ASSESSING THE IMPACT OF REGIONAL NATURAL RESOURCE MANAGEMENT ON LAND MANAGEMENT AND GROUND COVER IN THE UPPER MARANOA RIVER CATCHMENT

A Thesis submitted by

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Abstract

Australian governments have invested nearly $10 Billion in Natural Resource Management (NRM) from 1983 to 2018. Despite this significant investment, there is an ongoing struggle to demonstrate investments have led to better land management .

Significant work has been done with remote sensing data to estimate seasonal groundcover for all parts of Queensland from 1990 onwards. A Dynamic Reference Cover Method (DRCM) was used in previous studies to minimise the climate signal from these groundcover data to provide an indication of trends in land management.

This study used an adapted Dynamic Reference Cover Method to test the assumption that NRM investment led to improved grazing land management and groundcover. Climate and ground cover data were for the Upper Maranoa catchment in the Queensland Murray-Darling Basin. The climate signal was reduced to indicate management impact on ground cover.

Groundcover scores indicated that grazing land management had improved across the catchment during the NRM investment period. The improvements, however, were not limited to or significantly different for NRM supported properties than for other properties in the catchment. Across the catchment, improvements in management, and therefore groundcover, were more significant during the Regional NRM investment period (2004-2017) than in the previous Landcare period (1990-2004).

Catchment modelling quantified reductions in soil loss and stream sediment loads due to improved management. Aspirational groundcover values associated with seasonal climate conditions were synthesised allowing improvements to be compared with "what's possible" across the catchment. It was found that the reduced stream sediment loads amounted to 10% of what is possible during the Landcare period and a further 15% during the Regional NRM investment period. This suggests that improved management since 1990 has led to 25% of the maximum possible reductions in stream sediment load from hillslope erosion in grazing lands in the Upper Maranoa catchment.

Participating landholders were interviewed and some enablers and barriers to change were identified for consideration in supporting sustainable grazing landscapes.

Information and networking associated with NRM activities has enhanced knowledge and grazing land management. Climate, markets, cash flow, changes of ownership and vegetation legislation represent ongoing challenges to implementing better management practices.

The adapted DRCM showed value in its potential to reduce the climate signal from ground cover data. Identification of an unimpacted area, or control, was found to be a significant restraint in using the adapted DRCM to evaluate the NRM investment. The method showed capacity for retro analysis of ground cover from existing remote sensing programs to evaluate land management and current or previous program outcomes.

Certification of Thesis

This Thesis is entirely the work of Paul Webb except where otherwise acknowledged. The work is original and has not previously been submitted for any other award, except where acknowledged.

Principal Supervisor: Professor Geoff Cockfield

Associate Supervisor: Professor Armando Apan

Associate Supervisor: Principal Scientist David Waters

(Queensland Department of Natural Resources, Mines and Energy)

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

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Thanks is due in no small part to the range of USQ staff who have supported my research from start to finish. I thank them for bearing with me when I sent questions or administration information to "totally the wrong place". The gentle responses that

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Glossary and abbreviations

NRM	Natural Resource Management
DRCM	Dynamic Reference Cover Method (Basin et al, 2012)
aDRCM	adapted Dynamic Reverence Cover Method. The adaptation of the DRCM used in this study to derive ground cover scores to indicate management signal on ground cover.
Ground cover score	The score derived for a given area using the aDRCM to indicate management signal on ground cover.
Climate Cluster	Areas of similar climate based on cluster analysis of gridded climate data.
Climate Zone	Climate Cluster and land form (sub-regions from Interim Biogeographic Regionalisation for Australia) areas combined to identify areas of similar pasture production potential.
Climate Landscape	Climate Zone and woody vegetation (or lack of) charateristics combined to identify areas of expected ground cover homogeneity given consistend grazing management.
Regional NRM period	Period from the launch of the Regional NRM Plan for the study region untill the end of ground cover data available for the study (2004-2017).
Landcare period	(For the purposes of this study) the period from the start of available ground cover data up untill the start of the Regional NRM period (1990-2004). Note: Landcare contributions to NRM include periods prior and post this period.
QMDB	Queensland Murray-Darling Basin
QMDBB	Queensland Murray-Darling and Bulloo Basins

Chapter 1 Introduction

1.1 Global sustainability awareness and links to agriculture

For decades it has been acknowledged that the world’s natural capital is deteriorating and that dependant species, including humans, are consequently threatened (e.g., Pope Paul VI 1971; Ward & Dubos 1972; United Nations 1993). It is also widely acknowledged that agricultural landscapes are the basis for social, economic and environmental functions (Everard 2004; Pretty & Bharucha 2014). The ongoing or sustainable function of these landscapes requires that current activities do not degrade the natural resource base (Hatfield-Dodds 2006; Pretty & Bharucha 2014). Agricultural land is a key consideration as it “occupies one third of the land surface of the Earth, and is the central activity for much of the world's population” (United Nations 1993, Item 32.1).

Within agricultural landscapes, soil erosion has been highlighted as “a serious threat to global agricultural sustainability” (Vanwalleghem et al. 2017) with 56% of arable soils (1,100 million hectares) affected by (water) erosion (Holland, Luck & Max Finlayson 2015). Sediments generated from erosion are contributing to declines in water quality and freshwater ecosystem function (Panagos et al. 2015; Issaka & Ashraf 2017).

1.2 National support for sustainable agriculture as part of NRM

Commonwealth and state governments in Australia have invested heavily in Natural Resource Management (NRM) across agricultural landscapes (Ansell, Gibson & Salt 2016). Total investment amounts to nearly $10 Billion from 1983 to 2018, with investment peaking from 2002 to 2008 (see Figure 1-1 and Appendix 1.1).

1.2.1 Regional NRM investment

From 2002 a regional delivery model was adopted including planning and funding distribution through 56 community-based regional NRM bodies across Australia. This was to have “suited the specific circumstances of different regions and allowed the social, economic and environmental dimensions to be considered in an integrated way” (ANAO, 2008, p. 14). The regional delivery model was developed and delivered as a Commonwealth/States partnership (Markulev & Long 2013, p. 10; Department of Natural Resources and Mines 2016). By 2006 all the 56 regional NRM bodies established through these programs had accrediting NRM plans which allowed ongoing investment to be targeted towards significant regional issues (Hajkowicz 2009; Vella et al. 2015).

From 1983 rolling investments incorporated a wide range of activities and projects across NRM themes. The *Caring For Our Country Program* 2008-2013 claimed 80,000 participants in NRM activities (Commonwealth of Australia 2013, p. 7), and “over 430 projects have helped over 50,000 farmers to adopt improved and sustainable farm and land management practices to reduce soil loss and improve soil quality on their land” (Land and Coasts 2012, p. 5).

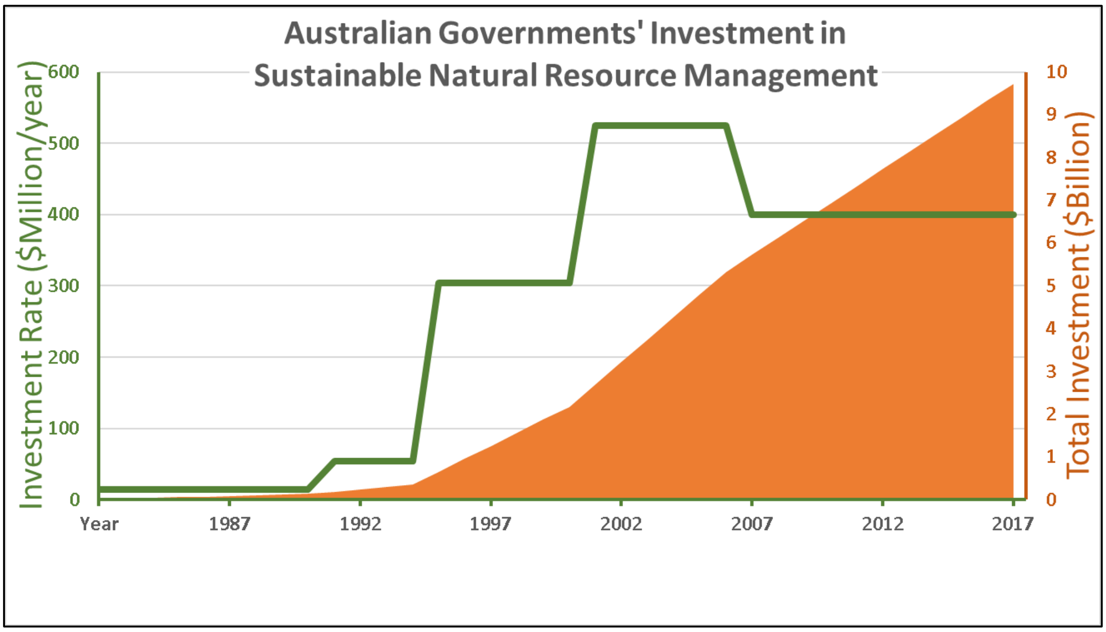

Figure 1-1: Australian Government Investment in NRM (adapted from Hajkowicz, 2009; Vella et al., 2015)

1.2.2 The Queensland Murray-Darling Committee

The Queensland Murray-Darling Committee Inc (QMDC)[1] was one of the 56 regional NRM bodies established as part of the Commonwealth and States’ partnership. QMDC

[1] QMDC was superseded in 2018 by the new NRM group, Southern Queensland Landscapes (SQL). Data collection was undertaken during QMDC operational period and with support from QMDC. SQL has supported the finalisation of the research but to avoid confusion, QMDC will be referred to as the NRM group associated with the study catchment.

produced a Regional NRM Plan (NRM Plan) in consultation with community groups, industry groups, Government representatives and other interested persons (QMDC, 2004). This NRM Plan was accredited by the Commonwealth in 2004 and has been used and updated since (QMDC, 2006; 2015b) as a guide for investment in NRM

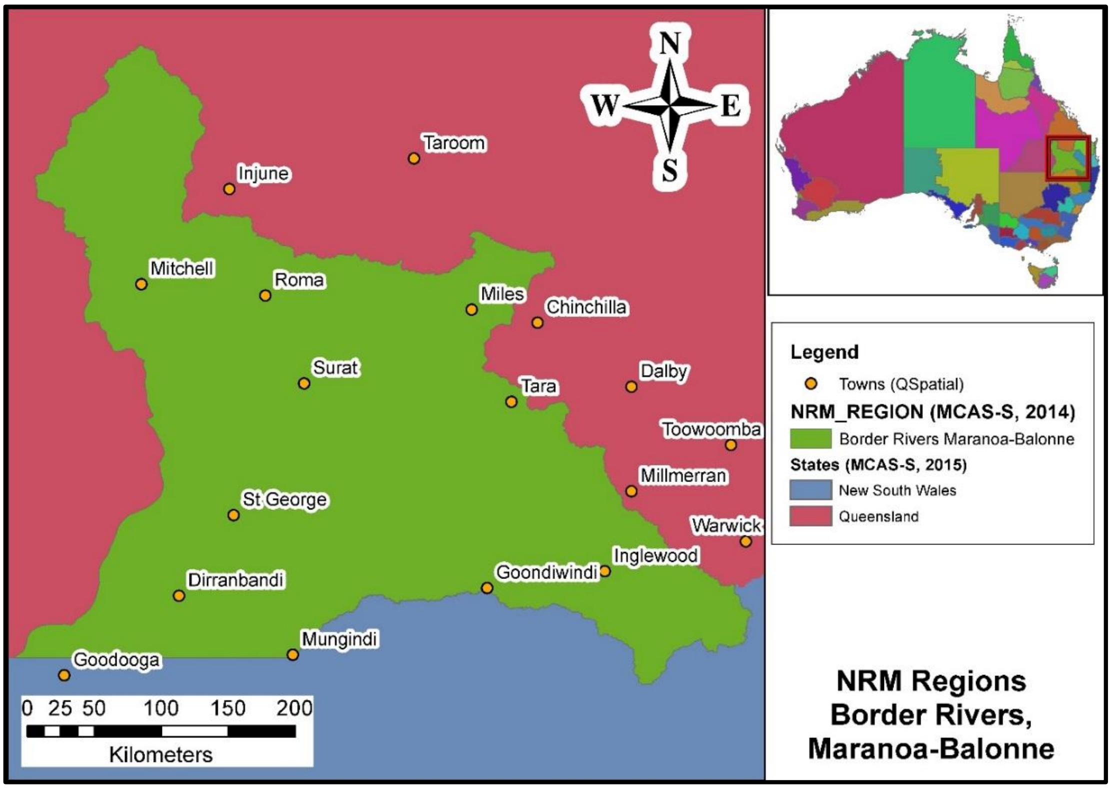

Figure 1-2: Australian NRM Regions – Border Rivers, Maranoa-Balonne

activities in the Border Rivers and Maranoa-Balonne, catchments.

Key mechanisms used to address NRM issues included extension and incentives programs such as:

- Sub-Catchment Planning (SCP),
- Environmental Management Systems (EMS) support, and,
- soil tenders (Queensland Murray-Darling Committee 2015a).

Through these and other activities, QMDC claimed a significant NRM footprint across the Maranoa-Balonne and Queensland Border Rivers catchments (see Figure 1-2). A wide range of extension activities and subsequent incentives projects for grazing lands were supported by QMDC. A significant amount of these included support for improved grazing land management practices to increase ground cover (QMDC, 2013, ref Goal 1).

1.3 NRM Program evaluation

Government programs are often closely scrutinised with activities and expenditure regularly reported and audited. The challenge with NRM programs has been to determine if funded activities are leading to outcomes. In 2008 the ANAO undertook a review of the NHT1 and NHT2 programs. Although the audit ratified the regional NRM approach, it gave strong criticism of the lack of ability to demonstrate outcomes against NRM targets. The report describes the relationship between activities, outputs, intermediate outcomes and outcomes (ANAO, 2008, p. 101) (Figure 1-3). It was indicated that annual reports gave detailed and auditable information on activities and outputs (projects) but were unable to demonstrate that these activates and outputs would lead to intermediate outcomes and final outcomes to be reflected in resource condition (p102).

