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Assessing the effect of using different APSIM model configurations on model outputs

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ABSTRACT

The three major sources of uncertainty in crop models are model inputs, structure and parameters. Model structure is one of the major contributors to this uncertainty, however, its quantification is difficult due to limitations in controlling confounding effects from parameter and input uncertainty. The objective of this study was to quantify the contribution of structural uncertainty to the variance in model outputs produced by the Agricultural Production Systems sIMulator (APSIM). Outputs investigated were yield, irrigation requirements, partial gross margin, drainage and nitrogen (N) leaching. Eight model structures differing in choice of soil water model, crop model and irrigation model were developed within a single APSIM version (v.7.10) and tested under three contrasting environments (climate × soil) across 120 years. We quantified: (i) the model structure uncertainty (from soil water, crop and irrigation models) using analysis of variance (ANOVA) and deviation analysis; and (ii) the variability of outputs due to model structure and climate using the coefficient of variation. Confounding effects from inputs, parameters and model users were controlled. Most structural uncertainty resulted from first order effects of the choice of model components (crop model: 12.2–98.9%, irrigation model: 0–78.4%, soil water model:1–33.7%) rather than second order interactions between components (0.1–18.9%). Furthermore, uncertainty from choice of sub-model/model used was not necessarily related to the structural complexity of these components. The effects of structural uncertainty on predictions commonly used to inform agronomic, ecological or policy decision making were strongly impacted by site and climate conditions *i.e.,* high rainfall site (~1330 mm $year^{-1}$) had less uncertainty and variability as compared to low rainfall site (~610 mm $year^{-1}$), highlighting the need for any uncertainty assessment to cover the entire range of conditions for model application. Here we show the value of a component-based modelling framework for quantifying uncertainty in crop modelling studies.

1. Introduction

The agricultural ecosystem, which covers a significant portion of the Earth's land, stands as the largest human-made ecosystem (Shah et al., 2019; Swinton et al., 2007; Zhang et al., 2007). It spans around 40 percent of the Earth's terrestrial surface (Foley et al., 2005; Gordon et al., 2010). The primary goal of managing agricultural ecosystems is to maximize the production of essential ecosystem services like food, fibre and fuel. This objective relies on a diverse range of supporting and regulating services, such as maintaining soil fertility, nutrient cycling, facilitating pollination etc., which directly influence the underlying biophysical capacity of agricultural ecosystems (Gordon et al., 2010; Reid et al., 2005; Zhang et al., 2007).

Crop models play a crucial role in agricultural and environmental planning by providing valuable guidance and information (Specka et al., 2015) to farmers, policy-makers and researchers (Meenken et al., 2021; Ramirez-Villegas et al., 2017). These models effectively combine ecological and agronomic expertise, allowing for the development of

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ecologically intensive cropping systems and a deeper understanding of the complex connections between agriculture, the environment and crop responses. They also enable the evaluation of the influence of various factors, including climate change, market dynamics, environmental variables and management practices on crops (Chapagain et al., 2022; Kamali et al., 2018; Manschadi et al., 2021; Porwollik et al., 2017). Moreover, crop models are instrumental in assessing the effect of human activities or environmental factors on ecosystem services (*e.g.* biomass production, carbon sequestration potential, water availability etc.) (Damour et al., 2012; Specka et al., 2015). During the last three decades, crop models were increasingly used to simulate crop production (Elliott et al., 2014; Folberth et al., 2014; Liu et al., 2013; Müller et al., 2021), agro-economic scenarios (Folberth et al., 2019; Müller and Robertson, 2014; Schneider et al., 2011), resource use efficiency (Hochman et al., 2009; Hunt et al., 2013; Hunt and Kirkegaard, 2011; Kirkegaard and Hunt, 2010) and environmental impacts (Dokoohaki et al., 2021; Liu et al., 2018). Various sources of uncertainty exist within crop models (Chapagain et al., 2022) which restricts their accuracy to predict the behaviour of the agro-ecosystem (Dokoohaki et al., 2021; Ramirez-Villegas et al., 2017). Uncertainty in crop modelling may be due to inputs such as climate models (Folberth et al., 2014; Rosenzweig et al., 2014) or soil characteristics (Folberth et al., 2016), crop management practices (Teixeira et al., 2017), model structure (Alderman and Stanfill, 2017; Sándor et al., 2017), parameterization (Sándor et al., 2017) and users preferences/biases (Confalonieri et al., 2016). To accurately interpret model results, it is essential to acknowledge and consider the inherent uncertainty associated with them (Specka et al., 2015).

Structural uncertainty may vary depending on the model, its type (*e.g.*, size of sub-units, lumped or distributed) and study area (Capell et al., 2012; Shoaib et al., 2021). However, there are fewer studies on structural uncertainty when compared to input and parameter uncertainty (Chapagain et al., 2022). Recently, efforts have been made to characterise the uncertainty in crop model processes and their configuration through collaborative initiatives such as Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013) and Modelling European Agriculture with Climate Change for Food Security (MACSUR) (König et al., 2014). As part of these initiatives, a range of crop models with different structures were used, where either different modelling groups run the same crop model (Asseng et al., 2015; Kuhnert et al., 2017; Porwollik et al., 2017; Sándor et al., 2017) or multiple models are run by a single group (Cammarano et al., 2017; Wallach et al., 2017). Additionally, several approaches used to model different processes determining crop growth (Kimball et al., 2019; Rettie et al., 2022) have been investigated. However, to date, there are few studies which have tried to quantify uncertainty in processes and structure under the same modelling platform (Ramirez-Villegas et al., 2017). Besides, structural uncertainty may often be confounded with that from inputs, parameters, and users when running crop models. Generally, agile systems approaches which use pair programming methods (Chen and Rea, 2018) can be used for quality control in such cases. However, to the best of our knowledge, this has not been applied in previous studies on structural model uncertainty.

Model uncertainty analysis has been focused mainly on crop yield and phenology outputs (Chapagain et al., 2022). There is a lack of crop modelling uncertainty analysis on economic and environmental x crop management (such as irrigation, nitrogen (N) fertilizer) indicators. The rapidly growing population along with climate change put increasing pressures on irrigation systems to ensure food security and social, environmental and economic sustainability (Fernández et al., 2020; Koech and Langat, 2018). In addition, the burning challenge is to ensure that the irrigation management allows rational economic gains to the growers and meets the food demand, while ensuring environmental needs are not comprised (Cosgrove and Loucks, 2015; Rockström et al., 2017). In this regard, growers must take prudent decisions about irrigation systems, methods, strategies and scheduling amongst other factors to manage in-field water effectively for which there is a need to weigh the implications of different options (Fernández et al., 2020).

Besides water, nitrogen is needed for sustainable agriculture production and growth (Tang et al., 2021; Zhang et al., 2015). However, N leaching from agricultural soils causes direct and indirect impacts to the environment and human settlements (Bouwman et al., 2013; Galloway et al., 2003, 2008; Griffis et al., 2013; Reay et al., 2012; Steffen et al., 2015). Therefore, these environmental and economic variables need to be assessed, along with agronomic variables (yield, biomass, phenology) when conducting model uncertainty studies.

In order to evaluate the sustainability of agroecological cropping systems, it is important to take a holistic approach, taking into account the various functions of the system, including agronomic, economic and ecological aspects (Chabert and Sarthou, 2020; Craheix et al., 2016; Garbach et al., 2017). Therefore, the aim of this research was to measure the uncertainty in model structure by analysing simulated agronomic (*i.e.* yield, irrigation requirement), environmental (*i.e.* water drainage, N leaching) and economic (*i.e.* partial gross margin (PGM)]) outputs in three environmentally distinct potato growing regions in Tasmania, Australia (Fig. 1). Hence, the authors have tried to isolate or eliminate uncertainty due to other sources (*i.e.* input, parameter). We presented a novel approach to identify and quantify the model structural uncertainty removing sources of uncertainty arising from inputs, parameters and skill of the model user. To achieve our objective, firstly we simulated different outputs using eight different model structures that differed in choice of soil water model, crop model and irrigation model ($2 \times 2 \times 2 = 8$ model structure combinations) in the same modelling platform - APSIM. We considered APSIM as a tool for the experimental design as it allows controlled experiment- we controlled everything in the model except the structural uncertainty as best as we could. Hence, the two models were selected to generate structural uncertainty and the inter-comparison of the two crop models is out of scope of this paper. Secondly, we quantified the mean proportion of variance (using analysis of variance (ANOVA) and coefficient of variation) on simulated model outputs from the eight model structures across space (environmentally diverse locations) and time (multiple years). Thirdly, we investigated the deviation in model outputs for different model structures. Finally, we quantified the variability in model outputs due to (i) model structure variability (CV_{model}) and (ii) inter-annual climate variability ($CV_{climate}$) to discriminate uncertainty from variability.

