton (ML/ha)', 'Water Cost
(AU$/ML)', 'Other growing Cost of Cotton (AU$/ha)', 'Price of Carbon (AU$/t CO2e)','Irrigation Water
of Wheat (ML/ha)','Irrigated Area of Wheat (ha)','Price of Wheat (AU$/t)','Effective Rainfall of Wheat
(ML/ha)','Other growing cost of Wheat (AU$/ha)'],
    'groups': None,
    'bounds': [[0.0, 8.17],
               [55.51, 11650.60],
               [480.0, 550.0],
               [0.0, 190.0],
               [1.2829, 2.3678],
               [72.0, 168.04],
               [1483.0, 2257.0],
               [13.95, 15.99],
               [0.0, 3.11],
               [278.11, 7767.61],
```

```
            [220.0, 400.0],
            [0.1559, 1.4775],
            [573.0, 639.0]]
}

# Generate the Morris samples
param_values = sample(problem, N=1000, num_levels=4, optimal_trajectories=None)

# Evaluate the model for each sample
y = np.zeros([param_values.shape[0]])
for i, x in enumerate(param_values):
    y[i] = BaselineRainfall(x)

# Perform the Morris sensitivity analysis
Si = morris.analyze(problem, param_values, y, conf_level=0.95, print_to_console=True,
num_levels=4, num_resamples=100)

# Print the results
print('Mu:', Si['mu'])
print('Sigma:', Si['sigma'])
print('Mu_star:', Si['mu_star'])
print('Mu_star_conf:', Si['mu_star_conf'])

fig, (ax1, ax2) = plt.subplots(1, 2)
horizontal_bar_plot(ax1, Si, (Australian Government 2022a), sortby="mu_star")
covariance_plot(ax2, Si, (Australian Government 2022a))

plt.show()
```

(2) Python codes for sensitivity analysis on the further developed model regarding crop residue management with a mulching or composting method:

```
import numpy as np
from SALib.analyze import morris
from SALib.sample.morris import sample
from SALib.plotting.morris import (
    horizontal_bar_plot,
    covariance_plot,
    sample_histograms,
)
import matplotlib.pyplot as plt

# Define the model function
def CropResidueMulchCompost(x):
    x1, x2, x3, x4, x5, x6, x7, x8, x9, x10, x11, x12, x13, x14, x15, x16, x17, x18, x19, x20, x21, x22, x23, x24, x25, x26, x27, x28 = x
    y = (0.42*4.4*x3+0.58*x4)*(0.85*6.21*(x1+x5)/(9.4542)+0.9315)*x2-x6*x1*x2-x7*x2-x8*0.1*x1*x2-x8*2.48*x2+x11*(1.05*6.00*(x9+x12)/(3.2640)-0.3)*x10-x6*x9*x10-x13*x10-x8*0.1*x9*x10-x8*2.49*x10-x14*x15*2*x16*x17*(0.42*4.4*x3+0.58*x4)*(0.85*6.21*(x1+x5)/(9.4542)+0.9315)*x2/25-x18*x16*x17*(0.42*4.4*x3+0.58*x4)*(0.85*6.21*(x1+x5)/(9.4542)+0.9315)*x2-x19*x2+x20*x2-x8*x21*x22*(x16*x17*(0.42*4.4*x3+0.58*x4)*(0.85*6.21*(x1+x5)/(9.4542)+0.9315)*x2+20*2)-x8*x23*x2+x8*x24*x2-x14*x15*2*x25*x26*(1.05*6.00*(x9+x12)/(3.2640)-0.3)*x10/25-x18*x25*x26*(1.05*6.00*(x9+x12)/(3.2640)-0.3)*x10-x19*x10+x27*x10-x8*(x21*x22*(1.05*6.00*(x9+x12)/(3.2640)-0.3)*x10+20*2)-x8*x23*x10+x8*x28*x10
    return y

# Define the bounds and levels for the input parameters
problem = {
    'num_vars': 28,
    'names': ['Irrigation Water of Cotton (ML/ha)', 'Irrigated Area of Cotton (ha)', 'Price of Cotton Lint (AU$/bale)', 'Price of Cotton Seed (AU$/t)', 'Effective Rainfall of Cotton (ML/ha)', 'Water Cost (AU$/ML)', 'Other growing Cost of Cotton (AU$/ha)', 'Price of Carbon (AU$/t CO2e)','Irrigation Water of Wheat (ML/ha)','Irrigated Area of Wheat (ha)','Price of Wheat (AU$/t)','Effective Rainfall of Wheat (ML/ha)','Other growing cost of Wheat (AU$/ha)', 'Logistic cost (AU$/hr)', 'Average time for freight to site (hr)', 'Coefficient of disposed cotton straw', 'Residue index of cotton', 'Disposal cost (AU$/t)', 'Reapplication cost (AU$/ha)', 'Avoided cost from cotton (AU$/ha)', 'GHGs from logistics (tCO2e/tkm)', 'Average distance for freight to site (km)', 'GHGs from disposal (tCO2e/ha)', 'Avoided GHGs from
```