1.3.1 QMDC Regional NRM evaluation

Estimates of reduced soil loss and reduced stream sediment loads have been made by QMDC (Waters & Webb 2007; Rattray 2009; Webb 2013). These studies estimated final outcomes from projects based on assumed intermediate outcomes from (extension) activities and (incentives project) outputs. Little is known, however, about the reliability of the estimates or the validity of some of the assumptions (i.e. about intermediate outputs) underpinning these estimates. In particular, many projects have been funded to support grazing practices that will increase ground cover and therefore reduce soil loss. It has been assumed that these works have resulted in improved ground cover in target areas as a direct benefit of incentives. It has also been assumed that extension activities leading up to incentives projects have influenced the management of land across whole properties where works were done as an indirect benefit of works and associated extension activities. The assumptions used to estimate benefits of extension and incentives projects have not previously been validated or tested.

This study used remote sensing data to test the assumption that NRM investment, through extension and incentive projects, has led to improved grazing land management and ground cover. The study quantified the changes in ground cover due to management in the Upper Maranoa Catchment during the NRM investment period from 2004-2017. The study includes the separation of climate signal and land management signals in ground cover trends. The study also quantified the likely impact of changed ground cover on soil loss and stream sediment loads in the study catchment.

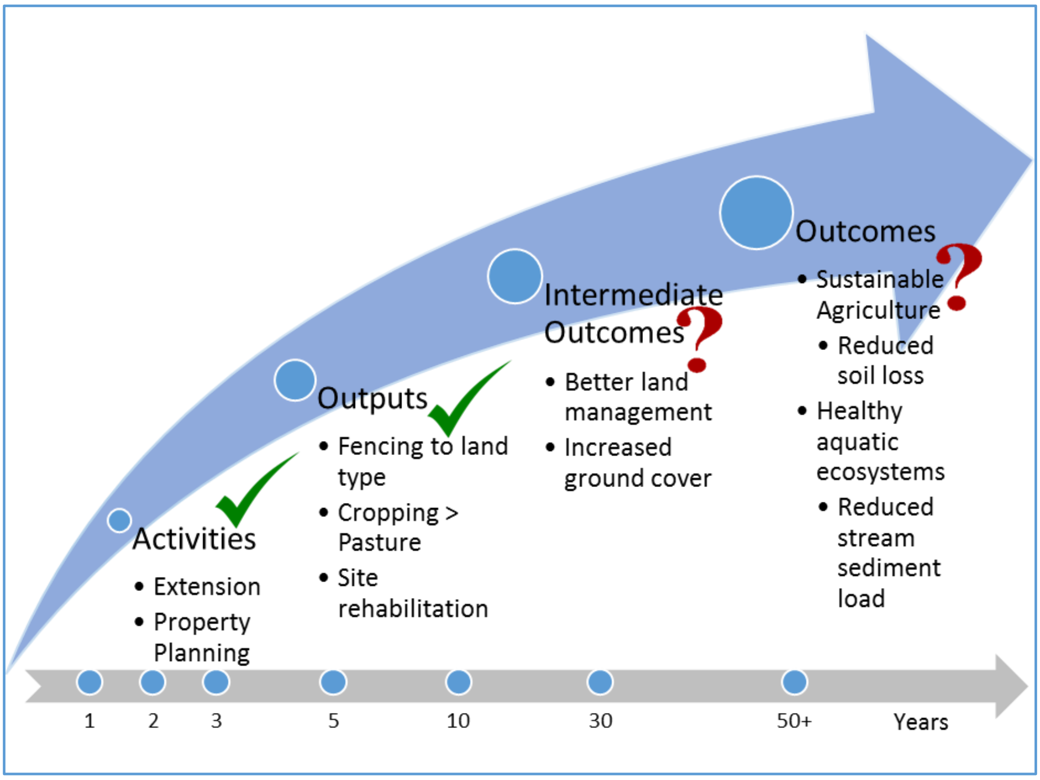

Figure 1-3: NRM activities outputs, intermediate outcomes and outcomes (after NRM Council, cited in Australian National Audit Office 2008, p. 101)

1.4 Research aims and objectives

1.4.1 Research aim

The aim of the research was to determine whether or not Natural Resource Management (NRM) program activities and outputs have led to the achievement of intermediate outcomes and final outcomes. In particular, the aim is to determine if NRM investments have influenced grazing land management with benefits for impacted environments.

1.4.2 Research question

What was the impact of NRM investment on grazing land management and subsequently on ground cover, soil loss and stream sediment loads in the Upper Maranoa study catchment?

The study considered the impacts of:

- Changed management on ground cover in grazing lands across the study catchment, and
- Changes in ground cover on soil loss and stream sediment loads in the study catchment.

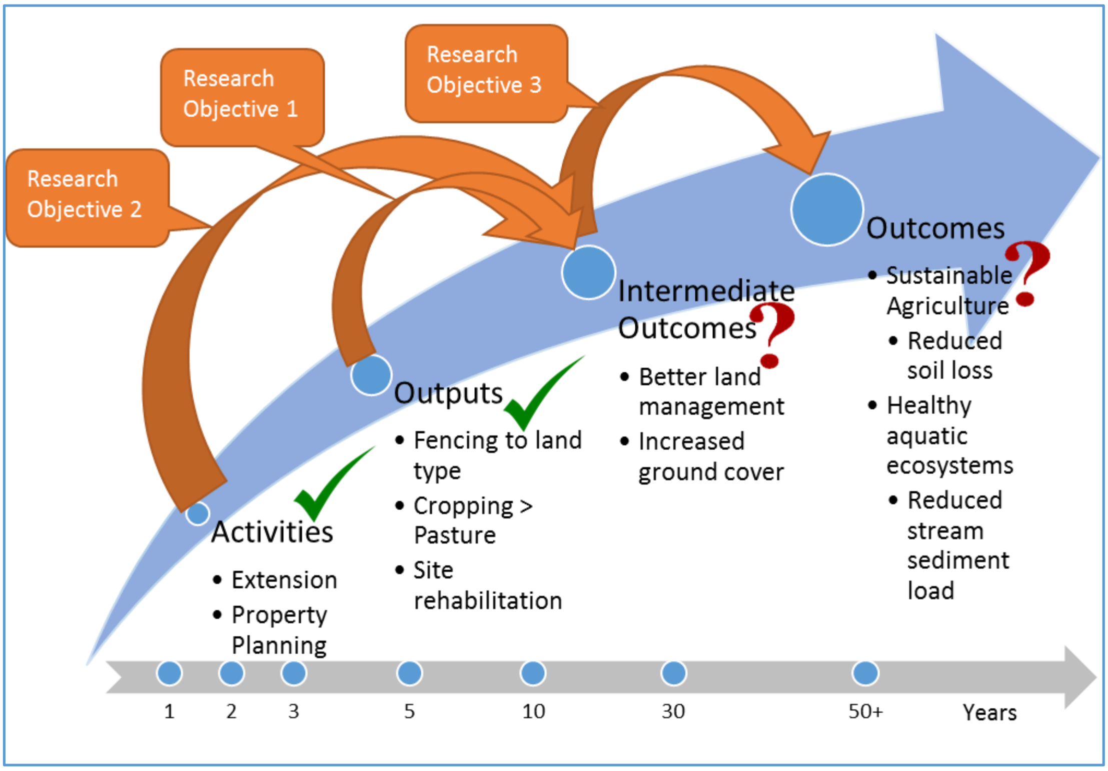

Figure 1-4: Research objectives' links to NRM outcomes (adapted from Figure 1-3)

1.4.3 Research objectives

1. To determine whether or not ground cover increased across <u>"properties" participating in extension programs</u> in grazing lands.
2. To determine whether or not ground cover increased at <u>incentive project "paddock" sites</u> in grazing lands.
3. To estimate <u>changes in soil loss and stream sediment loads</u> due to changes in ground cover in grazing lands within the study catchment.

Figure 1-4 shows how research objectives relate to NRM outcomes.

1.4.4 Assumptions and limitations of research

Research was confined to extension and incentives data made available by QMDC. From these data a study catchment was selected where available remote sensing data and catchment modelling tools could be used to analyse, ground cover, soil loss and stream sediment loads. Achievement of research objectives 1 and 2 required adaptation of an existing Dynamic Reference Cover Method (Bastin et al. 2012) to isolate the management signal from the climate signal in ground cover data. Achievement of research objective 3 required the development of a method and R scripts to adjust ground cover raster data for model inputs to reflect changes in management signal for a variety of scenarios.

As this research is confined to NRM extension and incentives data made available by QMDC, is limited in that:

1. It was not able to assess the degree to which NRM activities influenced areas outside properties mapped as having fully participated in extension and incentives programs, and,
2. It was not able to assess the degree to which other influences have impacted on land management in areas that participated in extension and incentives programs.

This study has also assumed that the management signal indicated by the spring ground cover scores (cf Bastin et al. 2012; 2014) represents all seasons. The legitimacy of spring having the strongest management signal was tested and confirmed in this study. The assumption that changes in ground cover due to management are consistent across seasons was not tested in this study. This would be a consideration for further work.

1.5 Study catchment

QMDC delivered extension and incentives activities across the Queensland Murray-Darling Basin but particularly in the Maranoa-Balonne, Moonie and Border Rivers catchments (Coppard et al. 2016). Activities were not limited to grazing lands with dryland farming, irrigated farming and nature refuge areas also being considered.

The Upper Maranoa was selected as the study catchment (Figure 1-5). It was selected for the study on the basis of the researcher's knowledge of the incentive scheme and the region, the fact that the region had a significant supported area, significant unsupported area (for a control) and was predominantly grazing land.

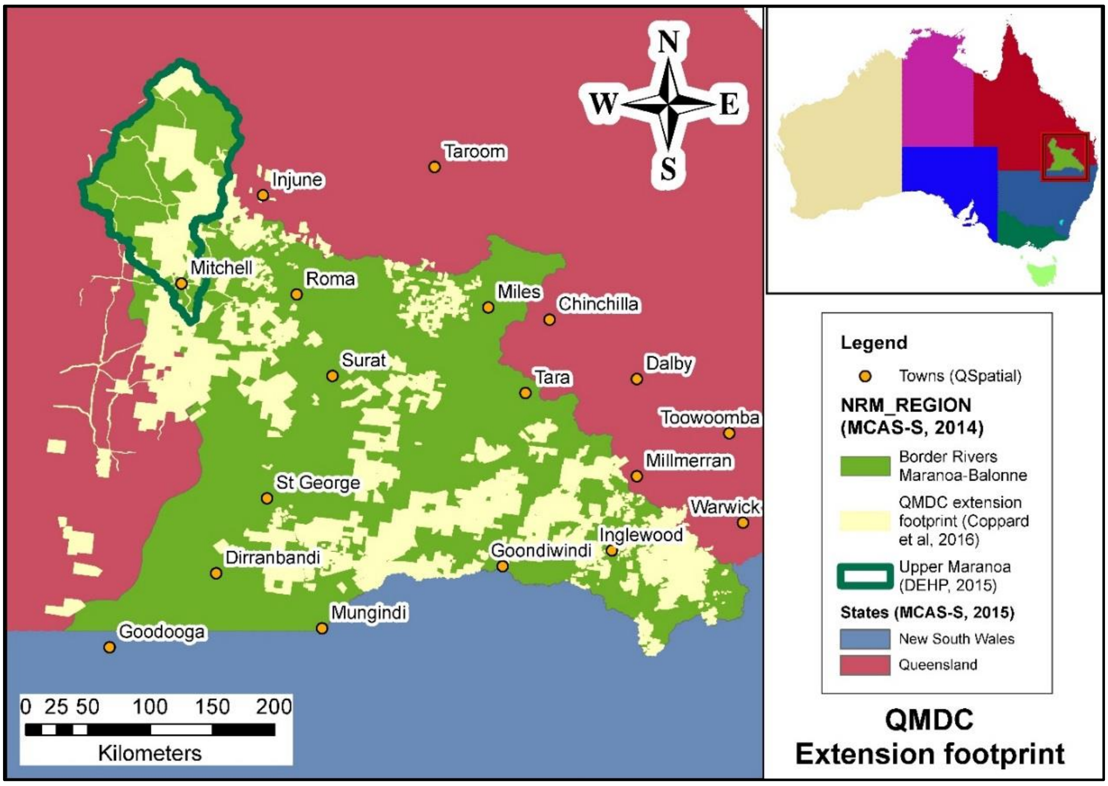

Figure 1-5: QMDC Extension footprint and Upper Maranoa study catchment

1.6 Significance of the study

Despite the $10 Billion investment in NRM (Hajkowicz 2009) and extensive targeted activities and outputs (Dale et al. 2014), evidence of outcomes from Regional NRM investments is limited (Australian National Audit Office 2008).

This study addresses this shortage of outcomes evaluations. It does so by using remote sensing data (Joint Remote Sensing Research Program 2018) to quantify improvements in land management. Improvements in land management were incorporated into a catchment model (following Davidson 2018) to quantify reductions in soil loss and stream sediment loads in the study catchment. The findings from this study, as well as the methods used to assess management of grazing lands, provide options for assessing other programs aimed at promoting and supporting sustainable grazing land management.

1.7 Organisation of the dissertation

This dissertation documents the aims of the study and the methods, results and conclusions. The documentation is structured into chapters with:

Chapter 1 (this chapter) outlining the context of the study in global, national and regional scales. This includes the aim, the research question and the research objectives addressed in the study.

Chapter 2 provides more detailed information on previous and related work in measuring outcomes from Natural Resource Management programs.