2. Material and methods

2.1. Study region

Tasmania, a state of Australia, is located between approximately 40–44°S and 144–149°E and has an area of 68,401 km^2. In Tasmania, the annual rainfall ranges from 300 mm in the Central Midlands to 3600 mm in the West Coast (Ojeda et al., 2021b), whereas annual mean temperature varies between 6 °C (Central Highlands) to 21 °C (Northeast Coast) (Corney et al., 2010) and mean annual evapotranspiration ranges between 600 and 700 mm (BOM, 2022). For this study, three environmentally diverse potato growing regions of Tasmania were considered (Fig. 2): Cressy, low rainfall (~610 mm year^{-1}); Forthside, moderate rainfall (~980 mm year^{-1}); and Gunns Plains, high rainfall (~1330 mm year^{-1}).

2.2. Uncertainty from model users

The same two model users (MU1 and MU2) were involved in the model simulation configuration and execution. One model user (MU1) had collected all relevant input data and agronomic information for the study locations. The second model user (MU2) was mainly involved in the configuration, implementation and running of APSIM. The entire modelling process was undertaken online with sharing of a common computer screen and recording of all modelling sessions. A paired programming approach (Ayub et al., 2019; Chen and Rea, 2018) was used in

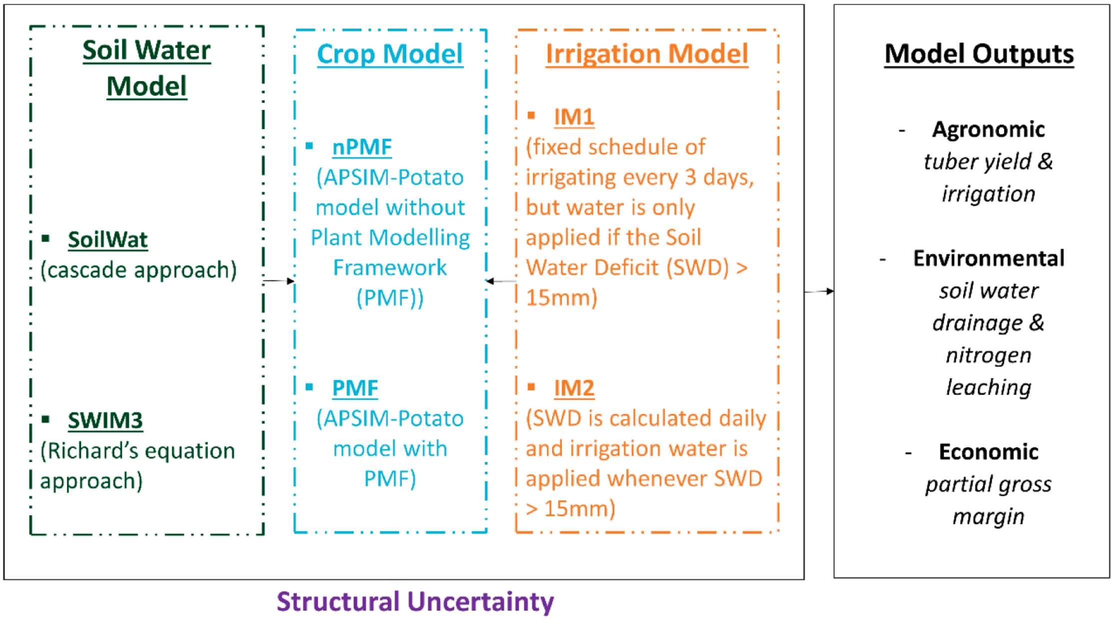

Fig. 1. Components of the structural model uncertainty considered in this study [soil water models (SoilWat and SWIM3), crop models (PMF and nPMF) and irrigation models (IM1 and IM2)]. Irrigation, soil water drainage and nitrogen leaching were accumulated from planting to full crop senescence. For details about model structure components and design see Section 2.5.

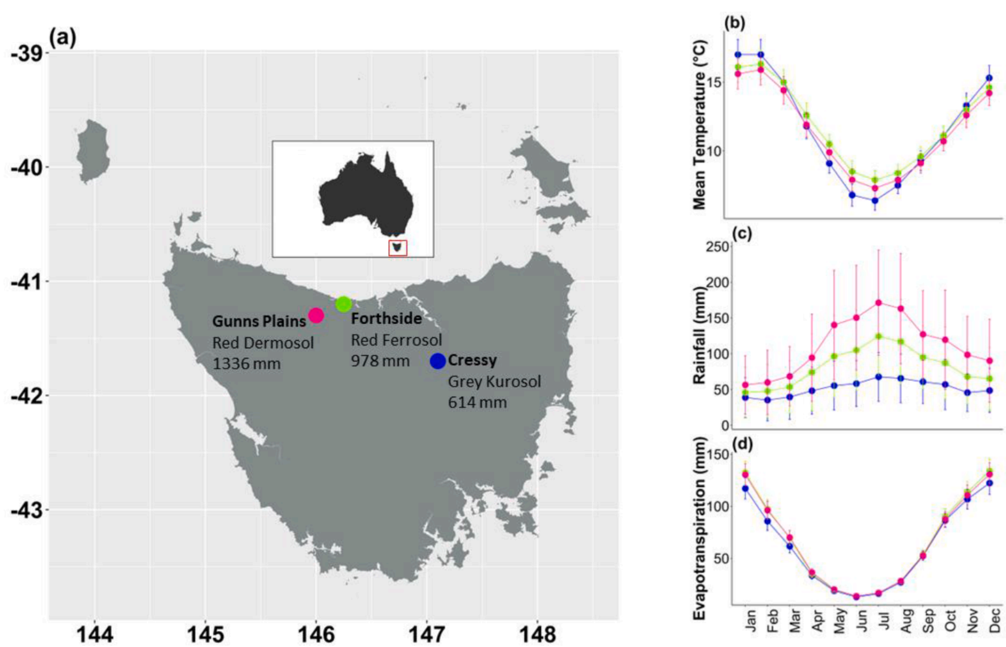

Fig. 2. *Map:* Locations used in this study to quantify crop model uncertainty. Observed soil type and mean annual rainfall are indicated after the location name. *Right panels:* Average observed monthly values since the beginning of observed records of: (b) mean monthly temperature, (c) monthly rainfall and (d) monthly observed evapotranspiration.

each activity. Such an approach is used within agile software development processes where one person (the driver) constructs the software while the second (the observer or navigator) provides ongoing review (Ayub et al., 2019; Chen and Rea, 2018; Wei et al., 2021). In this case, MU2 provided the role of driver while MU1 navigated the process. This process ensured correct representation of input data and implementation of model configurations by the same process and modellers for every simulation within this study reducing model uncertainty due to this source. The main aim of using peer programming for this study was not only to minimise errors in the building of the simulations but also to remove bias from having different people build different parts of the dataset.

2.3. Model inputs

An input is the information that is put into a model so that it can operate. It is a value, not a decision (Cambridge English Dictionary, 2022). For example, a given rainfall amount per day is an input to APSIM.

All model simulations were generated using data from the same source and spatial resolution. Historical daily weather data inputs of rainfall, maximum and minimum temperature, solar radiation, potential evapotranspiration and vapour pressure were obtained from the Scientific Information for Land Owners (SILO) database (longpaddock.qld.gov.au/silo/gridded-data) (Jeffrey et al., 2001). The SILO product uses interpolation techniques to fill gaps in space or time in the observational records, producing continuous records required for agricultural modelling. Soil types vary across the landscapes and topography of the study region (Cotching et al., 2009). Data for the dominant soil type at each location was used to parameterise the simulations *i.e.,* Grey Kurosol for Cressy, Red Ferrosol for Forthside and Red Dermosol for Gunns Plains (Isbell, 2016). The soil profiles in the models were created using soil sampling farm data from the Water for Profit Project (Hinton et al., 2018) (Table 1). Potatoes are sown between 15 October to 15 November in Tasmania (Ojeda et al., 2021a). We used a fixed planting date (3rd November), sowing density (11.55 seeds/m^2), row spacing (813 mm) and cultivar (Russet Burbank) based on the mean values calculated across 112 potato farm districts during the 2003–4, 2004–5, 2005–6 and 2006–7 growing seasons in Tasmania (Ojeda et al., 2021a). All crops were harvested when the crop reached full senescence.