```
cotton (tCO2e/ha)', 'Coefficient of disposed wheat straw', 'Residue index of wheat', 'Avoided cost from wheat (AU$/ha)', 'Avoided GHGs from wheat (tCO2e/ha)'],
    'groups': None,
    'bounds': [[0.0, 8.17],
               [55.51, 11650.60],
               [480.0, 550.0],
               [0.0, 190.0],
               [1.2829, 2.3678],
               [72.0, 168.04],
               [1483.0, 2257.0],
               [13.95, 15.99],
               [0.0, 3.11],
               [278.11, 7767.61],
               [220.0, 400.0],
               [0.1559, 1.4775],
               [573.0, 639.0],
               [130.0, 250.0],
               [0.57, 1.03],
               [0.4, 0.8],
               [0.0, 1.9],
               [10.0, 90.0],
               [0.0, 140.0],
               [0.0, 63.49],
               [0.0, 0.4],
               [44.7, 84.8],
               [0.04, 19.88],
               [0.0, 0.6],
               [0.4, 0.8],
               [0.0, 1.5],
               [0.0, 52.83],
               [0.0, 0.3]]
}

# Generate the Morris samples
param_values = sample(problem, N=1000, num_levels=4, optimal_trajectories=None)

# Evaluate the model for each sample
y = np.zeros([param_values.shape[0]])
for i, x in enumerate(param_values):
    y[i] = CropResidueMulchCompost(x)
```

```
# Perform the Morris sensitivity analysis
Si = morris.analyze(problem, param_values, y, conf_level=0.95, print_to_console=True, num_levels=4, num_resamples=100)

# Print the results
print('Mu:', Si['mu'])
print('Sigma:', Si['sigma'])
print('Mu_star:', Si['mu_star'])
print('Mu_star_conf:', Si['mu_star_conf'])

fig, (ax1, ax2) = plt.subplots(1, 2)
horizontal_bar_plot(ax1, Si, (Australian Government 2022a), sortby="mu_star")
covariance_plot(ax2, Si, (Australian Government 2022a))

plt.show()
```

(3) Python codes for sensitivity analysis on the further developed model regarding crop residue management with an incineration/combustion (with energy recovery) method:

```
import numpy as np
from SALib.analyze import morris
from SALib.sample.morris import sample
from SALib.plotting.morris import (
    horizontal_bar_plot,
    covariance_plot,
    sample_histograms,
)
import matplotlib.pyplot as plt

# Define the model function
def CropResidueCombustion(x):
    x1, x2, x3, x4, x5, x6, x7, x8, x9, x10, x11, x12, x13, x14, x15, x16, x17, x18, x19, x20, x21, x22, x23, x24, x25, x26, x27, x28, x29, x30, x31, x32 = x
    y = (0.42*4.4*x3+0.58*x4)*(0.85*6.21*(x1+x5)/(9.4542)+0.9315)*x2-x6*x1*x2-x7*x2-x8*0.1*x1*x2-x8*2.48*x2+x11*(1.05*6.00*(x9+x12)/(3.2640)-0.3)*x10-x6*x9*x10-x13*x10-x8*0.1*x9*x10-x8*2.49*x10-x14*x15*2*x16*x17*(0.42*4.4*x3+0.58*x4)*(0.85*6.21*(x1+x5)/(9.4542)+0.9315)*x2/25-x18*x16*x17*(0.42*4.4*x3+0.58*x4)*(0.85*6.21*(x1+x5)/(9.4542)+0.9315)*x2-x19*x2+x20*x2-x8*x21*x22*(x16*x17*(0.42*4.4*x3+0.58*x4)*(0.85*6.21*(x1+x5)/(9.4542)+0.9315)*x2+20*2)-x8*x23*x2+x8*x24*x2-x14*x15*2*x25*x26*(1.05*6.00*(x9+x12)/(3.2640)-0.3)*x10/25-x18*x25*x26*(1.05*6.00*(x9+x12)/(3.2640)-0.3)*x10-x19*x10+x27*x10-x8*(x21*x22*(1.05*6.00*(x9+x12)/(3.2640)-0.3)*x10+20*2)-x8*x23*x10+x8*x28*x10+x29*x16*x17*(0.42*4.4*x3+0.58*x4)*(0.85*6.21*(x1+x5)/(9.4542)+0.9315)*x2*x30*x31+x8*0.12/1000*x16*x17*(0.42*4.4*x3+0.58*x4)*(0.85*6.21*(x1+x5)/(9.4542)+0.9315)*x2*x30*x31+x29*x25*x26*(1.05*6.00*(x9+x12)/(3.2640)-0.3)*x10*x32*x31+x8*0.12/1000*x25*x26*(1.05*6.00*(x9+x12)/(3.2640)-0.3)*x10*x32*x31
    return y