Chapter 3 describes the methods used to address the research questions including data sources as well as analyses and modelling tools used.

Chapter 4 presents the results from the study including progression through the findings for each research objective.

Chapter 5 provides discussion on insights and limitations encountered during the study. This chapter also suggests opportunities for further work using or adapting findings from this study.

Chapter 6 gives brief conclusions from the study with key points relating to findings and future opportunities.

Appendices are included to provide more detail relating to some sections of the study. Also included in the appendices are R software scripts used in the study to ensure they can be used and adapted for other related works.

Chapter 2 Natural Resource Management investment

2.1 Introduction

This chapter will review the main Global, National and then Regional investments and activities intended to facilitate sustainable Natural Resource Management (NRM). There will then be a review of approaches to the evaluation of NRM outcomes. Ground cover, soil erosion and stream sediment loads will then be described as a component of NRM highlighting the sparsity of effective evaluations. Finally the regional issues and data used in evaluations of NRM investment in the Queensland Murray-Darling Basin are reviewed, foreshadowing the development of an evaluation framework for this study through Chapter 3.

2.2 Towards sustainable NRM

2.2.1 Global initiatives

Deteriorating conditions of the world's natural capital is an issue for many species including the human species (United Nations 1993; Pope Francis 2015; UNEP 2016). Sustainability, or maintaining life support systems and conserving resources for future use, requires a global response (Mazzanti & Gilli 2018). In preparation for the 1972 United Nations (UN) Conference on the Human Environment, UN Secretary-General Maurice Strong commissioned the report "Only One Earth – The Care and Maintenance of a Small Planet" intended to provide broad-based scientific and policy support to the launch of an international sustainability initiative (Ward & Dubos 1972, p. 9). It is also widely acknowledged that agricultural landscapes are the basis for social, economic and environmental functions (Everard 2004; Pretty & Bharucha 2014). The ongoing or sustainable function of these landscapes requires that current activities do not degrade the natural resource base (Hatfield-Dodds 2006; Pretty & Bharucha 2014). Of note is that "Soil erosion is a major environmental threat to the sustainability and productive capacity of agriculture." and that "the most serious off-site damages are caused by soil particles entering the water systems" (Pimentel et al. 1995, p. 1117 & 20).

Internationally, co-ordinated action to protect and repair landscape function has been promoted under banners of sustainable development (United Nations 1993), adaptation to climate change (Smith et al. 2007), social justice for current and future generations (Pope Francis 2015; UNEP 2016), sustaining economic growth (Jones

2010), and maintaining production (Pretty & Bharucha 2014). Although agriculture is not the only consideration in sustainability, it is the focus of this study and "occupies one third of the land surface of the Earth, and is the central activity for much of the world's population" (United Nations 1993, Item 32.1).

Different approaches to protection of agricultural land have been based on improved understanding and incentives to move towards sustainable systems (Dale et al. 2013; Chabbi et al. 2017; Miles, DeLonge & Carlisle 2017). Regulation is also proposed to restrain agricultural operations for environmental protection (Kroon et al. 2016). Complexity and political resistance to regulation, however, often lead to combined extension and incentive programs. Other agri-economic approaches include financial compensation for revoking of rights to natural assets (Wittwer 2011), environmental offsets and land condition indexed payments (Hajkowicz 2009; Hacker et al. 2010).

2.2.2 National support for NRM

Commonwealth and state governments in Australia have invested heavily in Natural Resource Management (NRM) across agricultural landscapes (Ansell, Gibson & Salt 2016). Hajkowicz (2009, p. 475) estimates that Commonwealth Government investments in NRM had a total value of $6.5 billion from 1990 to 2013. There was also some prior Landcare and soil conservation investment going back to 1983 (Love, C 2012, pp. 12-6) plus a further $2 billion invested or committed from 2013 to 2017 (Vella et al. 2015, p. 383). This put the total investment at nearly $10 Billion from 1983 to 2018, with investment peaking from 2002 to 2008 (see annual investment (green line) and cumulative total (orange area) in Figure 2-1).

These investments were not the first signs of public interest in land condition, production or habitat management. Drought and wind erosion from the 1930s generated an interest in soil conservation in Australia (Sauter 2015). In the 1960s some Australian states recognised that water had been over allocated and ongoing regulation has tried to manage reliability for irrigation and the environment (Wheeler et al. 2014). Landscape function and habitat concerns led to the evolution of grassroots Landcare groups from the 1970s. These progressed from paddock and farm focus to some broader regional focus activities from the 1990s (Curtis 1995; Sobels, Curtis & Lockie 2001).

2.3 Regional NRM

Concerns about overlapping environmental and agricultural sustainability issues were evident from the 1980s in Australia. Ansell et al, 2016, describe the initial focus on engaging the community and building capacity in the 1980s through Landcare and the National Soil Conservation Program. This progressed to the National Landcare Program (NLP) from 1990 with a significant increase in investment. A further increase in investment followed with the National Heritage Trust (NHT) from 1996. NHT from 1996 to 2002 focussed on building new institutional capacity that complemented NLP (Hajkowicz 2009, p. 472). From 2002, activities focussed on regional delivery of targeted incentives under a number of programs including: NHT, National Action Plan for Salinity and Water Quality, Caring for Our Country and a new NLP (after Hajkowicz 2009, p. 472; Vella et al. 2015, p. 382). Figure 2-1 shows investment programs and phases as blue lines and arrows. Appendix 1.1 details how the investment figures and phases were determined from Hajkowicz, 2009 and Bella et al, 2015.

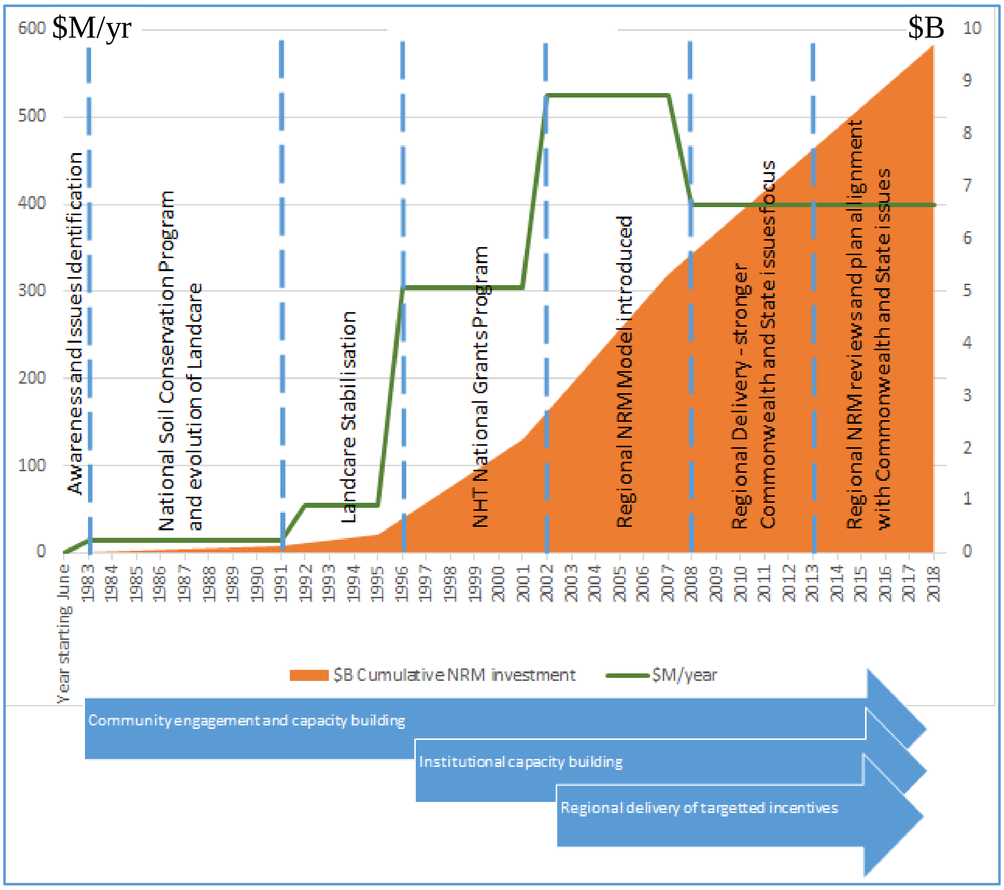

Figure 2-1: Australian Governments' NRM Investment (after Hajkowicz 2009, p. 475; Vella et al. 2015, p. 383)

To encourage change, the Australian Government initially leant towards extension programs and modest incentive payments in line with voluntary participation and limited financial outlay (Pannell & Roberts 2015). The electoral popularity of government funding for regional environmental activity through Landcare, combined with the need for a farmer centred approach (see section 1.2), led to regional delivery of increasing NRM program investments (Ansell, Gibson & Salt 2016). From 2002, a regional delivery model was adopted including planning and funding distribution through 56 community-based regional NRM bodies across Australia. This was to have "suited the specific circumstances of different regions and allowed the social, economic and environmental dimensions to be considered in an integrated way" (ANAO, 2008, p. 14). The regional delivery model was developed and delivered as a Commonwealth/States partnership (Markulev & Long 2013, p. 10; Department of Natural Resources and Mines 2016). Some of the bodies were statutory (Victoria and NSW) and therefore much more directly controlled by state governments, whereas other states including Queensland incorporated community bodies (Lockwood et al. 2009). That meant that bodies such as QMDC had no statutory powers and therefore were restricted to instruments such as information provision, extension, persuasion and incentives for voluntary changes in management[2].

By 2006 all the 56 regional NRM bodies established through these programs had accrediting NRM plans which allowed ongoing investment to be targeted to significant regional issues (Hajkowicz 2009; Vella et al. 2015). This grass roots approach had a regional focus but allowed "all land holders in most regions across the nation, for the first time, … to become part of the NRM process via extension, training and incentive-based activities." (Dale et al. 2014, p. 3). With the devolution of issue prioritisation, a variety of statutory and non-statutory models of NRM evolved in different states. With changes of government and with ongoing reviews, the prioritising and implementation of actions alternated between the local interests and state or national interests (Dale et al. 2014, Table 1).

[2] The NRM bodies in Victoria and NSW did have some statutory powers but as with the long-standing reluctance to directly regulate agricultural land use, these bodies also largely relied on the same sorts of instruments to induce voluntary change.

From 1983 rolling investments incorporated a wide range of activities and projects across NRM themes. The Caring For Our Country Program 2008-2013 claimed 80,000 participants in NRM activities (Commonwealth of Australia 2013, p. 7), and "over 430 projects have helped over 50,000 farmers to adopt improved and sustainable farm and land management practices to reduce soil loss and improve soil quality on their land" (Land and Coasts 2012, p. 5).

2.3.1 Regional issues

The Queensland Murray-Darling Committee Inc. (QMDC) was one of the 56 regional NRM bodies established as part of the Commonwealth and States' partnership. QMDC produced a Regional NRM Plan (NRM Plan) in consultation with community groups, industry groups, Government representatives and other interested persons (QMDC, 2004). This NRM Plan was accredited by the Commonwealth in 2004 and has been used and updated since (QMDC, 2006; 2015b) as a guide for investment in NRM activities in the Maranoa-Balonne, Moonie and Border Rivers catchments.

The NRM Plan deals with regional issues through groups acting at more localised levels. In this way the "*NRM Plan sits between 'bottom-up' community planning and 'top-down' institutional planning*" (QMDC, 2004, p. 4). Throughout its evolution, the NRM Plan has provided the framework for QMDC planning and action ordered towards best achievable management of NRM in the region. This has in turn guided investment from the Commonwealth and state governments and from other stakeholders in the region for NRM activities (QMDC, 2015b).

As with national and international NRM initiatives, the NRM Plan included erosion and soil loss as a key concern for the environment and for agricultural sustainability (Queensland Murray-Darling Committee 2004, 2015b). Erosion takes many forms including wind erosion, splash and sheet erosion (Freebairn, Loch & Silburn 1996; McClymont DJ et al. 2012), and concentrated flow, or gully erosion (Nouwakpo et al. 2016). The value of increasing ground cover to reduce erosion is established internationally (Grudzinski et al. 2016), nationally (Osborn 1952; Bastin et al. 2012) and in southern inland Queensland (Silburn et al. 1992; Loch 2000). It has been indicated that "soil loss rates decrease exponentially as vegetation cover increases (Gyssels et al., 2005 cited in Panagos P et al. 2015). Ground cover directly influences wind (Chappell et al. 2018), splash and sheet erosion (Freebairn, Loch & Silburn 1996;

Loch 2000). It also impacts on infiltration and runoff rates which in turn effect gully erosion (Fraser & Stone 2016; Nouwakpo et al. 2016).

Links between soil loss and stream sediment loads are also well established (Wilkinson et al. 2014; Kroon et al. 2016). Soil loss from hillslope erosion in the Queensland Murray-Darling Basin results in annual stream sediment load exports of 380,000 t/year (Davidson 2018). Davidson (2018) also indicates that gully and stream bank erosion have even greater inputs into stream sediment loads.