2.4. Model parameters

A parameter is a set of facts or a fixed limit that establishes or limits how something can or must happen or be done (Cambridge English Dictionary, 2022). In APSIM a parameter is static, *i.e.*, you select a number, and that number will be used in the entire simulation. For this study, by parameters, we identified two types *1- non-fixed parameters* that are estimated by calibration and *2- fixed parameters* not estimated using calibration but inherent in the structure which are considered to be part of model structure as they are not available for users to be changed, *i.e.*, model developers change them as part of a model improvement process and then users use the released values. For example, dry upper limit (or field capacity), lower limit (or wilting point) and bulk density are non-fixed soil parameters in APSIM calibrated using ground data, whereas Radiation Use Efficiency (RUE) is a fixed parameter which is a part of the model structure.

In any ideal world, to understand just model structural uncertainty, two models which have the same parameters are required but that does not happen in a practical scenario. In this study, most parameters are kept constant between the different modelling options in APSIM, except for parameters that are specific to SoilWAT (Table S2) and SWIM3 (Table S3). SoilWAT has evaporation parameters which are not in SWIM3, and the authors have just taken them as they were in the database. Likewise, the authors have used the default values for parameters in SWIM3.

Fixed parameters (not estimated using calibration) are considered to be part of model structure in this study as they are inherent in model structure and not available for the average users to change (only developers can change them). Hence, the authors have used the default values. In case of non-fixed parameters that are same between the different modelling options, the authors haven't changed any of the released calibration parameters in this study and treated them as a black box.

2.5. Design of model structures

In this paper, we defined model structure as the different algorithms and processes that explains soil-climate-crop interactions as well as values of fixed parameters in the model. For example, SoilWAT and SWIM3 in APSIM.

We generated isolation of the modelling framework using only one modelling platform (APSIM) to catch the uncertainty arising from model algorithms and equations. This was done to avoid introducing other uncertainties that are not part of model structure but due to different modelling platforms or the way in which different models input data and provide output. Hence, we selected APSIM as the modelling platform for this paper.

APSIM uses a component-based approach for simulating biophysical processes in agricultural systems that enables models to interact dynamically during a simulation (Holzworth et al., 2014). A suite of models is available for more than thirty crop, pasture and tree species and for assessing main soil processes that affects agricultural systems (for example, soil water; nitrogen, carbon and phosphorus dynamic; and erosion). The APSIM allows flexible management of agricultural operations enabling the users to reproduce decision making processes used by land managers (Moore et al., 2014).

For the purposes of this study, a set of different model structures were created within APSIM through the choice of combinations of differing soil water, crop and irrigation models. Two model components from each category were chosen (2 crop models, PMF and nPMF; 2 soil water models, SoilWAT and SWIM3; and 2 irrigation models, IM1 and IM2), resulting in 8 independent model structures (Fig. 1). Each of these 8 permutations were run for each of the 3 locations (*i.e.*, 8 model structures × 3 locations = 24 model simulations). Simulations were carried out for each season within the long-term weather record from 1900 to 2020 (*i.e.*, 24 simulations × 120 years = 2880 simulated growing seasons). All simulations were undertaken using APSIM Classic (v7.10) (Holzworth et al., 2014).

2.5.1. Crop models

We selected two potato models available within APSIM Classic v7.10

Table 1
Soil parameters by layer used to parametrise the soil water models (BD = bulk density; LL15 = lower limit; DUL = drained upper limit or field capacity; SAT = saturated volumetric water content; PAWC = plant available water capacity per soil layer; OC = organic carbon; EC = electrical conductivity; pH = pH in a 1:5 suspension of soil in water; * Australian Soil Classification (Isbell, 2016); ** Approximate FAO equivalent (Ojeda et al., 2021a; Schad, 2016)).

Site	Soil type*	Texture	Depth *(cm)*	BD *(g cm^{-3})*	Air Dry *(mm^{-1})*	LL15	DUL	SAT	PAWC *(mm)*	OC *(%)*	EC *(dS/m)*	pH
Cressy	Grey Kurosol (GrK)	sandy loam	0–17	1.51	0.043	0.086	0.360	0.415	46.6	1.75	0.166	5.5
	(Alisols)**	sandy loam	17–40	1.64	0.053	0.059	0.276	0.355	49.9	0.45	0.125	6.0
		gravelly sandy loam	40–51	1.45	0.257	0.257	0.407	0.453	16.5	0.23	0.070	6.6
		heavy clay	51–115	1.19	0.455	0.455	0.538	0.551	53.1	0.36	0.339	5.7
									166.1			
Forthside	Red Ferrosol (ReF)	heavy clay loam	0–28	1.18	0.148	0.295	0.467	0.554	48.2	3.72	0.075	6.0
	(Ferralsols)**	light clay	28–41	1.12	0.333	0.37	0.46	0.576	11.7	2.73	0.083	5.1
		light clay	41–81	1.25	0.328	0.328	0.413	0.527	34.0	0.88	0.201	5.6
		medium clay	81–110	1.39	0.337	0.337	0.432	0.475	27.6	0.86	0.045	5.4
									121.5			
Gunns Plains	Red Dermosol (ReD)	fine sand	0–30	1.25	0.059	0.119	0.430	0.492	93.3	1.90	0.140	6.8
	(Chernozems) **	light clay	30–55	1.43	0.189	0.210	0.380	0.457	42.5	0.75	0.046	7.2
		light clay	55–90	1.61	0.170	0.170	0.356	0.390	65.1	0.52	0.027	7.4
									200.9			

to create isolation in the modelling framework to avoid uncertainty arising due to modelling platform. The first has been developed using the Plant Modelling Framework (Brown et al., 2011) (hereafter PMF) and tested in several environment × management combinations in Tasmania (Borus et al., 2016, 2018; Lisson and Cotching, 2011). The second was developed by Robertson et al. (2002) using a legume-based model in the default APSIM Classic v7.10 structure, referred to here as the nPMF crop model. These two crop models are implemented into different languages and they have several differences in terms of evapotranspiration calculation, phenological stages, dry matter production and partitioning, nitrogen uptake etc. nPMF uses C++ (Holzworth and Huth, 2009), whereas PMF uses C# programming language (Brown et al., 2011). Evapotranspiration (ET) is calculated using a transpiration efficiency (TE) approach (Wang et al., 2004) in nPMF, whereas ET is calculated externally to the crop model in PMF using the Micromet module (Snow and Huth, 2004). There are eight phenological stages in nPMF *vs*. six in PMF. Further, these two models differ in approaches to calculate total dry matter production, biomass partitioning and nitrogen uptake (Brown et al., 2011; Ridwan Saleh, 2009). The models have been developed and tested using different datasets - nPMF model has been developed using datasets from Tasmania, Australia (Ridwan Saleh, 2009) whereas PMF model has been developed using datasets from Lincoln, New Zealand (Borus et al., 2018; Brown et al., 2011). The detailed description of nPMF model can be found in Ridwan Saleh (2009) and PMF in Brown et al. (2011). However, both models use same hydrological parameters for water uptake [lower limit or wilting point (LL15), drained upper limit or field capacity (DUL), saturated volumetric water content (SAT), root exploration factor (XF) and water extraction parameter (KL)].

2.5.2. Soil water models

Two soil water models within APSIM were chosen to provide models of differing complexity, SoilWAT and Soil Water Infiltration and Movement (SWIM3). SoilWAT (Jones and Kiniry, 1986; Littleboy et al., 1992) uses a simple cascading water balance model to calculate the soil water movement and is a commonly used model in APSIM (Hao et al., 2021). SWIM3 (Huth et al., 2012) calculates the soil water movement, which provides numerical solutions to the Richards' equation (Richards, 1931; Richardson, 1922). SWIM3 has been explicitly designed to use the same input parameters for soil water retention and runoff processes to assist in its application by users of SoilWAT and use of existing soil parameter databases developed for SoilWAT. These design features are of great value to this study in minimising any confounding of uncertainty by model structure and parameterisation. The shared soil parameters between soil water models are described in Table 1. The only differences in parameterisation involved soil parameters unique to each model (*e.g.*, parameters for numerical integration within SWIM3). For example, SWCON (the fraction of water below SAT and above DUL that drains each day from each soil layer), is a unique parameter to SoilWAT. Whereas, K_{DUL}, the hydraulic conductivity at DUL tension, is a unique parameter to SWIM3 (Vogeler et al., 2022).

2.5.3. Irrigation models

The two different irrigation models are slightly different codes/ algorithms that describe differing irrigation interventions within an APSIM simulation. These different algorithms (Appendix A) have the same parameters within them and are part of the model structure uncertainty because they influence behaviour of the simulated irrigation. In this study, the amount of water being applied is not known prior to the model execution as the time and amount of water to be applied is calculated within the simulation (considering daily rainfall, evapotranspiration, etc.) as part of each simulation.