# Define the bounds and levels for the input parameters
problem = {
    'num_vars': 32,
    'names': ['Irrigation Water of Cotton (ML/ha)', 'Irrigated Area of Cotton (ha)', 'Price of Cotton Lint (AU$/bale)', 'Price of Cotton Seed (AU$/t)', 'Effective Rainfall of Cotton (ML/ha)', 'Water Cost (AU$/ML)', 'Other growing Cost of Cotton (AU$/ha)', 'Price of Carbon (AU$/t CO2e)','Irrigation Water of Wheat (ML/ha)','Irrigated Area of Wheat (ha)','Price of Wheat (AU$/t)','Effective Rainfall of Wheat
```

```
(ML/ha)','Other growing cost of Wheat (AU$/ha)', 'Logistic cost (AU$/hr)', 'Average time for freight to site (hr)', 'Coefficient of disposed cotton straw', 'Residue index of cotton', 'Disposal cost (AU$/t)', 'Reapplication cost (AU$/ha)', 'Avoided cost from cotton (AU$/ha)', 'GHGs from logistics (tCO2e/tkm)', 'Average distance for freight to site (km)', 'GHGs from disposal (tCO2e/ha)', 'Avoided GHGs from cotton (tCO2e/ha)', 'Coefficient of disposed wheat straw', 'Residue index of wheat', 'Avoided cost from wheat (AU$/ha)', 'Avoided GHGs from wheat (tCO2e/ha)', 'Price of on-grid electricity (AU$/kWh)', 'Lower Heating Value of cotton straw (kWh/t)', 'Electricity generation efficiency of regular power plants', 'Lower Heating Value of wheat straw (kWh/t)'],
        'groups': None,
        'bounds': [[0.0, 8.17],
              [55.51, 11650.60],
              [480.0, 550.0],
              [0.0, 190.0],
              [1.2829, 2.3678],
              [72.0, 168.04],
              [1483.0, 2257.0],
              [13.95, 15.99],
              [0.0, 3.11],
              [278.11, 7767.61],
              [220.0, 400.0],
              [0.1559, 1.4775],
              [573.0, 639.0],
              [130.0, 250.0],
              [0.57, 1.03],
              [0.4, 0.8],
              [0.0, 1.9],
              [10.0, 90.0],
              [0.0, 140.0],
              [0.0, 63.49],
              [0.0, 0.4],
              [44.7, 84.8],
              [0.04, 19.88],
              [0.0, 0.6],
              [0.4, 0.8],
              [0.0, 1.5],
              [0.0, 52.83],
              [0.0, 0.3],
              [0.12, 0.24],
              [3800.0, 4160.83],
              [0.2, 0.6],
```

```
        [3600.0, 4101.67]]
}

# Generate the Morris samples
param_values = sample(problem, N=1000, num_levels=4, optimal_trajectories=None)

# Evaluate the model for each sample
y = np.zeros([param_values.shape[0]])
for i, x in enumerate(param_values):
    y[i] = CropResidueCombustion(x)

# Perform the Morris sensitivity analysis
Si = morris.analyze(problem, param_values, y, conf_level=0.95, print_to_console=True,
num_levels=4, num_resamples=100)

# Print the results
print('Mu:', Si['mu'])
print('Sigma:', Si['sigma'])
print('Mu_star:', Si['mu_star'])
print('Mu_star_conf:', Si['mu_star_conf'])

fig, (ax1, ax2) = plt.subplots(1, 2)
horizontal_bar_plot(ax1, Si, {}, sortby="mu_star", unit=r"AUD/year")
covariance_plot(ax2, Si, {}, unit=r"AUD/year")

plt.show()
```

APPENDIX H

Table H.1. Summary of costs associated with services for disposing the crop residues provided by local companies.

No.	Business	Services and indicative costs			
		Collection & transport: freight to site	Treatment & disposal (quote)	End products (re-sale)	Re-application of end products
1	SoilWealth Nurturing Crops	—— [a]	Composting (AU$45-80/t [c])	Compost (——)	AU$140/ha for spreading
2	WestRex	——	Composting (——)	Compost (AU$50-70/t)	——
3	Zilch Waste Recycles	AU$130-175/hr [b]	Mulching (AU$37/t)	Mulch (AU$20-29/t)	
4	Remondis	——	Mulching (AU$10-50/t) Composting (AU$30-80/t) Combustion (AU$30-70/t)	Mulch (——) Compost (——) Electricity [d] (——)	
5	Cleanaway	AU$250/hr	Mulching (AU$70/t)	Mulch (——)	
6	Phoenix Power Recycles	AU$180/hr	Composting (AU$90/t)	Compost (AU$35/t)	

[a] "——" means there is no charge for this part.

[b] The unit cost for collection and transport for crop residues is on an AU$ per hour basis (AU$/hr).

[c] The unit tonne "t" here means crop residues per unit tonne.

[d] "Electricity" is the generated power by the combustion processing that can be returned to the network for some returns.

Note:

Four major parts of costs are identified: 1) collection & transport, namely gathering and delivering crop residues by freight from targeted cropping areas/farms to site/facility for disposal, 2) treatment & disposal, namely facilities processing and disposing residues to environmental-friendly end products, 3) re-sale of end products, namely selling the end products after disposal, 4) re-application, namely returning and applying end products to farms.