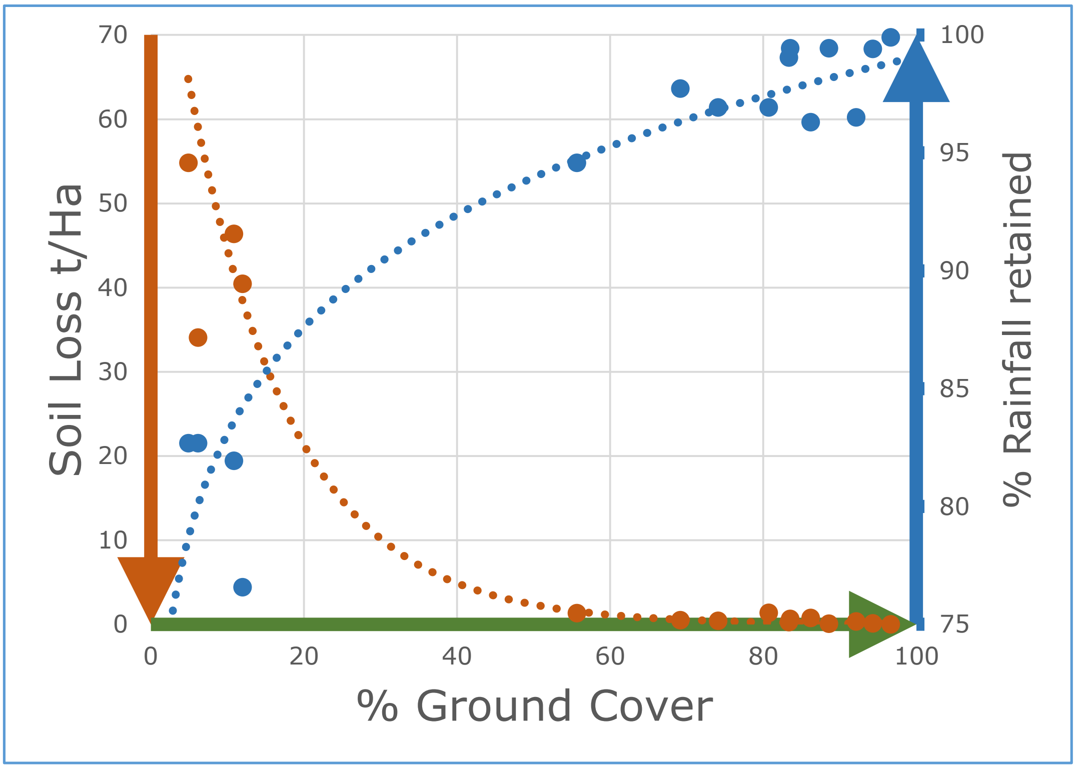

Figure 2-2: Ground cover relationship to soil loss and water retention (after Freebairn, Loch & Silburn 1996; Silburn et al. 2011, this plot developed from data provided by the authors)

In these and other studies increased groundcover has also been associated with enhanced production capacity due to associated increased water infiltration (E.G. Freebairn, Loch & Silburn 1996; Fraser & Stone 2016). Recognising the environmental and production benefits, promoting and supporting grazing land management practices that increase groundcover was seen as a key NRM issue (see Figure 2-2).

Other key NRM issues in the NRM Plan related to social, economic and environmental sustainability. Activities and outcomes in this study occurred together with those relating to other NRM issues. This study, however, only addressed evaluation of ground cover and associated soil loss and stream sediment loads.

2.3.2 Regional NRM extension activities

All delivery mechanisms for QMDC programs in the study region included elements of extension (see Figure 1-5), group social cohesion, visioning, planning and then individual property planning and incentives (QMDC, 2011). This approach aligns with the United Nations imperative for a "farmer centred approach" outlined in Section 1.1. The approach also promotes a degree of common ownership as promoted by Costanza et al (2013). This mitigates the Tragedy of the Commons risk through the extension of profitability interests together with the building of social acceptance for sustainable management (cf Uphoff & Langholz 1998; Kraak 2011; Costanza et al. 2013).

A wide range of *extension* activities and subsequent incentives projects for grazing lands were supported by QMDC. For example, in a 2013 community report it was indicated that:

> Extension activities incorporated 31 groups of landholders with a cumulative footprint of 820,000 Ha (see figure 7). Works supported by incentives funding included: 19,000 Ha of pasture established; 16.500 Ha of pasture renovation; and, 100,000 Ha fencing to land type with installation of alternate water points to distribute grazing pressure (QMDC, 2013, ref Goal 1).

Key mechanisms for the delivery of extension was through the development and implementation of Sub-Catchment Plans (SCPs), Environmental Management Systems (EMS) or through soil tenders (Queensland Murray-Darling Committee 2015b). Extension activities included elements of: information exchange workshops; property mapping; facilitated landscape issue identification; property visits by technical experts; support for individual property action plan preparation and landholder networking

2.3.3 Regional NRM incentives project outputs

Where individual property action plan projects (evolving from extension activities outlined previously) were expected to have a public benefit, landholders were eligible to apply for incentives to achieve the project outputs. QMDC has used incentives extensively in supporting NRM, particularly in agricultural landscapes. To qualify for incentives, landholders or other stakeholders were routinely required to co-invest in change (see Table 2-1) and to ensure investment considers all NRM themes – even if only addressing one or two themes.

Table 2-1: Funding ratios for incentives projects
Source (Queensland Murray-Darling Committee 2011)

Activities	Funding ratios QMDC/Landholder
Reducing soil erosion	
Earthworks……	50/50
Conversion of conventional planting equipment to zero tillage……	50/50
Establishment of pastures……	40/60
Fencing to land type changes (not including external boundaries)……	40/60
Managing riparian condition	
Controlling stock access to watercourses (e.g. fencing)……	70/30
Providing alternative watering points for stock……	70/30
Managing salinity risk	
Establishment of deep rooted permanent pastures……	40/60
Establishment of native local species (including grasses and/or trees & shrubs)…	70/30
Managing biodiversity	
Controlling stock access to protect and preserve habitat (e.g. fencing)……	70/30
Planting of local native species for biodiversity conservation or habitat purposes (including grasses and/or trees and shrubs)……	70/30
Controlling feral animals and weeds……	30/70
Monitoring	
Water quality, species, habitats, or other resources identified as performance indicators in the sub-catchment plan	50/50
Communication	
Field days/media stories/newsletters	90/10
Training	
Workshops/training events	75/25
Other activities	*To be negotiated*

The broad stakeholder extension and narrower incentives footprint reflects the national NRM program where extension activities had a much broader reach than subsidised projects (Land and Coasts 2012, p. 7; Commonwealth of Australia 2013, p. 5; Queensland Murray-Darling Committee 2013, Goal 1).

2.4 Regional NRM evaluation

Globally, nationally and regionally, it has been established that there has been significant interest and investment in NRM. It follows that in the interests of good governance, this investment should be evaluated (Verbeek et al. 2016). Evaluation should include consideration of "how successful an intervention has been and the identification of areas for improvement" (Pal, 2014 cited in Guyadeen & Seasons 2016).

2.4.1 National outcomes evaluation

Evaluation of NRM is particularly challenging as it encompasses diverse policy objectives, numerous projects and stakeholders, and benefits may not be realised for a significant period (Verbeek et al. 2016, p. 383). This has been very evident in Australian NRM with the evolution of funding programs (Hajkowicz 2009; see Figure 1; Vella et al. 2015) and some inconsistencies in prioritisation and delivery processes (Dale et al. 2014). Individual programs implemented around election cycles only allow for recording activities and outputs. Intermediate outcomes and final outcomes require 10 years or more to be realised (see Chapter 1, Figure 1-3).

In 2008 the ANAO undertook a review of the NHT1 and NHT2 programs. Although the audit ratified the regional NRM approach, it gave strong criticism of the lack of ability to demonstrate outcomes against NRM targets. The report describes the relationship between activities, outputs, intermediate outcomes and final outcomes (ANAO, 2008, pp. 101-2). It was indicated that annual reports gave detailed and auditable information on activities and outputs (projects) but were unable to demonstrate that these activates and outputs would lead to intermediate outcomes and the final outcomes to be reflected in resource condition.

Since 2008 reviews have highlighted how, despite ongoing activities and incentives projects to promote the uptake of Best Management Practice, there are a number of challenges in determining if works will lead to desired resource condition (E.G. Kroon et al. 2016; Hansen et al. 2019). Despite enhancements to modelling frameworks to assess the likely outcome of extension activities and incentives projects,

> Assessing true progress towards the targets is more difficult because practices may or may not be fully adopted, they may only be trialled or adopted for a limited period of time, or they may be modified with unintended reduced environmental benefits" (Pannell and Vanclay, 2011, cited in Kroon et al. 2016, p. 9).

These adoption limitations can be compounded by immediate pressures on land managers due to externalities such as climate, markets and farm family dynamics.

Compounding these issues of uptake and adherence to changed practices are assessment issues such as delayed impact of changes on natural resource condition (Australian National Audit Office 2008). The delayed impact of actions is highlighted by the NRM Council in ANAO (2008) with intermediate and final outcomes requiring 10, 30 or even 50 years to be realised and measurable.

Quantification of outcomes can also be constrained by limited understanding of cause and effect across scales (Prager et al. 2015, p. 121). In particular, climate signals are not easily separated from management signals in assessing natural resource conditions (Bastin et al. 2012).Bastin et al (2012 and 2014) indicate that the variations in ground cover occur due to the high inter annual rainfall variation (climate signal). Also, that further variations in ground cover occur due to grazing management (management signal). Section 2.5.1.1 outlines how Bastin et al (2012) used remote sensing data to (retro) analyse ground cover and isolate the management signal from the climate signal. Resourcing for evaluation for Australian NRM programs has also been limited. Even when planned at initiation such as with Australia's Monitoring Evaluation Reporting and Improvement 'MERI' framework, data "is likely to be less than what is needed for comprehensive program evaluations" (Verbeek et al. 2016). This study aimed to address this evaluation shortfall with the research aim "to determine whether Natural Resource Management (NRM) program activities and outputs have led to the achievement of intermediate outcomes and final outcomes" (Section 1.4).

2.4.2 Regional evaluation

Estimates of reduced soil loss and reduced stream sediment loads have been made by QMDC for reporting to stakeholders (Waters & Webb 2007; Rattray 2009; Webb 2013). These studies estimated outcomes from projects based on assumed intermediate outcomes from (extension) activities and (incentives project) outputs. Little is known, however, about the reliability of the estimates or the validity of some of the assumptions (i.e. about intermediate outcomes) underpinning these estimates. In particular, many projects have been funded to support grazing practices that will increase ground cover and therefore reduce soil loss. It has been assumed that these works have resulted in improved ground cover in the incentives works area as a direct benefit. It has also been assumed that extension activities leading up to incentives projects have influenced the management of land across whole properties where works were done as an indirect benefit of works and associated extension activities (Waters & Webb 2007, p. 891; Webb 2012, pp. 6-7).

The assumptions used to estimate outcomes of extension activities and incentives outputs have not previously been validated or tested. This study aimed to address this with the particular aim to "determine if NRM investments have influenced grazing land management with benefits for affected environments" (Section 1.4).

2.5 This study - evaluating Regional NRM

From Section 2.4 it has been identified that evaluation is ordered towards determining the success of interventions in achieving objectives. Globally, nationally and regionally it has been established that agricultural practices are causing erosion and subsequent deterioration of aquatic ecosystems (Sections 2.2 and 2.3). Improving agricultural practices to reduce erosion and impact on aquatic ecosystems is thus a key objective of NRM activities and is the focus of this study.

In addressing this objective, the value of increasing ground cover has been demonstrated (Section 2.3.1). From 2004 to 2017, QMDC has attempted to address this objective with interventions consisting of extension programs and incentives for focussed projects. The evaluation challenge was then to determine if interventions led to increased ground cover and, if so, whether that has significantly decreased soil loss and stream sediment loads. Other studies have investigated the use of a range of remote sensing data (Kumar & Mutanga 2017) to evaluate ground cover and the impact of grazing. In a US study, grazing management, bare ground coverage and their links to sediment movements were undertaken using remote sensing and field measurements of groundcover (Grudzinski et al. 2016). In a Canadian study, remote sensing data were analysed to confirm the relationship between productivity (cover and biomass) and biodiversity in grasslands, and the value of remote sensing to objectively evaluate these elements (Wang et al. 2016).

In Australian grazing lands significant work has been done to identify ways to use remote sensing data to complement other information in identifying grazing land condition (Scarth et al. 2010; Bastin et al. 2012; Bastin et al. 2014; Scarth et al. 2015).

This work has made significant progress in the use of remote sensing to assess condition and trend of grazing lands and has developed means to isolate impacts of climate and management. Limited study has been done, however, on the impact of NRM investment programs on property level changes in management to reduce soil loss and stream sediment loads.

Waters et al. (2014) outlined how monitoring and modelling are being combined to target and evaluate programs to reduce sediment and other pollutant loads in catchments of the Great Barrier Reef (GBR). The Source Catchments modelling framework has proven to be an appropriate tool for assessing load reductions due to improved land management practices" (Waters et al. 2014, p. vi). The use of catchment models addresses the challenge of "differentiating the effects of climate impacts from those associated with land use and management practices" (Fu et al. 2019).

This study has used remote sensing data to test the assumption that NRM investment, through extension and incentive projects, has led to improved grazing land management and ground cover. The study quantified the changes in ground cover due to management in the Upper Maranoa catchment during the NRM investment period from 2004-2017. The study includes the separation of climate signal and land management signals in ground cover trends. This addressed the research question concerning impacts of "Changed management on ground cover in grazing lands across the study catchment" (Section 1.4.2). More specifically, this addressed research questions 1 and 2 (Section 1.4.3 and Figure 1-4).

This study then used catchment modelling to quantify the likely impact of changed ground cover (due to management) on soil loss and stream sediment loads in the study catchment. This addressed the research question concerning impacts of "Changes in ground cover on soil loss and stream sediment loads in the study catchment" (Section 1.4.2). More specifically, this addressed research question 3 (Section 1.4.3 and Figure 1-4).

2.5.1 Evaluating changed management from ground cover data

2.5.1.1 Isolation of management signal from climate signal

Bastin et al. (2012) developed a methodology for the use of remote sensing data to identify the effect of management on ground cover with a Dynamic Reference Cover

Method (DRCM) (Bastin et al. 2012). In this study and subsequent work (Bastin et al. 2014), the authors highlight some of the challenges in separating the climate signal from the management signal in grazing lands. They then outline how the DRCM uses near best data from non-timbered pixels (i.e. not including any observation pixels with significant woody vegetation) in proximity to any study pixel as a reference or aspirational cover value for the study pixel.