APSIM has the option to create manager scripts (defined by the user) to implement crop management practices. In some cases, subtle differences can occur between manager scripts developed for the same purpose. Two simple irrigation models (IM1 and IM2) were used to provide 15 mm of irrigation between the dates of 3rd Nov and 7th Feb based on Tasmanian farmer practices reported by Ojeda et al. (2021a). The difference was in the handling of 'soil water deficit' (SWD), which is calculated as the difference between soil moisture at field capacity (DUL) and simulated soil water content to the maximum rooting depth. IM1 had a fixed schedule of irrigating every 3 days but only applied the irrigation if the SWD was greater than 15 mm. IM2 differed only slightly from IM1. For IM2, SWD is calculated daily and irrigation water is applied whenever SWD > 15 mm. The calculations and management parameters (irrigation efficiency, amount of irrigation water and parameters used in SWD) involved as inputs to the decision were the same, however the application of those within the 'decision making logic' was different. Therefore, both IM1 and IM2 represented different models of farmers decision making processes.

2.6. Model outputs

Model output is the amount of something that is produced (Cambridge English Dictionary, 2022). For this study, it is the result we obtain from the model after running the simulations. For example, crop yield and drainage are model outputs in APSIM.

We assessed structural uncertainty in five model outputs: dry potato tuber yield at full senescence (yield); cumulative in-season irrigation (irrigation); cumulative in-season soil water drainage (drainage); cumulative in-season nitrate leaching (N leaching); and partial gross margin (PGM). A season was defined as the period from planting to full crop senescence (which varied per year). Yield, irrigation, drainage and N leaching are direct outputs from APSIM. PGM was calculated using yield, commodity price (a constant in this study) and input costs. All other costs and inputs were the same between model structures and locations. The PGM was calculated as follows:

$$PGM = (Y \times P) - (irrigation \times IC) \tag{1}$$

Where: Y is the dry potato tuber yield (t ha^{-1}); P is the income per ton of potato tubers (342 USD t^{-1}, a constant in this study); *irrigation* is the cumulaive irrigation from planting to full crop senescence; and IC is the irrigation cost, which includes the cost for irrigation water, tractor, plant and labour in Tasmania (35 USD ML^{-1}, a constant in this study). Yield and irrigation are APSIM outputs, whereas P and IC have been obtained from AgroGrowth Tasmania (2021) (the values were reported in AUD and converted to USD using conversion rate of 1 AUD = 0.7USD).

2.7. Structural uncertainty quantification

To quantify sources of structural uncertainty, a three-way analysis of variance (ANOVA) approach was used (Aryal et al., 2019; Biegler et al., 2011) to partition the total output variance from various model structures into different uncertainty sources. The three factors used were, soil water (SWM), crop (CM) and irrigation model (IM).

The total sum of squares (TSS) was calculated using Eq. (2). The calculated TSS was divided into two terms: main effects (Eq. (3)) and interaction effects (Eq. (4)).

$$TSS = Main\ Effect + Interactions \tag{2}$$

$$Main\ Effect = SS_{SWM} + SS_{CM} + SS_{IM} \tag{3}$$

$$Interactions = SS_{SWM*CM} + SS_{CM*IM} + SS_{SWM*IM} + SS_{CM*SWM*IM} \tag{4}$$

where SS_{SWM}, SS_{CM} and SS_{IM} represent the main effect corresponding to the soil water model, crop model and irrigation model, respectively. Then, we summarize all the interaction terms as SSI. After calculating the sum of the squares for all components, the mean proportion of variance for each model component (SWM, CM and IM) was determined using Eqs. (5), (6), (7) and (8) respectively.

$$Variance_{SWM} = \frac{1}{N}\sum_{i=0}^{N}\frac{SS_{SWM(i)}}{TSS_i} \tag{5}$$

$$Variance_{CM} = \frac{1}{N}\sum_{i=0}^{N}\frac{SS_{CM(i)}}{TSS_i} \tag{6}$$

$$Variance_{IM} = \frac{1}{N}\sum_{i=0}^{N}\frac{SS_{IM(i)}}{TSS_i} \tag{7}$$

$$Variance_{SSI} = \frac{1}{N}\sum_{i=0}^{N}\frac{SSI_{(i)}}{TSS_i} \tag{8}$$

Mean proportion of variance varies between 0 and 1 and corresponds to the contribution of an effect to the total ensemble variance (*i.e.*, uncertainty in this paper). In addition, TSS was separately calculated by seasonal rainfall patterns within each location. The rainfall conditions were classified into dry, average, and wet categories based on percentile thresholds, *i.e.*, the dry period falls below the 33% percentile, an average period falls between the 33% and 66% percentiles, and a wet period falls above the 66% percentile of climatological distribution.

2.8. Quantifying deviation of model outputs using different model structures

The variance between model outputs generated using different model structures were compared by calculating the deviation (D) between the model outputs generated using two model structures as follows:

$$D = \mathrm{Ma} - \mathrm{Mb} \tag{9}$$

where Ma was the model output (yield, irrigation, drainage, N leaching or PGM) generated by model structure a, and Mb was the model output generated with model structure b. In other words, D represents the difference in simulated outputs between the different model structures. Comparisons between any two model structures were conducted by computing the coefficient of determination (R^2), Root Mean Square Error (RMSE) and Concordance Correlation Coefficient (CCC) calculated as follows:

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(Mb_i - Mb_{avg}\right)\left(Ma_i - Ma_{avg}\right)\right]^2}{\sum_{i=1}^{n}\left(Mb_i - Mb_{avg}\right)^2\sum_{i=1}^{n}\left(Ma_i - Ma_{avg}\right)^2} \tag{10}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Ma - Mb)^2} \tag{11}$$

$$CCC = \frac{2r\,\sigma_a\,\sigma_b}{\left(Ma_{avg} - Mb_{avg}\right)^2 + \sigma_a^2 + \sigma_b^2} \tag{12}$$

Where: Ma_i and Mb_i are the simulated values for model a and model b; Ma_{avg} and Mb_{avg} are the mean of model a (Ma) and model b (Mb), respectively; n is the number of years, r is the correlation coefficient between model a and b; σ_a and σ_b are the standard deviations for model a and b, respectively which is calculated using 1/N. CCC varies between -1 and 1. When CCC was close to 1, the differences between models were low.

2.9. Inter-annual variability of model outputs

We calculated the coefficient of variation (CV = standard deviation/mean x 100; standard deviation calculated using 1/N) as a measure of variability of model outputs. The CV was calculated amongst model structures ($n = 8$) for a given year (CV_{model}) and for 8 model structures across 120 years (1900–2020) to capture the inter-annual variability due to weather conditions ($CV_{climate}$).

3. Results

3.1. Structural uncertainty quantification

Overall, the choice of crop model caused the greatest variance in simulated model output, followed by choice of irrigation model and soil water model (Fig. 3). The structural uncertainty ranged from 12.2 to 98.9% for crop model, from 0 to 78.4% for irrigation model, from 1 to 33.7% for soil water model and from 0.1 to 18.9% for interactions. The uncertainty due to the choice of crop models was larger in all model outputs except irrigation, in which irrigation model contributed the highest (31.7–78.4%). A large part of the uncertainty in tuber yield was caused by variations in the crop model (79.7–98.8%) followed by irrigation model (0–12.7%) and soil water model (1.1–3.9%). Drainage, N leaching and PGM followed the similar trend in terms of uncertainty contribution. The second order interactions between model components contributed the least (0.1–18.9%) to structural uncertainty. Most structural uncertainty resulted from first order effects of the choice of model components rather than second order interactions between components. A similar pattern was observed when decomposing uncertainty of model outputs between dry, average and wet years (Figure S1). The uncertainty coming from choice of model was independent of model structure complexity, *for example,* the choice of irrigation model in few cases was as important as choice between soil water models or crop models (Fig. 3, Table 2).

To examine, whether the majority is really the majority in other regions too, we analysed the variance in additional two potato growing regions, Epping (~ 564 mm $year^{-1}$) and Devonport (~ 785 mm $year^{-1}$) which have average annual rainfall smaller and greater than Cressy (~610 mm $year^{-1}$) respectively. From our analysis, we found that irrigation model contributed the largest for irrigation and nitrogen leaching for drier sites (Fig. 3, Figure S2). However, choice of crop model caused the largest uncertainty for all other simulated outcomes and sites. Hence, we conclude that in general, choice of crop model caused the greatest variance in model outputs.

Although the same set of input data and parameters were used in APSIM, simulated model outputs varied between different models in the range of 8–18.8 t ha^{-1} for yield, 55–495 mm for irrigation, 0–353.4 mm for drainage, 0–76.6 kg ha^{-1} for N leaching and 2644–6360 USD $ha^{-1}$for PGM. PMF model predicted slightly higher values of yield, irrigation and PGM across the three sites as compared to nPMF model, whereas drainage and N leaching showed an opposite trend*,* where nPMF model predicted higher values for drainage and N leaching across all three sites (Figure S3). A detailed statistical analysis of the differences between model structures is presented in Table S1.

It is important to diagnose the contributing factors of uncertainty in each use case, as they are not the same across space or time (dry *vs* wet years) (Fig. 4, Figure S1). Particularly, D_y, D_i and D_{PGM} decreased with increase in rainfall, whereas D_d and D_N showed opposite trend (Fig. 4). The soil water model generated maximum D values for yield (D_y: 6.8 t ha^{-1}) and PGM (D_{PGM}: 2275 USD ha^{-1}), the irrigation model for irrigation (D_i: 165 mm) and the crop model for drainage (D_d: 126 mm) and N leaching (D_N: 51.5 kg ha^{-1}) (Fig. 4, Table 2).

3.2. Variability of model outputs due to model (CV_{model}) and climate ($CV_{climate}$)

The CV of model simulations varied due to model structure and climate in different ways for different model outputs (Fig. 5, Fig. 6). In general, the CV across model structures (CV_{model}) decreased from low- to high-rainfall environments. It was extremely high for drainage (7.7–152.4%) and N leaching (23.4–160.9%) as compared to yield (0.7–20.7%), irrigation (4.8–31%) and PGM (0.6–21.2%). A similar pattern was found when analysing climate inter-annual variability ($CV_{climate}$; Fig. 6). Overall, the $CV_{climate}$ varied largely for the different model structures in the low-rainfall environment (Cressy), whereas

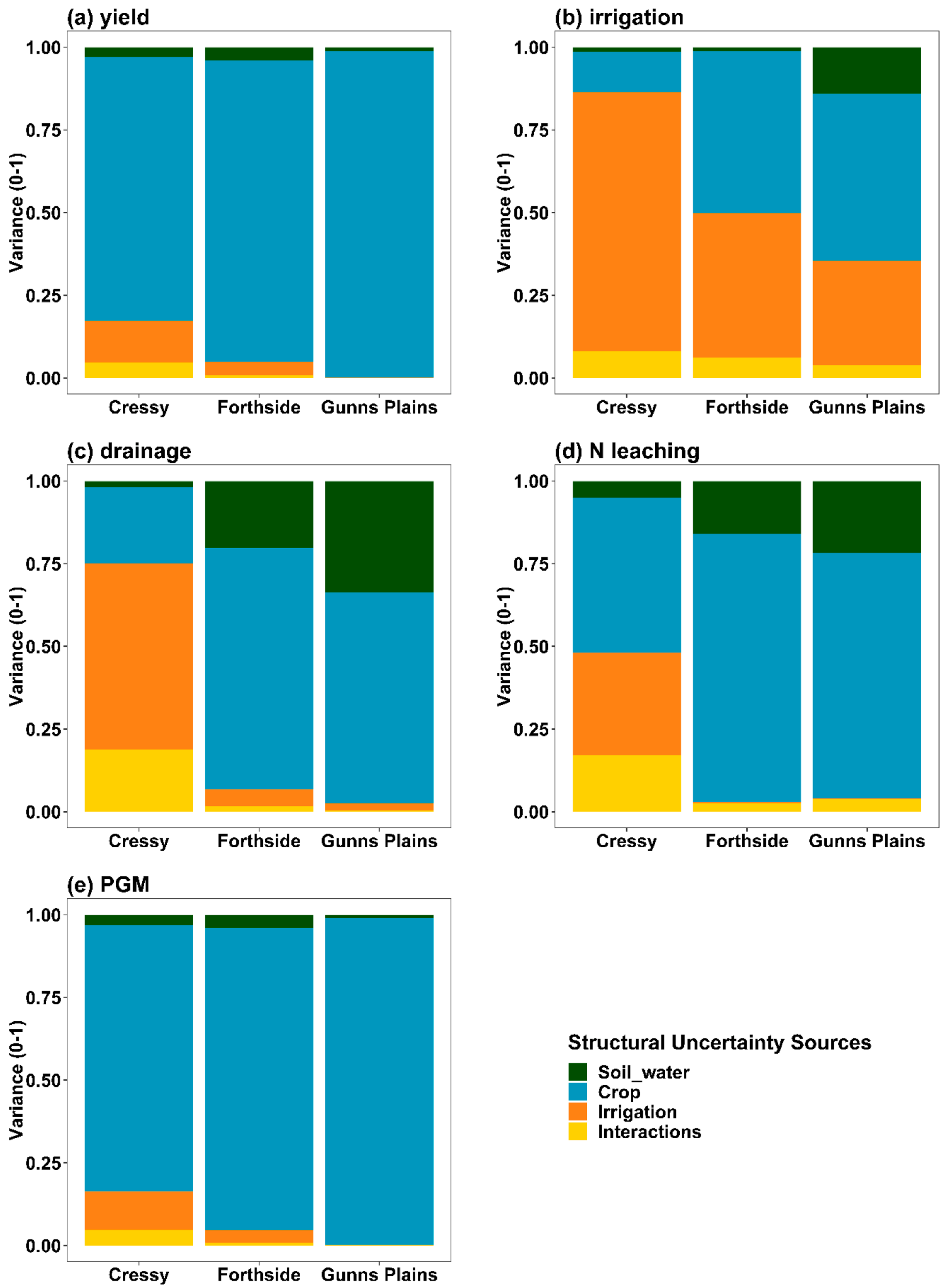

Fig. 3. Structural uncertainty decomposition (soil water, crop and irrigation model and interaction) represented by the mean proportion of variance for simulated a) yield, b) irrigation, c) drainage, d) N leaching and e) partial gross margin (PGM) by location (Cressy, Forthside and Gunns Plains).

there was lower variability of model outputs in the average (Forthside) and high-rainfall environment (Gunns Plain). The range of CV for each variable is considerable too. For yield and PGM it is <15%, but for the drainage and N leaching, it is very high >100%. Hence, when the CV is higher, the uncertainty is higher, thus the decisions are less certain.

CV is dependant on both mean and standard deviation. However, higher CV values in our study were mainly driven by higher values of standard deviation (Table S4). For example, mean yield for Cressy, Forthside and Gunns Plains was 14±2 t ha^{-1}, 14±2 t ha^{-1} and 15±1 t ha^{-1} respectively, resulting lower values of CV. On the other hand, values for

Table 2
Minimum, maximum, mean and median deviation (D) of model outputs (yield, y; irrigation, i; drainage, d; N leaching, N; PGM, partial gross Margin) using different soil water, crop and irrigation models.

Output	Model	Minimum	Maximum	Mean	Median
D_y ($t\ ha^{-1}$)	Soil water	0	6.8	0.4	0.2
	Crop	0	6.0	2.4	2.3
	Irrigation	0	6.3	0.6	0.3
D_i (mm)	Soil water	0	120.0	19.6	15.0
	Crop	5.0	155.0	32.3	25.0
	Irrigation	0	165.0	43.3	30.0
D_d (mm)	Soil water	0	78.8	15.3	11.3
	Crop	0	125.8	21.6	12.7
	Irrigation	0	92.8	9.6	5.8
D_N ($kg\ ha^{-1}$)	Soil water	0	16.3	2.0	1.0
	Crop	0	51.5	3.8	1.7
	Irrigation	0	8.7	0.7	0.3
D_{PGM} ($USD\ ha^{-1}$)	Soil water	0	2275	148	70
	Crop	9.0	2025	812	761
	Irrigation	0	2113	206	106

mean N leaching were 0.78±1.1 kg ha^{-1} for Cressy, 3.04±3.72 kg ha^{-1} for Forthside and 6.73±9.02 kg ha^{-1} for Gunns Plains resulting in higher values of CV.

4. Discussion

Structural uncertainty in crop modelling studies have gained recognition in recent years. However, most studies are conducted using different crop models operated by different people and research teams. There are only a few notable studies which have quantified structural uncertainty using the same modelling framework (Ramirez-Villegas et al., 2017). In this study, we applied common statistics to quantify the uncertainty in various crop model outputs that arises from different model structures within the same modelling framework with careful safeguards to manage uncertainty from inputs, parameters and model users.