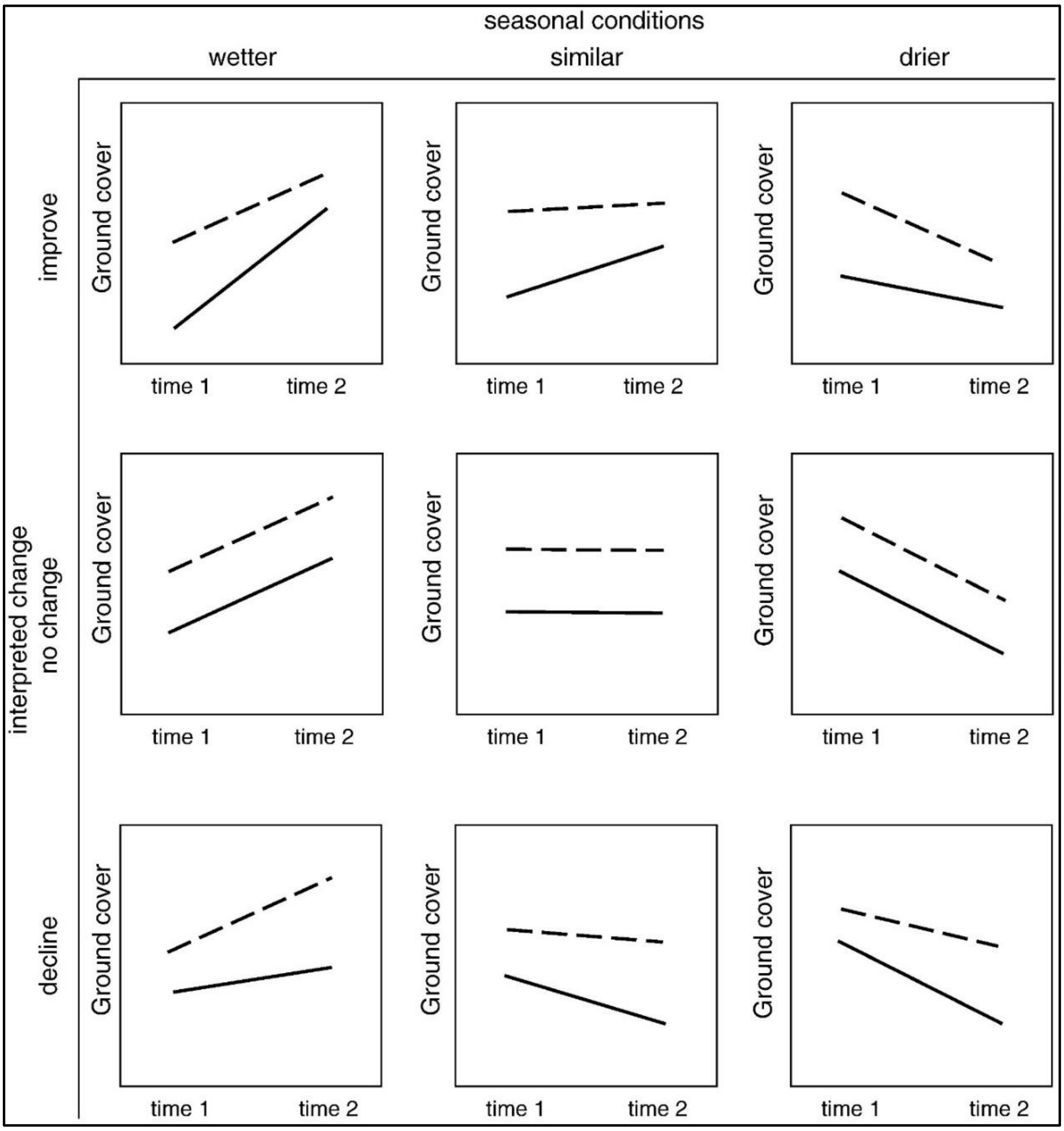

Figure 2-3: Framework for interpreting relative change in ground cover.
Cover Scores (solid line) and reference (dashed line). Seasonal conditions determined by reference trend and management signal determined by cover score trend relative to reference.. (after Bastin et al. 2012)

This method showed value in identifying the management signal for a study pixel when applied to a dry period with averaging across a paddock or property then providing an indicative ground cover score. Comparison of ground cover scores with reference cover values between successive dry periods provided a qualitative indication of trends in management signal between two dry periods (Figure 2-3).

Limitations of this approach for application in the QMDB included:

- The DRCM did not assess ground cover in timbered areas, which constitute a significant portion of grazing lands in the QMDB.
- The DRCM provided a qualitative measure of the trend of the management signal on ground cover but a quantitative measure was required for the QMDB to estimate the impact of management on soil loss and stream sediment loads.
- The DRCM was limited to assessing change from one dry period to another whilst a continuous measure through wet, normal and dry seasons was required for the QMDB.
- The DRCM has only been applied or tested in rangelands and not in areas that have been cleared for grazing such as large parts of the non-rangeland parts of the QMDB.
- The DRCM did not utilise more recently available ground cover products, specifically the seasonal composite totals of fractional ground cover and the inclusion of ground cover estimates for areas with up to 60% foliage projective cover (fpc) (Gill et al. 2017). The DRCM used annual ground cover values excluding areas above 20% fpc.

The DRCM did demonstrate the value of identifying a reference or aspirational ground cover value for a given season based on parts of the landscape that reflect high cover values that relate to a pixel or area of interest. This objective approach was preferable to previous works based on assumed changes in ground cover (Waters & Webb 2007; Rattray 2009; Webb 2012) or catchment averages (van den Berg, Trevithick & Tindall 2015).

Application of the DRCM was found to be adequate in reasonably homogeneous rangelands but not in areas with less definitive landscape stratifications (Barnetson et al. 2017, p. 24).

Barnetson et al. (2017) outline how a different approach was trialled in arid rangelands with the use of high-powered (cloud) computing (HPC) and extensive field data in arid areas. This approach “Characterising irregular ground cover growth cycles utilising dense time series methods” (p 24) shows capacity to decouple management effects from climate. The extensive field data and HPC resources were not available, however, for the study in the QMDB. What was adopted from Barnetson et al. (2017) was the use of standardised data to measure confluence or divergence of datasets. The approach of comparing linear models of standard deviations was considered useful in moving from the qualitative information in the schematic framework from Figure 2-3 to a quantitative trend for defined periods as required for catchment modelling.

2.5.1.2 Definition of homogenous grazing landscape units

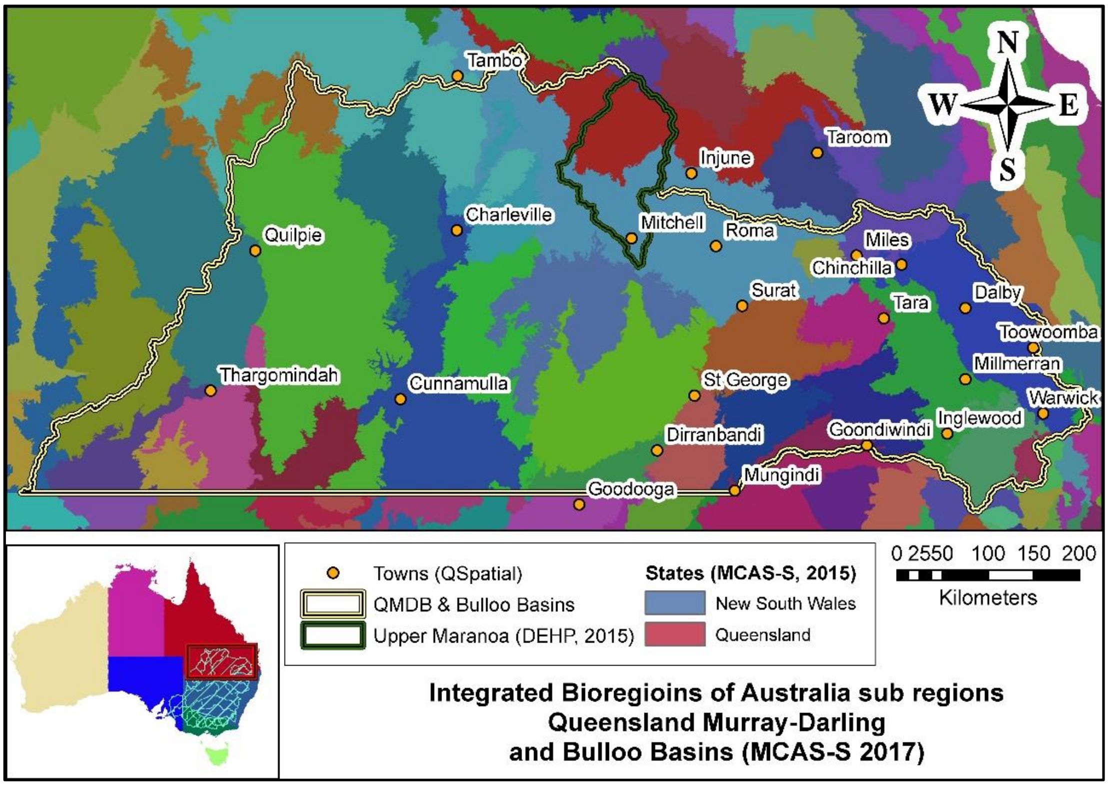

Figure 2-4: IBRA subregions in the Queensland

Bioregions and subregions have been established and refined across Australia in the Interim Biogeographic Regionalisation for Australia (IBRA) (IBRA 2014). The subregions (Figure 2-4) are based on broad climate and landscape characteristics that would lead to variations in vegetation types. Although these would give some guidance to zones with similar pasture performance, they are large areas and include wide variations in both average and annual climate within regions. Similarly, previous zoning of Australia into climate regions (Figure 2-5) has been based on generic climate descriptions resulting in even greater variations in average and annual climate within zones (Bureau of Meteorology 2005)

Finer resolution landscape zones have been established with Land Types and Land Systems zoning which incorporate topography and soil characteristics within broader regions (State of Queensland 2017). These are conceptually useful indicators for potential pasture production. Interaction between land types or land systems within a management unit (property), however, can make these units unsuitable for assessing impact of management on groundcover at property scale or wider (Bastin et al., 2012). Bastin et al. (2012) also highlighted that local levels of woody vegetation cover should be considered when establishing reference areas and homogeneous landscape units (cf p 447).

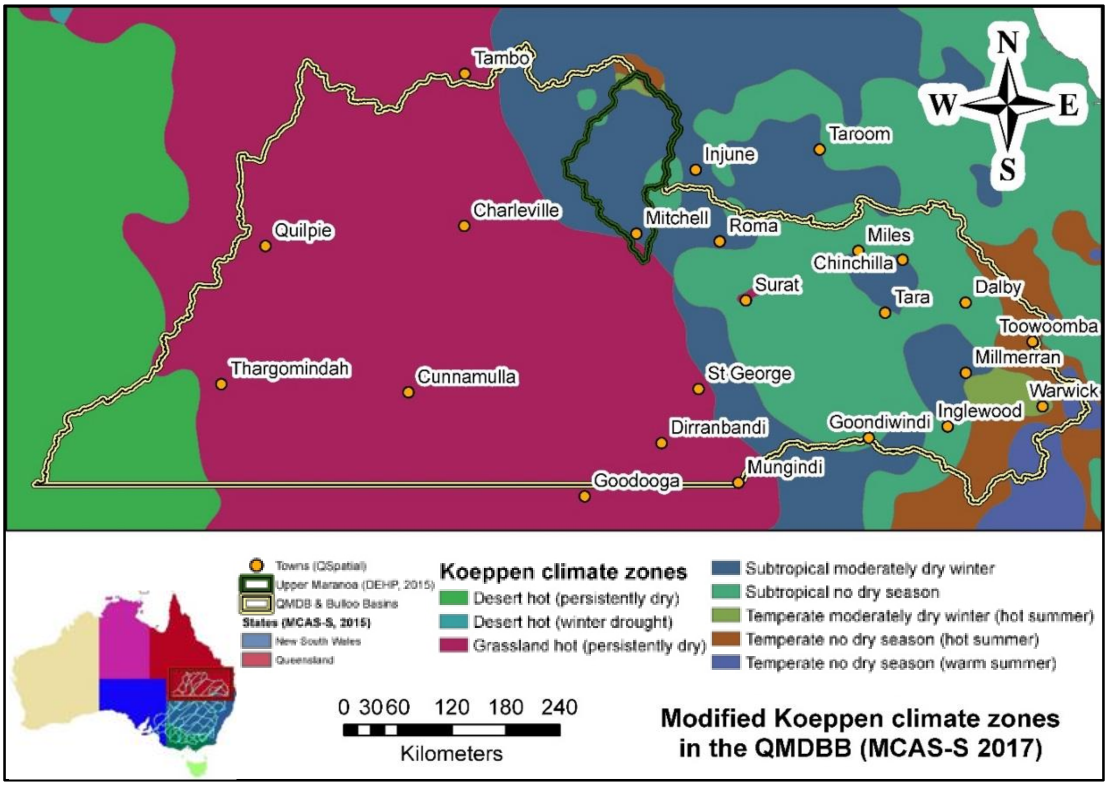

Figure 2-5: Modified Koeppen Climate Zones

From these previous works, zones where management impact on grazing in varying climate conditions could reasonably be compared should be finer than subIBRA zones and Koeppen climate zones, should not go down to Land Type or Land System resolution, and should consider levels of woody vegetation cover.