4.1. Structural uncertainty quantification

Interestingly, uncertainty from choice of the model was not necessarily related to the complexity of the model (Fig. 3, Table 2). For example, in many cases, the impact of subtle differences in irrigation management was more significant than the choice between soil water models differing significantly in numerical complexity. Whilst this is not surprising in many ways, much work has focussed on complexity metrics involving numbers of parameters or lines of code (Manschadi et al., 2021). Amongst the different models we considered in this study, variance due to crop model selection outweighs the variance due to irrigation model or soil water model selection (Fig. 3). Our results align with previous studies of uncertainty quantification (Asseng et al., 2013; Li et al., 2015; Rettie et al., 2022; Tao et al., 2018). Tao et al. (2018) used 7 crop models for barley growth and found that uncertainty in crop models outweighs other uncertainty sources (climate models and crop model parameters). Similarly, Rettie et al. (2022) ran 48 crop growth x soil submodel configurations with 10 global climate models and compared the uncertainty contribution of the different weather/climate inputs on grain yield. These authors found that uncertainties in crop model were largest, followed by climate models, soil water flow, soil organic matter and soil heat sub-models. Our results also show that structural uncertainty varied amongst model outputs, but further highlight how uncertainty contributions vary across environment (Fig. 3, Figure S1). The relatively different trend in various outputs amongst locations suggests that uncertainty contribution from different sources may be dependant on climate and soil conditions (Li et al., 2015; Rettie et al., 2022). There was a substantial amount of uncertainty surrounding irrigation and soil water models (Fig. 3). However, structural

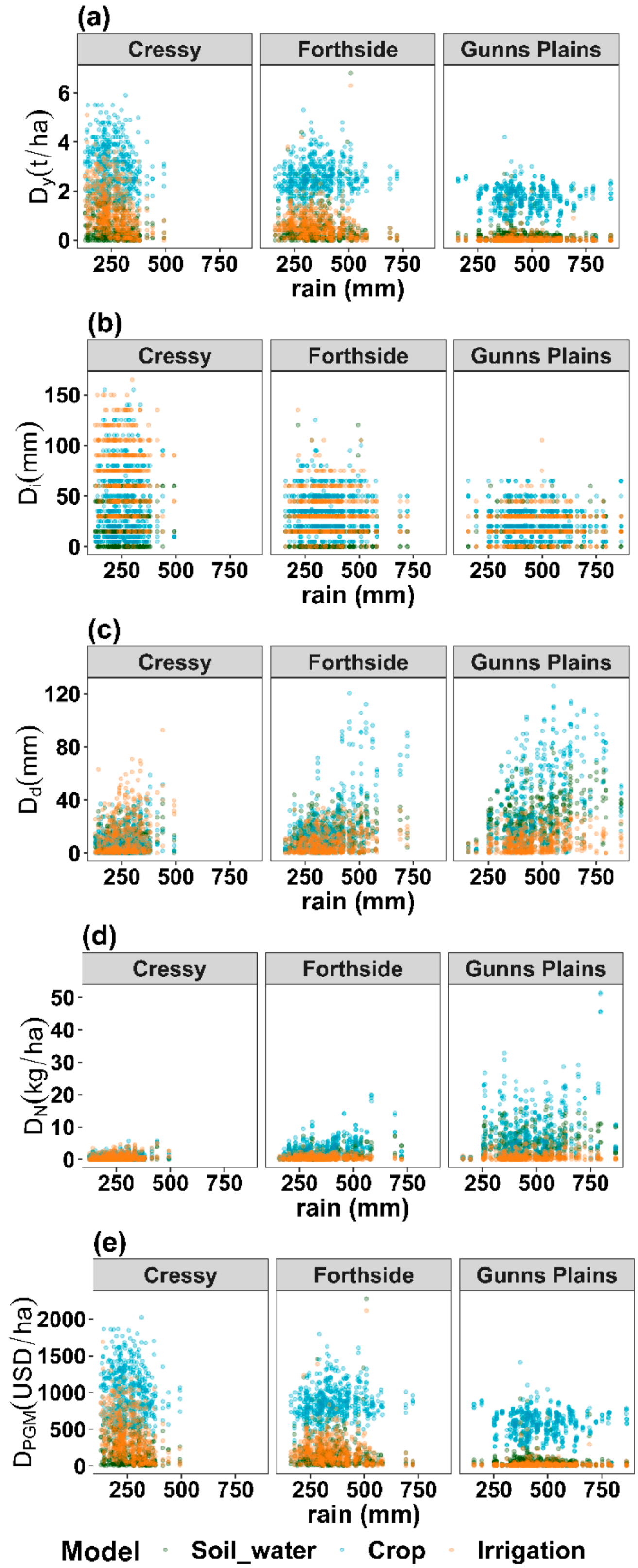

Fig. 4. Deviation (D) of a) yield (y), b) irrigation (i), c) drainage (d), d) N leaching (N) and e) partial gross margin (PGM) generated using two different model structures for soil water, crop and irrigation *vs.* cumulative rainfall (rain) from planting to full crop senescence.

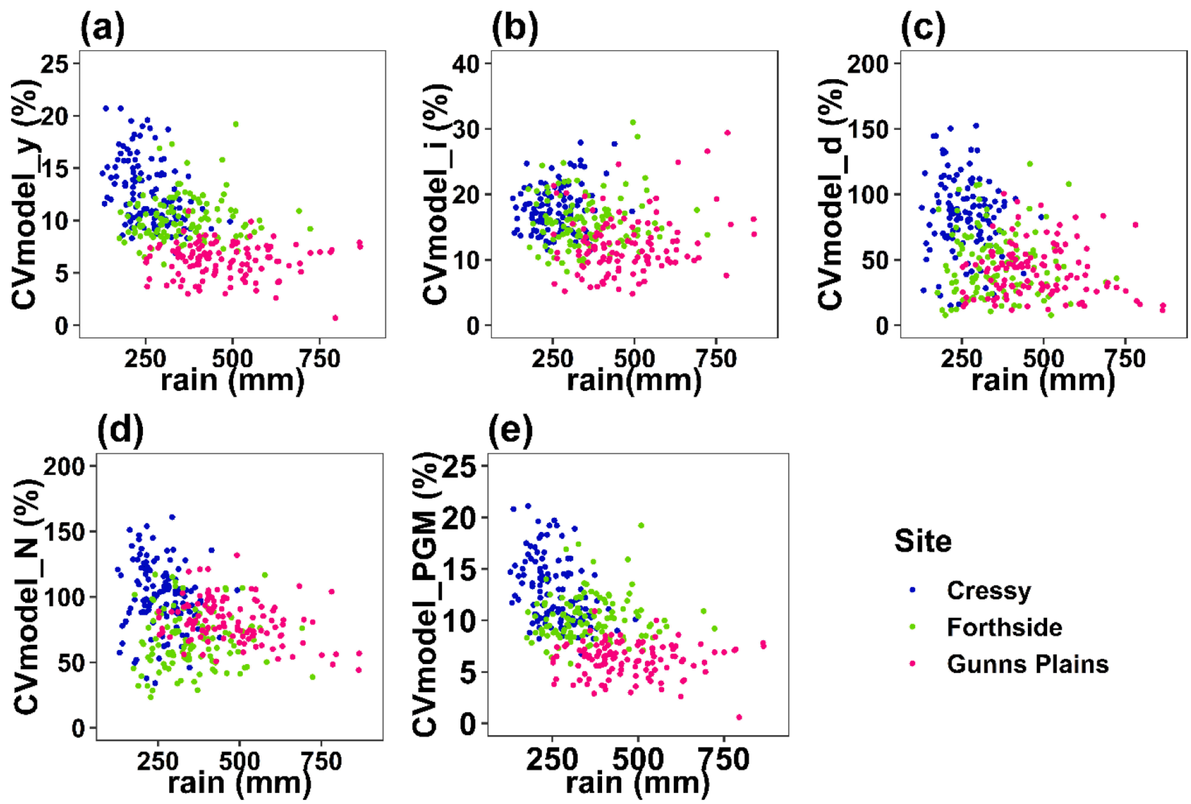

Fig. 5. Coefficient of variation amongst model structures (CV_{model}) for each year for a) yield (y), b) irrigation (i), c) drainage (d) d) N leaching (N) and e) partial gross margin (PGM) *vs.* cumulative rainfall (rain) from planting to full crop senescence in the low (Cressy), average (Forthside) and high rainfall environment (Gunns Plains).

uncertainty from crop model accounts for the majority of variance observed in model outputs across environments (Fig. 3). This is because crop models differ the most in their approaches to representing key processes such as biomass accumulation and crop phenology (Wöhling et al., 2013). For example, the nPMF model uses a transpiration efficiency approach (Wang et al., 2004) for ET calculations whereas PMF uses different algorithms driven by Micromet in APSIM (Snow and Huth, 2004). These results highlight the need to carefully identify, assess and describe the methods of calculation behind each crop model process before conducting any uncertainty analysis in future crop modelling studies.