2.5.2 Catchment modelling to estimate stream sediment loads

In Queensland Great Barrier Reef Catchments (Reef Catchments), changes in soil loss from grazing lands and associated changes in stream sediment loads are estimated based on assumed changes in land management practices (Waters et al. 2014). From the eWater Source modelling framework, "In grazing areas, the Universal Soil Loss Equation (USLE) was used to generate daily loads, with the grazing systems model GRASP used to derive changes in ground cover (C-factor) in the USLE model, reflecting different grazing management practice" (p iii).

Within the QMDB, a Source Model has been established with C-factor values calculated from (satellite) observed ground cover from 1986 to 2017 (Davidson 2018). The model is hosted by the Department of Natural Resources Mines and Energy (DNRME) and was made available for this study. Availability was based on the understanding that DRNME staff would run model scenarios with C-factors recalculated from synthesised ground cover datasets developed in this study. That is, the only variation in model inputs for all model runs is the groundcover data values which is provided as 124 raster scenes based on the findings and spatial data manipulation work of this study.

Fu et al, 2019 list the differentiation of climate impacts and land management effects as one of 11 key challenges for catchment models (Fu et al. 2019, p. 75). This study seeks to address this issue in a way that uses existing public datasets and tools to assess the outcomes of NRM investment.

2.6 Summary

In Sections 2.1 to 2.3 it was demonstrated that Australian Governments have made significant investment in NRM and, since 2002, in Regional NRM delivery. Section 2.4 described how although activities and outputs are well documented, intermediate outcomes and final outcomes have not been adequately quantified. This work affirmed the value of addressing the research aims and objectives documented in Chapter 1.

Section 2.5 described how ground cover and hillslope erosion would be used to evaluate outcomes including previous work that would be used or adapted to achieve the research objectives. Previous work included the use of ground cover data to evaluate changed management (intermediate outcome) and the use of catchment modelling to assess the impact of change on soil loss and stream sediment loads (final outcome).

Chapter 3 will provide more detail on the datasets, tools and methods that will be used to evaluate NRM intermediate outcomes and final outcomes in a study catchment in the QMDB.

Chapter 3 Methods

3.1 Introduction

Chapter 2 demonstrated that activities and outputs from NRM investment are well documented but that intermediate and final outcomes have not been adequately assessed. In this context this study was to evaluate a "slice" of regional NRM investment in the Queensland Murray-Darling Basin to determine if intermediate expected outcomes were achieved.

The regional NRM investment program evaluated was that delivered by the Queensland Murray-Darling Committee (QMDC) to change management practices in grazing lands. Changed practices were expected to lead to improved ground cover leading to reduced erosion and stream sediment loads. The QMDC NRM program had two key components intended to promote and support changed (improved) management practices. Components were:

- Extension **activities**, and,
- Incentives projects (**outputs**).

These activities and outputs were expected to result in:

- **Intermediate outcomes** of increased ground cover, and subsequently,
- **Final outcomes** of reduced erosion and reduced stream sediment loads.

NRM program evaluation was undertaken in line with the research objectives listed in Chapter 1, Section 1.4. These can be summarised as:

1. To determine whether or not ground cover increased across properties involved in extension activities,
2. To determine whether or not ground cover increased at incentive project areas, and,
3. To estimate changes in soil loss and stream sediment loads due to changes in ground cover.

Literature reviewed in Chapter 2 demonstrated the capacity of remote sensing ground cover data, tempered with climate data, to address objectives one and two. The eWater Source catchment model, also reviewed in Chapter 2 was used to address objective three.

3.2 Study area

QMDC delivered extension and incentives activities across the Queensland Murray-Darling Basin but particularly in the Maranoa-Balonne, Moonie and Border Rivers catchments. Activities were not limited to grazing lands with dryland farming, irrigated farming and nature refuge areas also being considered. For this study, to get a clear indication of any benefits of incentives for ground cover in grazing lands the criteria for site selection were a significant extension (supported) area, a significant unsupported area (control) and predominantly grazing land. With grazing land, the number of variables that might affect both ground cover and sediment loads are reduced, through exclusion of cultivation.

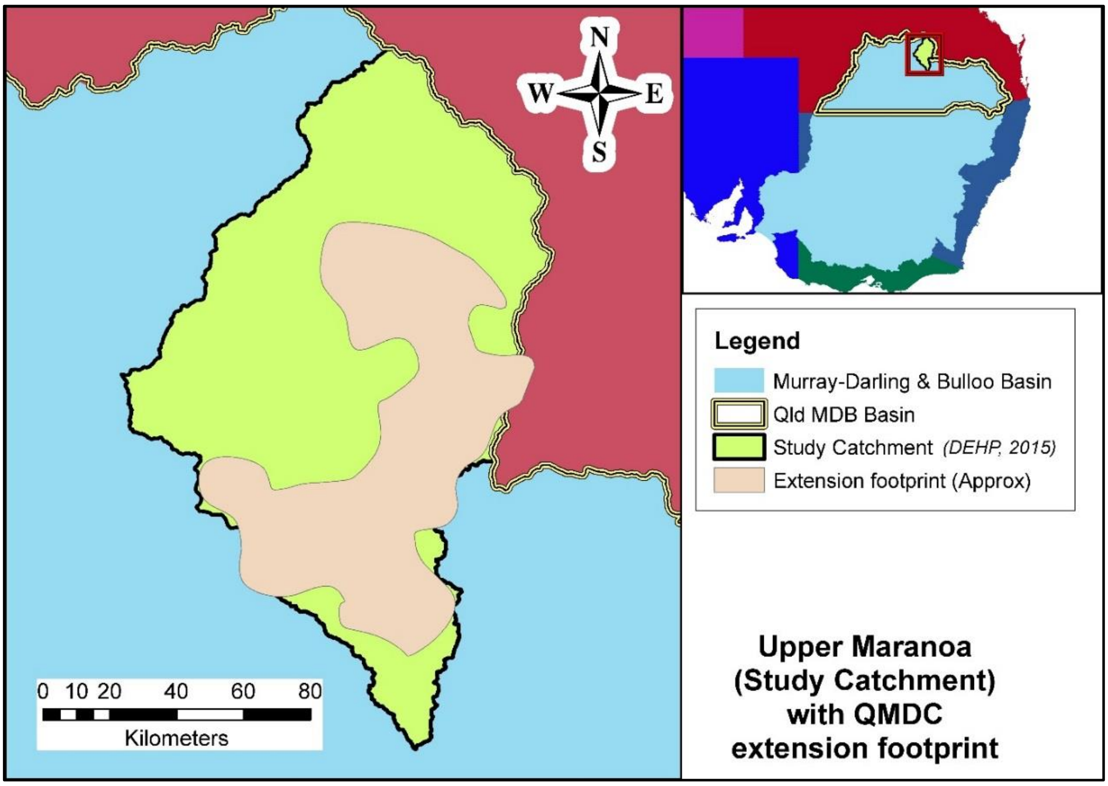

Figure 3-1: QMDC supported properties in the study catchment (adapted from Coppard et al. 2016)

The Upper Maranoa was selected as an ideal study catchment (Figure 3-1). The total catchment area is 12,152 square kilometres (Department of Environment and Heritage

Protection 2015), of which 96% is grazing land and only 4% non-grazing land (Queensland Land Use Mapping Program (QLUMP) 2017). Approximately 60% was grazing land with no direct NRM support, 36% was grazing land with direct NRM support through extension programs, 8% (by area) also received incentives payments (Coppard et al. 2016) (Figure 3-2 and Table 3-1).

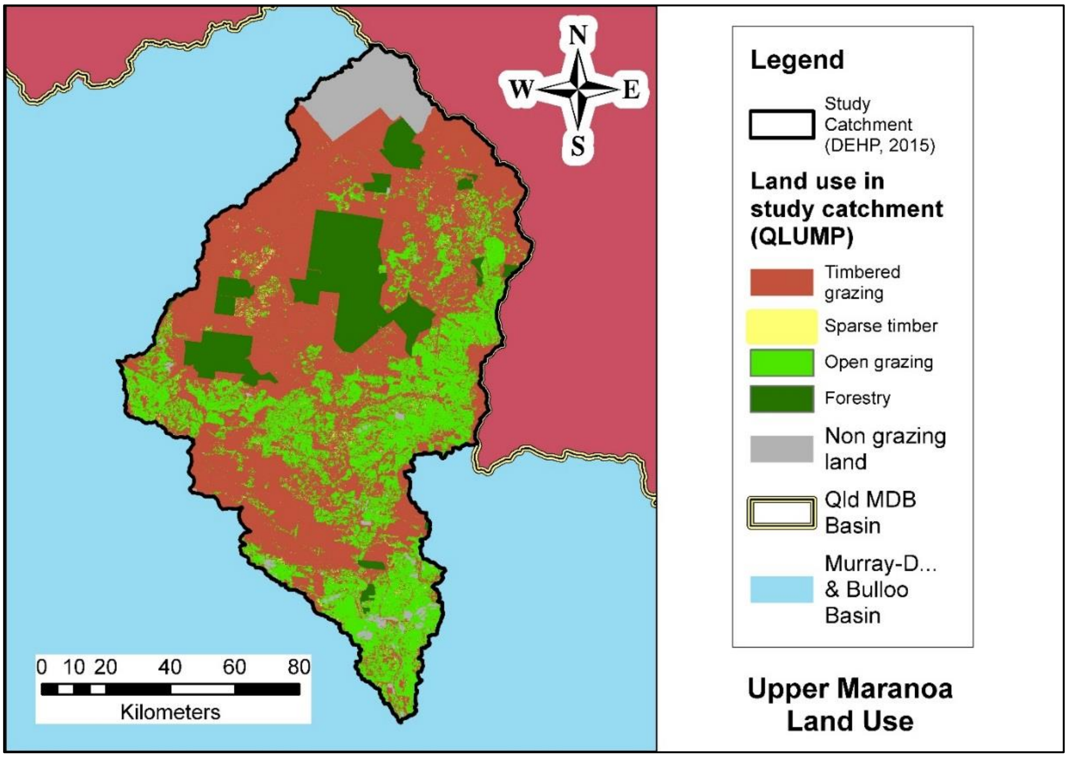

Figure 3-2: Land use in the study catchment

Table 3-1: Upper Maranoa Catchment extension and incentive areas

Upper Maranoa	**Area (km^2)**	**%**
Catchment	12,152	100
Grazing lands not directly supported with NRM activities	7,320	60
Grazing lands directly supported with NRM extension programs	4,368	36
Grazing lands directly supported with NRM extension programs and incentives	(920)	(8)
Non grazing lands	464	4

3.3 Datasets and tools

A range of data were used and in some cases produced to enable this Regional NRM Evaluation. Groundcover data were required to enable comparison between different areas through time as required for research objectives 1 & 2:

- **Remote sensing groundcover data were** used in the study due to the availability from the Queensland Government of seasonal data developed from USGS Landsat imagery for a period including both the Regional NRM period and a significant prior period (Scarth et al. 2015). The prior period included activities undertaken through Landcare and the associated National Grants Programs (Hajkowicz 2009).
- **Regional NRM investment area data** were required to identify areas within the study catchment where properties did, or did not, receive support from NRM programs.
- **Climate data** were required to identify areas where groundcover could reasonably be compared and to facilitate the isolation of the management signal from the climate signal in seasonal groundcover data.
- **Additional spatial datasets** were used to refine areas for comparison and to support the interpretation and presentation of data and results from this study.

In addition to the datasets used, a number of tools were used to collate, analyse and present data for the purposes of NRM Program evaluation. These included:

- **The eWater Source Catchment Model** which was required to achieve research objective 3 using data outputs from work undertaken to achieve objectives 1 & 2.
- **The R language and environment for statistical computing** was used to collate, manipulate and analyse large temporal and spatial datasets identified above.

- **Microsoft Office** software including Word, Excel and PowerPoint provided under licence by USQ, and,
- **ESRI Arcmap** Geographic Information Systems (GIS) software for mapping and spatial data analyses, provide under licence by USQ.

In addition to these formal datasets and tools, there is a critical link between research, policy and sustainable landscapes and the **land managers**. In this study, initial findings were presented to landholders who were able to provide advice and caveats on how the datasets and analyses relate to the experiences of the programs and the Regional NRM period. Access to landholders for the purposes of this study was itself both reliant on and a potential contribution to the “**social capital**” that may have come from NRM investment. This highlights the “importance of relationships alongside economic, human and natural capital in solving collective action problems” (Sobels, Curtis & Lockie 2001).

3.3.1 Remote sensing groundcover data

To enable a study of groundcover across the study catchment through the extended NRM investment period, consistent and accessible groundcover data were required. Such data needed to be for all supported and unsupported areas in the catchment to enable comparison of different areas through time. Although a number of landholders were known to collect groundcover monitoring data, the extent, consistency and continuity of such data were not expected to be suitable for this study. Remote sensing groundcover data were seen as a preferred alternative due to the consistency, extent and availability of the data.

Seasonal ground cover estimates at 30m square cell size derived from USGS Landsat images are developed and maintained by the Queensland Department of Environment and Science (DES) Remote Sensing Unit (Joint Remote Sensing Research Program 2018). This study mapped discrete project areas as reference, control or supported areas in or near the study catchment. Spatial data files for each of 330 project areas were provided to DES staff. DES staff used these files to query the seasonal ground cover archives and supply seasonal ground cover data for use in this study. This study then collated and analysed these data together with climate data, NRM investment information, landholder interview data and other spatial datasets to evaluate management within and outside NRM project areas.

3.3.2 Regional NRM investment areas as study sites

To enable the comparison of properties that had received support under the Regional NRM programs with other areas, it was necessary to have detailed data on the spatial extent of properties that received support. QMDC provided spatial data which included properties that participated in extension activities as well as details of incentives project areas within these properties that were the specific focus on the funding.