The use of different approaches to estimate a specific process, for example- evaporation, frequently results in differences in the outcomes generated by the models. This variation becomes evident when comparing two crop models, as it emphasizes the disparities in how each model calculates different processes, as demonstrated by our two potato models. Hence, based on this observation, we believe that if similar analyses were carried out for other crops, the findings would probably be similar, underscoring that crop model may have the largest contribution to total uncertainty.

Partial gross margin was calculated using yield and irrigation values. The yield price was higher as compared to irrigation cost. Thus, the calculated PGM mirrors the yield patterns (Figs. 3–6). Similar results have been reported in the study conducted by Tang et al. (2021), where the authors investigated potato response under different N fertilizer and irrigation levels and found that income trend was similar to potato yield. In our study, drainage and N leaching showed similar trends (Figs. 3–6). This may be because, N leaching is heavily influenced by soil type, rainfall and crop management (Sapkota et al., 2012; Thorup-Kristensen et al., 2003) and is directly associated to water drainage (Arauzo and Valladolid, 2013) in mechanistic models such as APSIM. Additionally, drainage and N leaching are higher in environments with low soil water holding capacity and high rainfall, than in those with high water holding capacity and low rainfall (Askegaard and Eriksen, 2007; Ojeda et al., 2018). Our three sites (Cressy, Forthside and Gunns Plains) not only differed in terms of rainfall but also in the soil type (therefore in their water holder capacity: Table 1) and other climate variables (Fig. 2). The highest N leaching was found in the high rainfall, low water holding capacity site (Gunns Plains: Figs. 4, 6). This aligns with expectations and previous studies, such as the study carried out by Hess et al. (2020), which reported that N leaching increases with increased rainfall for tilled cropping systems. Our results demonstrated that the inclusion of a set of agronomic and environmental variables is a mandatory step of uncertainty quantification to assess the potential trade-offs between productivity and sustainability using crop models.

4.2. Spatio-temporal resolution of the analysis

The effects of structural uncertainty on predictions commonly used to inform agronomic or policy decision making were strongly impacted by location and seasonal conditions, highlighting the need for any uncertainty assessment to cover the entire range of conditions for model application. For example, the CV_{model} and $CV_{climate}$ were extremely high for drainage and N leaching as compared to yield, irrigation and PGM (Figs. 5 and 6). Our study underlined the value of long-term climate records to capture a wide range of seasonal conditions. Spatial data on soils and climate is becoming more readily accessible and these should be employed to provide a wide range of conditions in any structural uncertainty assessment given the ease of model execution.

4.3. Ecological implications of this study

The ecological implication of this study lies in the recognition that the selection of a crop model heavily influences the extent and nature of

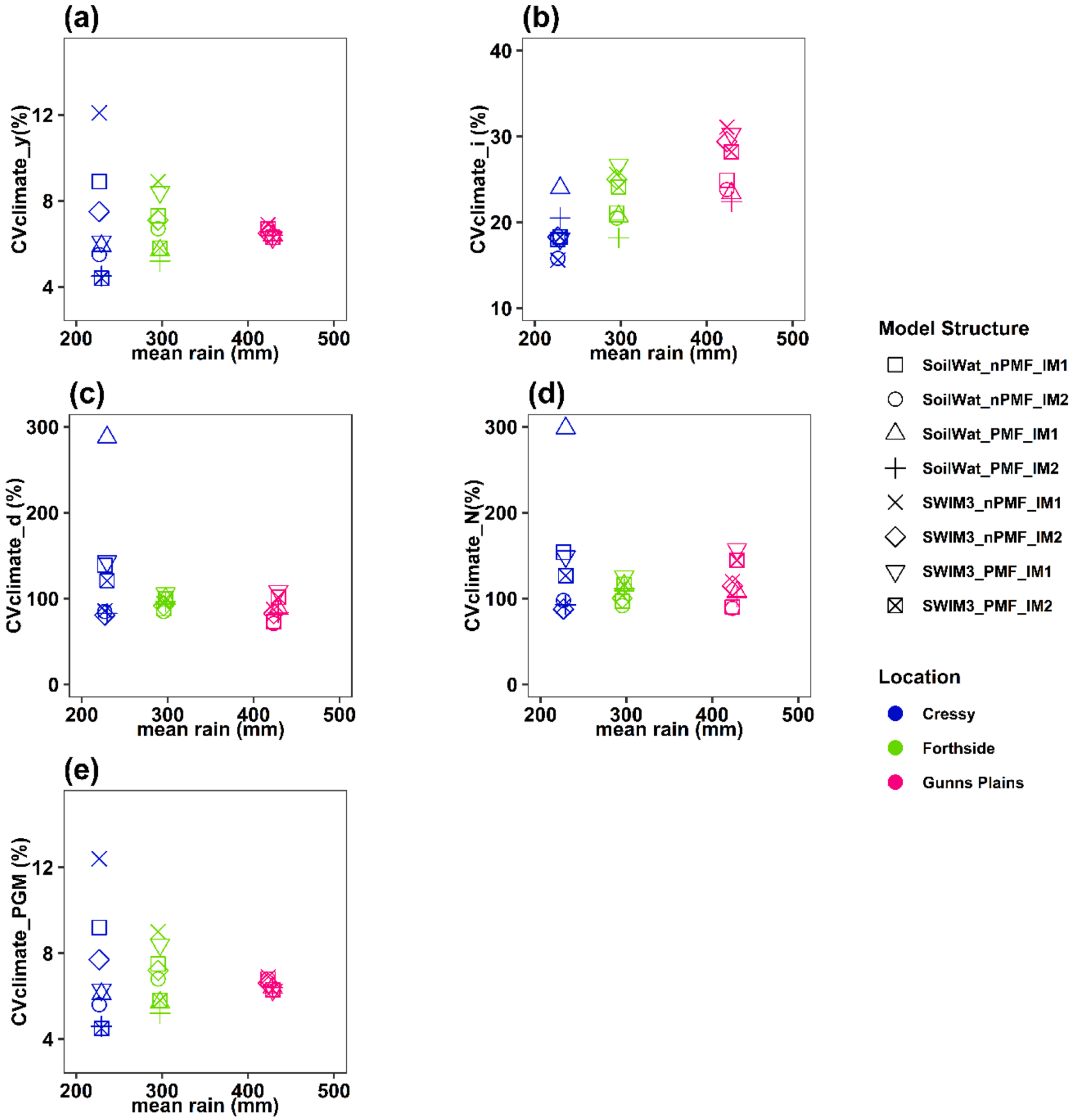

Fig. 6. Coefficient of variation across years ($CV_{climate}$) for a) yield (y), b) irrigation (i), c) drainage (d) d) N leaching (N) and (e) partial gross Margin (PGM) *vs.* mean cumulative rainfall [across 120 years (1900–2020)] from planting to full crop senescence (rain) for eight model structures in the low (Cressy), average (Forthside) and high rainfall environment (Gunns Plains). Model structures represents each combination of soil water model, crop model and irrigation model. For example, SoilWat_nPMF_IM1 combines SoilWat, crop model without plant modelling framework (nPMF) and the fixed schedule irrigation model (IM1).

uncertainty in simulated model outputs. This finding emphasizes the importance of employing a crop model that can accurately simulate local farm conditions and produce comparable outputs.

Our study reveals that uncertainty resulting from choice of crop model contributed the largest to the uncertainty of model outputs (Fig. 3). When the choice of crop model contributes the largest source of uncertainty in simulated model outputs, it can have significant implications for ecological systems. Uncertainty in models affects the accuracy of predictions related to crop yield (Asseng et al., 2013; Tao et al., 2018), water requirements (Webber et al., 2016), nutrient cycling (Kronvang et al., 2009) and other ecological outputs (Joetzjer et al., 2017; Prentice et al., 2015). This, in turn, can impact the understanding and management of ecological systems in several ways.

The presence of uncertainty in crop models can undermine the confidence of decision-makers in using model outputs for informed decision-making, highlighting the importance of assessing uncertainty to gain a realistic understanding of model outcomes (Burgman, 2005; Power and McCarty, 2006) and facilitate consistent and justifiable decision-making (Uusitalo et al., 2015). Additionally, accurate crop models are essential for effective resource management, such as irrigation scheduling and fertilizer application. If there is a high level of uncertainty in crop models, it becomes challenging to optimise resource allocation, leading to potential inefficiencies or overuse of resources that can negatively impact ecological systems, such as water availability and nutrient cycling. Furthermore, these models are often used to understand the interactions between agricultural practices and ecological processes. Uncertainty in model outputs can affect our understanding of these interactions, making it difficult to assess the ecological consequences of specific agricultural practices. This can hinder efforts to develop sustainable agricultural systems that maintain biodiversity, ecosystem services, and overall ecosystem health. Hence, addressing and reducing this uncertainty is crucial for improving the understanding and management of ecological systems (Rounsevell et al., 2021), promoting sustainability (Diwekar et al., 2021) and minimizing negative ecological impacts of agricultural practices (Cardenas and Halman, 2016).