Spatial data were available for all QMDC activities but was scrutinised and used only for the Upper Maranoa catchment. This study catchment was selected due to the significant QMDC footprint and the dominant grazing land use (see Section 3.2). QMDC data were provided through the QMDC Community Resource Information System (Coppard et al. 2016). Data were made available for use in this study only and subject to maintenance of anonymity of individuals who participated in extension activities or incentive projects.

3.3.3 Climate data for the modelling

In order to evaluate changes in grazing management and the impact on ground cover, it was first necessary to remove or minimise the climate signal from the seasonal groundcover data. This required fine resolution climate data that could be collated with groundcover data to support spatial and temporal analyses.

Climate data were accessed through the Queensland Government's (Scientific Information for Land Owners (SILO) database (Department of Environment and Science 2018). Daily data were accessed for approximately 7,000 sites based on a 0.1 degree grid across the Queensland Murray-Darling and Bulloo Basins (QMDB) plus a buffer area. This included areas well beyond the study area allowing findings of this study to be validated with work in other areas (for example, the Bulloo Downs data analysis described in Appendix 3.1). Inclusion of the wider QMDB also means findings from this study can be used for further studies such as water quality target setting across the basin (Newham et al. 2018).

Climate data were in the standard SILO format using the "FAO56" data template (Jeffrey et al. 2001). This included daily rainfall, maximum and minimum temperature, pan evaporation, solar radiation, vapour pressure, relative humidity and potential evapotranspiration calculated using the FAO Penman-Monteith formula (Allen et al. 1998).

3.3.4 Other spatial datasets

A number of other key spatial datasets were acquired from the Queensland Spatial Catalogue (QSpatial) to define areas for groundcover data analyses. These included:

- The Queensland Digital Cadastre Database (Queensland Department of Natural Resources and Mines 2016) which was used to determine land tenure and to confirm property boundaries for properties supported in NRM projects.
- Land use mapping (Queensland Land Use Mapping Program (QLUMP) 2017) was used to determine grazing areas and forestry areas.
- Foliage Projective Cover data (Queensland Remote Sensing Centre 2014) was used to assign land use classes based on the (canopy) foliage cover.
- Water Quality type zones (Department of Environment and Heritage Protection 2015) were used to define catchments for this study with alignment to ongoing development of water quality related catchment targets (Newham et al. 2018).

Additional datasets used for displaying data on maps were obtained from QSpatial (Department of Natural Resources Mines and Energy) and MCAS-S (Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) 2015). These included layers such as towns, roads, rail and rivers.

3.3.5 The catchment model

Research Objective 3 required that changes in groundcover due to management be translated in to estimated soil loss and stream sediment loads in the study catchment and receiving waters. This required a mechanism to quantify sediment generated from known climate data with a range of seasonal groundcover “scenarios”. The Queensland Department of Natural Resources, Mines and Energy (DNRME) had developed a model suitable for this purpose and the QMDB Source catchment model was made available for the study (Davidson 2018).

This model uses seasonal "visual ground cover" data (VGC) derived from Landsat Satellite images (cf Queensland Remote Sensing Centre 2014) to estimate soil loss from surface erosion. This study synthesised VGC (124 raster scenes) for each of a number of model run scenarios based on the findings from groundcover management signal analyses. These VGC scenarios were imported into the Source model by DNRME staff who then executed model runs and made outputs available for interpretation and reporting.

3.3.6 The application of R software to process large datasets

As outlined in previous sections, a number of datasets were acquired for this study including temporal and spatial data. To achieve Research Objectives 1 and 2 approximately 7,000 climate datasets were accessed with monthly data for over 100 years. Also acquired for these objectives were seasonal groundcover data for more than 400 discrete areas with data for 30 years. These data needed to be collated and analysed in a documented and repeatable manner. To then incorporate findings from the temporal data analyses into the catchment model (Research Objective 3 requirement), spatial data manipulation was required for numerous large raster files for ground cover data inputs into the Source model.

Temporal and Spatial data collation and analyses for this study was undertaken using the free R language and environment (version 3.5.2).

> R is a language and environment for statistical computing and graphics. R provides a wide variety of statistical (linear and nonlinear modelling, classical statistical tests, time-series analysis, classification, clustering, …) and graphical techniques, and is highly extensible (R Core Team 2018).

Scripts developed with R for this study are set out in Appendix R. These scripts were developed and run on the RStudio platform (version 1.1.463) provided by the jQuery Foundation (https://jquery.org/).

The use of this open source software and the inclusion of the scripts in Appendix R ensures capacity to review the study methods in detail and to repeat or adapt methods for future studies.

3.4 Developing a model of Climate Landscapes

To facilitate the comparison of groundcover across different areas to evaluate management, it was first required that homogeneous "Climate Landscapes" be defined where groundcover could reasonably be compared. From the previous works outlined in Section 2.5.1, landscapes where management impact on grazing in varying climate conditions could reasonably be compared should be finer than IBRA sub regions and Koeppen Climate Zones (Figure 2-4 and Figure 2-5) to avoid gross variations in climate variables within zones. Conversely, zones should not go down to Land Type or Land System resolution that is to property level and subject to topographic variations such as run-on (Bastin et al. 2012). Figure 3.3 shows a flow path for the derivation of Climate Landscapes.

3.4.1 Climate Clusters

The SILO daily climate data were for a region that included the QMDB and Bulloo Basins (QMDBB) from a data drill at 0.1-Degree intervals for the area bounded by 141.5 to 153.0 Degrees East and 24.0 to 30 Degrees South. These data for 6,941 sites (omitting 19 sites over the ocean) were provided by DES staff on request following an online data query on the Long Paddock/SILO website (Department of Environment and Science 2018). The SILO data were collated and summarised by season using purpose written R Script *010_SILO climate data preparation* (Appendix R).

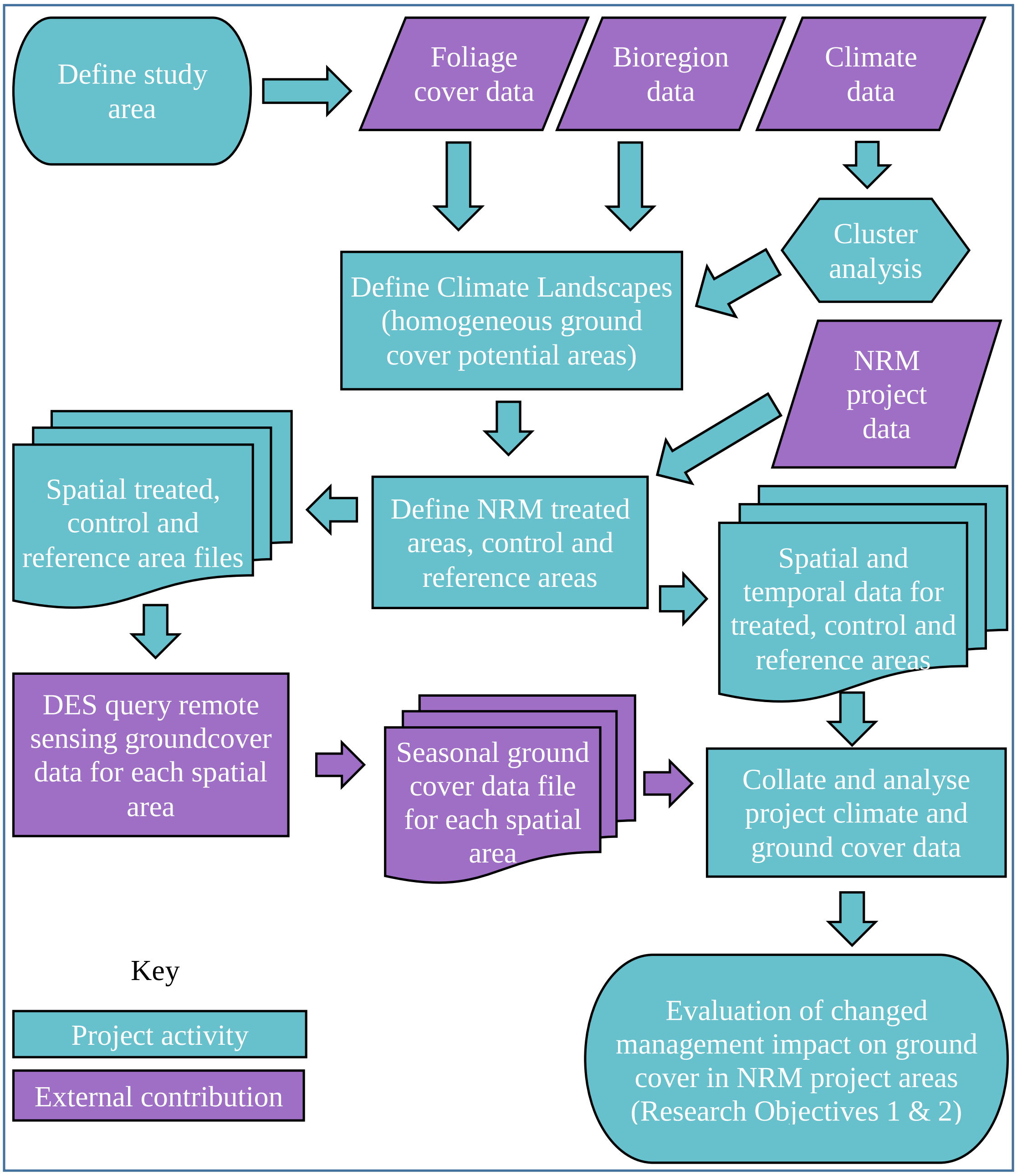

Figure 3-3: Flow path for data access and analyses for ground cover evaluation

The SILO data were to be analysed using the HiClimR package (Badr, Zaitchik & Dezfuli 2014) to divide the QMDBB into Climate Clusters. That is, areas determined from sites with similar climate based on a similarity analysis of gridded climate data. Before running the HiClimR analyses, however, a suitable number of clusters was investigated. To achieve this, data were analysed to determine "natural breaks" where the data itself indicated degrees of homogeneity between different sites.

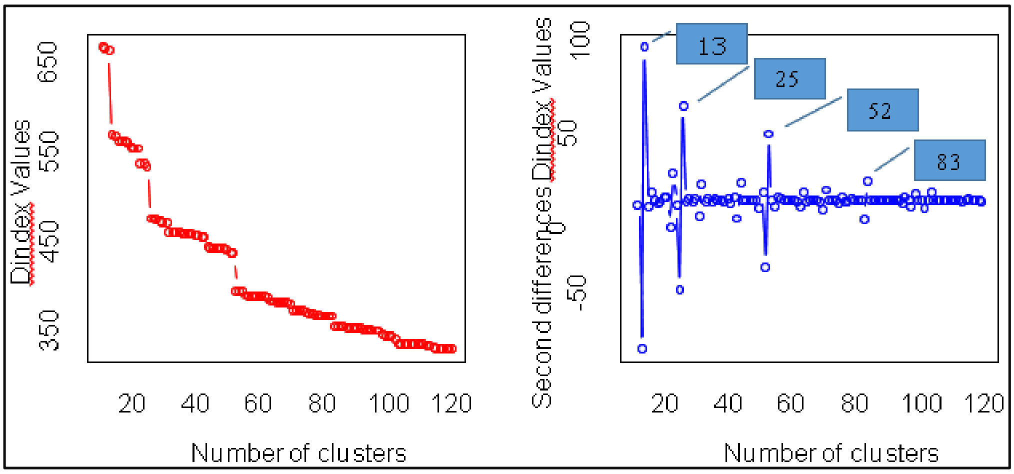

Figure 3-4: Dindex analyses of climate data
Values and second differences for clustering showing breaks at 13, 25, 52 and 83

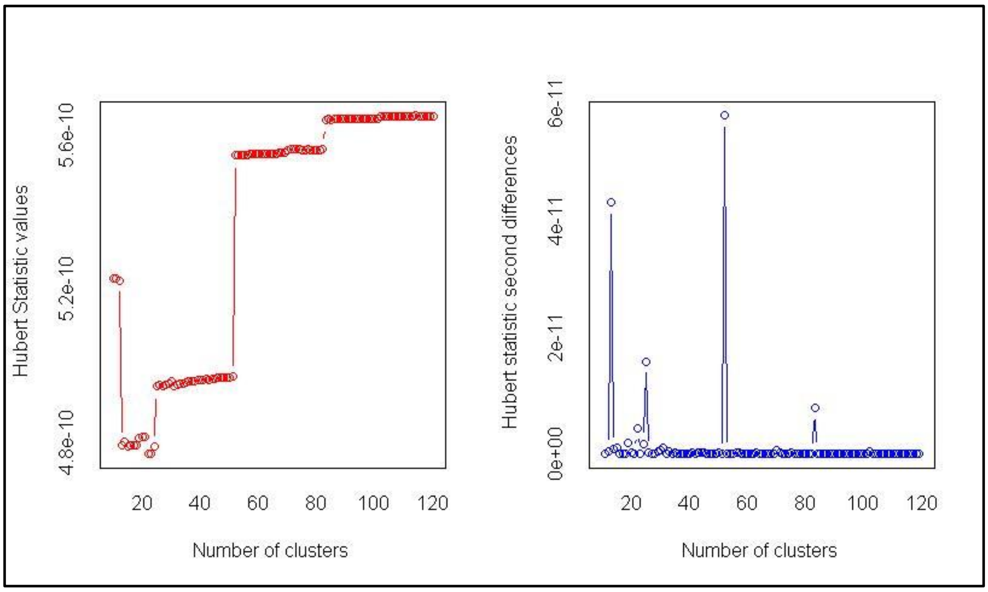

Figure 3-5: Hubert Statistic analyses of climate data
Values and second differences for clustering showing breaks at 13, 25, 52 and 83

Natural breaks in data were found at 13, 25, 52 and 83 clusters with both the Dindex and Hubert Statistic (Figure 3-4 and Figure 3-5 respectively) obtained by the use of the NbClust package in R (Charrad et al. 2014)). The Hubert Statistic and second difference (Hubert & Arabie 1985) indicated a major break at 52 clusters (Figure 3-5) and no major break after this, indicating having at least 52 clusters will achieve significant homogeneity but that improvements after that are modest and gradual. 52 was adopted as the number of clusters to discern using the McQuitty analysis with consideration of seasonal rainfall, minimum temperature, maximum temperature and evapotranspiration for 1990-2017 (period of available ground cover data). The

McQuitty "Similarity Analysis by Reciprocal Pairs" is suited to analysing continuous data into hierarchical Types (McQuitty 1966). Climate data were analysed to create 52 Climate Clusters (Figure 3-6) using the HiClimR package in R (Badr, Zaitchik & Dezfuli 2015).