This research goes beyond quantifying the impact of different APSIM model configurations on outputs by highlighting the importance of integrating agronomic, economic and environmental variables in uncertainty studies, enabling a comprehensive evaluation of trade-offs between productivity, profitability and sustainability in agricultural ecosystems. For instance, the PMF model yielded slightly higher predictions for agronomic and economic outputs, while the nPMF model exhibited higher values for environmental outputs. Thus, when selecting a suitable model, trade-offs between these variables must be considered. Additionally, our findings underscore the strong influence of location and seasonal conditions on the effects of structural uncertainty, emphasizing the need for comprehensive uncertainty assessments that cover the full range of environmental conditions relevant to the model's application.

4.4. Limitations of this study

1 Our study provides lessons about structural uncertainty in crop models generated using different model structures within a single crop model version (APSIM Classic 7.10). Although we consider a wide range of years (120) to catch the inter-annual variability, we only considered three point-based locations for our case-study. Future research should include a wider range of environments (soil × climate) and spatial resolutions using gridded data to up-scale the analysis to regional or national scales.

2 We developed two irrigation models and used two soil water models and crop models in APSIM Classic 7.10. Crop model resulted in the largest proportion of uncertainty. However, there is a lack of crop model description for the PMF crop model in the literature and source code that limited us to deeply compared the crop models in this paper. Therefore, future efforts should be concentrated in the development of proper metadata about new crop models within modelling frameworks such as the latest APSIM version (Next Generation; https://apsimnextgeneration.netlify.app).

3 This study focused on three types of model outputs - agronomic (yield and irrigation), economic (partial gross margin) and environmental outputs (drainage and N leaching). However, there are several other model outputs such as evapotranspiration, leaf area index, harvest index and others should be considered in future structural crop model uncertainty analyses.

4 The focus of this study was to quantify structural uncertainty; hence the authors have tried to isolate other factors of analysis. However, often the temporal and spatial variability contribute to large variance in model output when compared to model uncertainty. Hence, future research should consider comparing the variance contribution of uncertainty *vs*. variability in model outputs which would provide more information for further model improvements.

5 In this study, we used default values for the non-fixed parameters that are available when the model was released. These values are only one choice amongst possible choices and the selection of other different parameter values may lead to different simulated values, affecting the differences between APSIM model configurations. Since, the focus of this paper was to quantify model structural uncertainty, the authors have isolated other factors including parameter uncertainty. However, parameter uncertainty might also have some contribution in the total uncertainty. Hence, practical uncertainty studies should consider all possible sources of uncertainty.

5. Conclusions

The results from this study suggest that most structural uncertainty resulted from first order effects of the choice of model components rather than second order interactions between components. This may be due to biases arising from the choice of crop or management models. In the case of crop model choice, these biases arose from changes in each system's water balance, due to differences in crop water use, as well as a general difference in productivity. Simple differences in assumptions about irrigation frequencies were sufficient to strongly influence irrigation volumes in response to rainfall patterns. Our study highlights that model structures can be accentuated when it affects highly sensitive model processes. Models are often used to inform management because of the strong links between crop management and model outputs. This would suggest that uncertainty from choice of irrigation model is likely to be high in many model applications.

Our study demonstrates opportunities to use component-based modelling frameworks to explore the effects of model structural uncertainty in agroecological systems. The common data requirements for many models within APSIM also assists researchers in minimising confounding effects of uncertainty in parameters or inputs. Further exploration, using a wider range of alternatives available within APSIM, to developed within APSIM for this purpose, would allow a richer exploration of crop model uncertainty, especially if combined with other uncertainty and sensitivity tools currently available within the APSIM modelling framework.

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Code availability

Upon reasonable request, the corresponding author can provide the R code used for results processing and illustration.

Ethics approval

Not applicable.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

CRediT authorship contribution statement

Ranju Chapagain: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Visualization, Writing – original draft, Resources. **Neil Huth:** Conceptualization, Methodology, Software, Investigation, Writing – review & editing, Resources, Supervision. **Tomas A. Remenyi:** Writing – review & editing, Supervision. **Caroline L. Mohammed:** Writing – review & editing, Supervision. **Jonathan J. Ojeda:** Conceptualization, Methodology, Investigation, Writing – review & editing, Funding acquisition, Resources, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ecolmodel.2023.110451.

Appendix A

Code for Irrigation Model 1 (IM1)

```
using System;
  using ModelFramework;
  using CSGeneral;
  public class Script
  {
  [Link] Irrigation;
    [Input] DateTime today;
    [Param] string[] irrigDatesStr; //a string array holding the dates as text
    [Param] string sameDays;         //if yes, we ignore the year component
    [Param] float amount;          //amount of irrigation to apply (mm)
    [Param] float eff;             //irrigation efficiency
    private DateTime[] irrigDates;   //an array to hold the converted dates
    private bool irrigToday = false; //a variable to hold whether or not we irrigate today
    private int year;
    private string[] split;
    [EventHandler] public void OnInitialised()
    {
      //convert the date strings to APSIM dates
      irrigDates = new DateTime[irrigDatesStr.Length];
      for (int i = 0; i < irrigDates.Length; i++)
      {
        split = irrigDatesStr[i].Split('-');
        if (split.Length == 3)
        {
          year = Convert.ToInt32(split[2]);
          irrigDates[i] = DateUtility.GetDate(irrigDatesStr[i], year);
        }
        else
          irrigDates[i] = DateUtility.GetDate(irrigDatesStr[i]);
      }
    }
    // The following event handler will be called each day at the start of the day
    [EventHandler] public void OnPrepare()
    {
      irrigToday = false;
      //for every date in our date array
      foreach (DateTime day in irrigDates)
      {
        if (sameDays.ToLower().Equals("yes") && day.Day.Equals(today.Day) && day.Month.Equals(today.Month))
          irrigToday = true;
        else if (day.Day.Equals(today.Day) && day.Month.Equals(today.Month) && day.Year.Equals(today.Year))
          irrigToday = true;
      }
      if (irrigToday && Irrigation.irr_deficit>15)
      {
        IrrigationApplicationType data = new IrrigationApplicationType();
        data.Amount = amount;
        Irrigation.Set("irrigation_efficiency", eff);
        Irrigation.Apply(data);
      }
    }
  }
```

Code for Irrigation Model 2 (IM2)

```
using System;
  using ModelFramework;
  using CSGeneral;
  public class Script
  {
    [Link] Irrigation;
    [Input] DateTime today;
    [Input] double[] dul_dep;   //drained upper limit (field capacity)
```

(continued on next page)

(*continued*)

Code for Irrigation Model 2 (IM2)

```
    [Input] double[] sw_dep;      //soil water
    [Param] int deficit;          //allowable soil water deficit
    [Param] double eff;           //irrigation efficiency
    [Param] string start;         //no irrigation will be applied before this date
    [Param] string end;           //no irrigation will be applied after this date
    [Param] int maxlayer;         //calculate soil water deficit to this layer (inclusive)
    [Param] int amount;
    [Output] double totalSWD;   //total soil water deficit for given layers
    [EventHandler] public void OnInitialised()
    {
      if (maxlayer > dul_dep.Length)
      {
        Console.WriteLine("Warning: max layer is greater than number of layers.");
        Console.WriteLine("Using full profile for soil water deficit calculations.");
        maxlayer = 0;
      }
    }
    // The following event handler will be called each day at the beginning of the day
    [EventHandler] public void OnPrepare()
    {
      double[] SWD = new double[dul_dep.Length];
      for (int i = 0; i < (maxlayer > 0 ? maxlayer: dul_dep.Length); i++)
      {
        SWD[i] = Math.Max(0.0, dul_dep[i] - sw_dep[i]);
      }
      totalSWD = MathUtility.Sum(SWD);
      //if the soil water deficit is higer than the allowed deficit, and today is within the irrigation window
      if (totalSWD > deficit && DateUtility.WithinDates(start, today, end))
      {
        IrrigationApplicationType data = new IrrigationApplicationType(); //using a type means we can use defaults for
  values we don't change
        data.Amount = amount == 0 ? (int) totalSWD: amount;
        Irrigation.Set("irrigation_efficiency", eff);
        Irrigation.Apply(data);
      }
    }
  }
```

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