Analyses were performed using purpose written R Script *020_Cluster analysis and landscape mapping* (Appendix R).

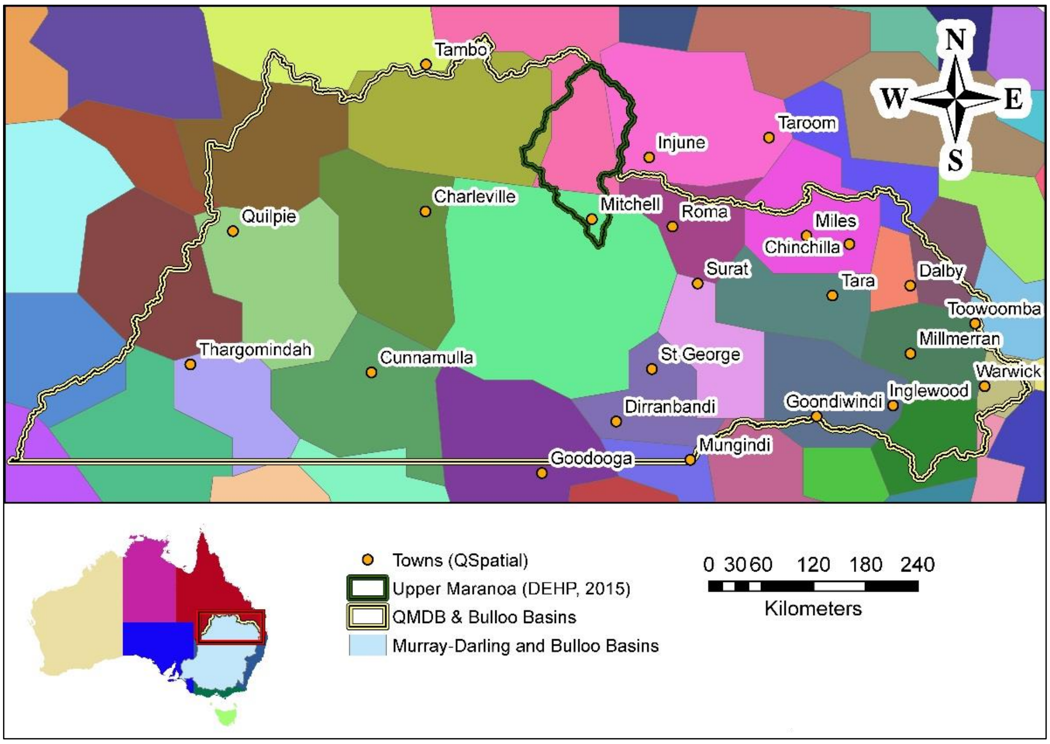

Figure 3-6: Climate Clusters for the QMDBB

3.4.2 Climate Zones – Climate Clusters and IBRA Sub Regions

Gross changes in landform can lead to changes in pasture performance within an area exposed to similar climate. For example, ground cover data for Bulloo Downs in channel country showed variations in ground cover characteristics aligning with IBRA subregions within a climate zone (data from Berman, Brennan & Elsworth 2011 described in Appendix 3.1). The 52 Climate Clusters for the QMDBB (Figure 3-6) were combined with IBRA subregions to define Climate Zones where pasture production potential, and ground cover, would be similar given constant tree cover and management (Figure 3-7 for the QMDBB and Figure 3-8 for grazing lands in the Upper Maranoa study catchment).

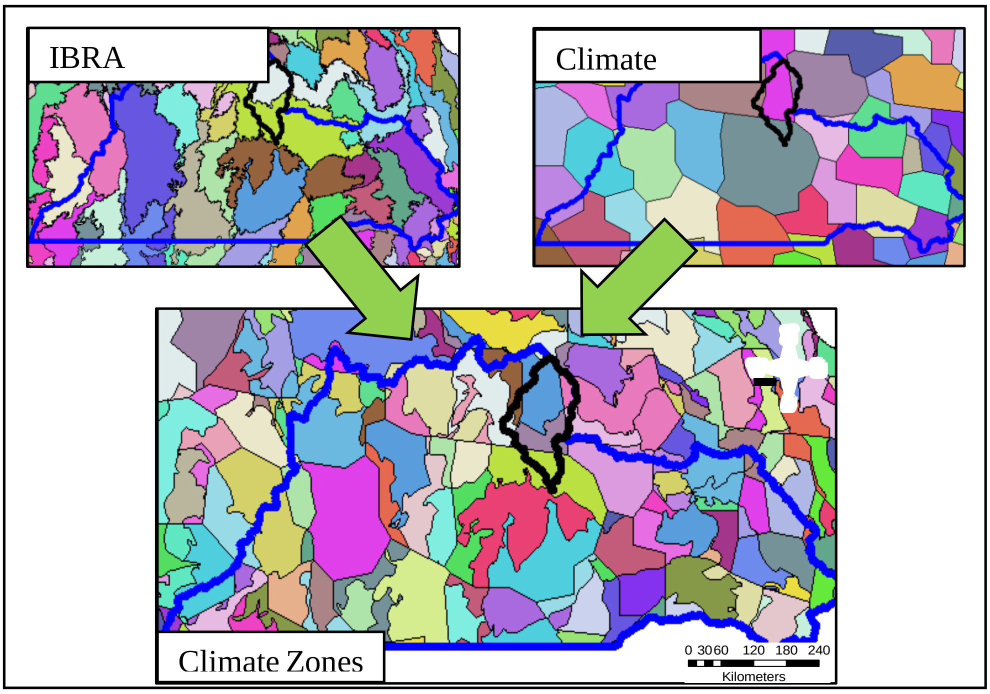

Figure 3-7: Climate Zones for the QMDBB

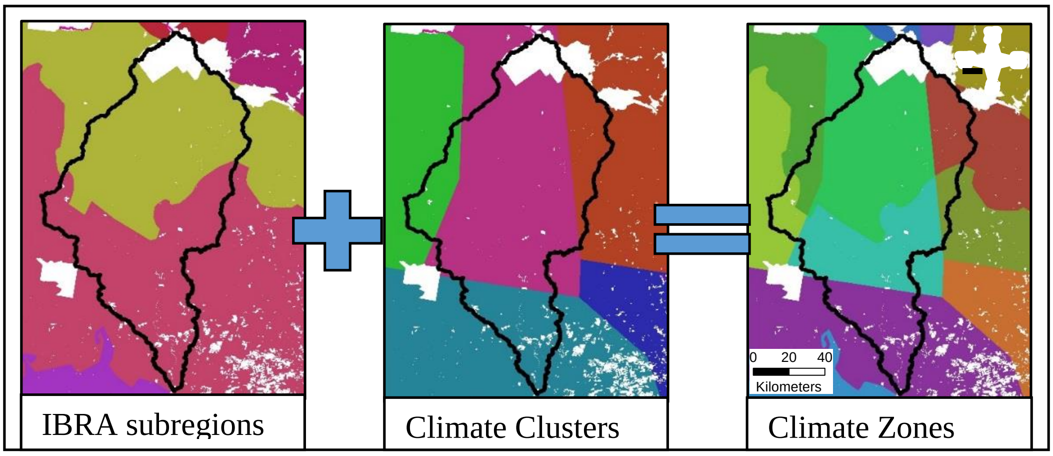

Figure 3-8: Climate Zones for the Upper Maranoa study catchment

3.4.3 Climate Landscapes from Zones and Vegetation Classes

In the previous section, Climate Zones were defined by combining areas with similar climate characteristics (Climate Clusters) and broad land forms defined by IBRA subregions. In early work described in Chapter 1, Section 2.5 and in more detail in Appendix 3.2, it was determined that vegetation classes also affected groundcover. Specifically, ground cover in timbered areas was less volatile than in adjacent non-timbered areas. It was therefore necessary to further divide Climate Zones based on timbered vegetation classes within areas of grazing land use. Classes used are described in Table 3-2.

Table 3-2: Grazing land use classes based on vegetation and tenure

Grazing land use vegetation class	**Definition**	**Source**
Open Grazing	< 1% SLATS Foliage Projective Cover	"isolated trees" in NVIS and SLATS
Sparse Timber	1-10% SLATS Foliage Projective Cover	"isolated clumps of trees" and "open woodland" in NVIS and SLATS
Timbered Grazing	> 10% SLATS Foliage Projective Cover	"woodland" and "forests" in NVIS and SLATS
Forestry	Forestry tenure over land parcel	DCDB

SLATS = Statewide Landcover and Trees Study , Queensland (SLATS 2017)
NVIS = National Vegetation Information System, Version 7
(NVIS Technical Working Group 2017)
DCDB = Digital Cadastre DataBase (DNRM, 2016)

Three classes align with Foliage Projected Cover based classes in SLATS and NVIS (NVIS Technical Working Group 2017, p. 39 Table 7; Queensland Department of Environment and Science 2018, p. 2 Table 1). The separation of Forestry areas as a fourth grazing land use class was based on the assumption that grazing management was different in these areas held under forestry lease arrangements. The Climate Zones (Figure 3-7 and Figure 3-8) were split on these four land use classes to establish Climate Landscapes (Figure 3-9). With pasture production potential expected to be similar within each of these Climate Landscapes, variations in ground cover characteristics were assumed to be due to management.

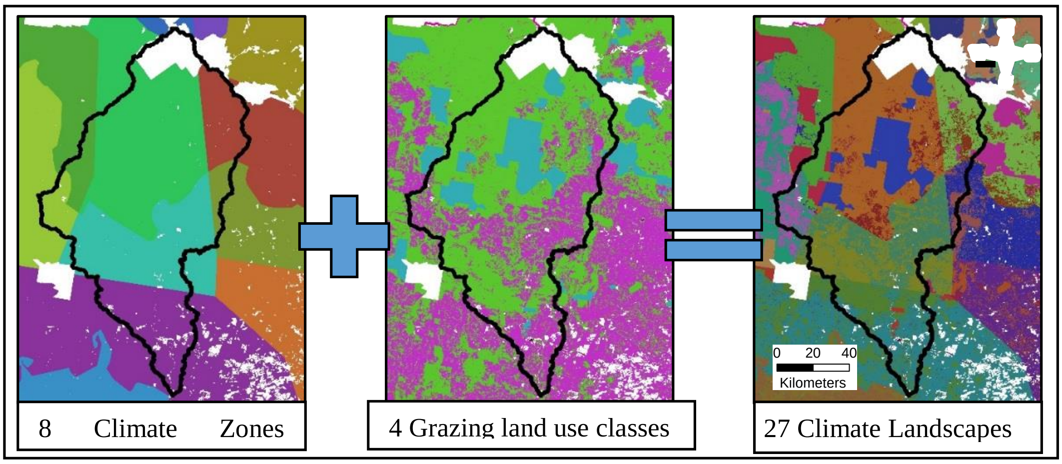

Figure 3-9: Climate Landscape components intersecting the Upper Maranoa study catchment
Note that sparse timber areas were mostly small cluster of pixels and don't show in maps

The Climate Landscape mapping process was undertaken and documented in R Script *020_Cluster analysis and landscape mapping* (Appendix R).

3.5 Supported property areas, controls and reference areas

From data used in reporting to government funding bodies, QMDC provided information about properties that were supported with NRM program funding between 2004 and 2017 (Coppard et al. 2016). For purposes of landholder privacy, individual property details and project locations have been allocated random identification codes which are used for any outcomes analyses reporting. Individual property information is not included in any project maps or reports. This is a requirement of both the USQ Ethics permit and of the MOU between the researcher and QMDC in relation to this study. Properties were assigned to a climate zone according to their (within boundary) centroids. All areas within a property were assumed to be in the same climate zone. That is, if a property included areas in more than one climate zone, all climate landscape areas for that property were assumed to be in the climate zone in which the property centroid was located. This affected 10 of the 58 properties but was not considered to be a significant problem as management and land use zoning across each property was expected to influence ground cover variations more than small variations in average climate within properties (cf Bastin et al. 2012, pp. 445-6; Addinsoft 2013).

Within **supported properties**, available information was reviewed to isolate areas within individual properties where incentive projects were funded with an expectation of increased groundcover (cf Blakely 2016). These were identified as **incentives paddocks** within supported properties. Climate Landscapes and associated supported properties, incentives paddocks, controls and reference areas were mapped. Individual ArcGIS shapefiles were produced for each Climate Landscape unit within: each supported property and each incentives paddock. Shapefiles were also produced for each Climate Landscape within control areas and reference areas that intersected supported properties.

Supported properties included whole properties listed as having participated in NRM activities (see Figure 3-10 right). Areas within supported properties for which incentives payments were made were mapped as *incentives paddocks* (not shown due to landholder privacy commitments). Areas within each climate landscape that did not fall within supported areas but that were within the Upper Maranoa catchment area were determined to be *control* areas (Figure 3-10 centre).

Climate Landscapes were deemed to be *reference* areas for the determination of Aspirational, or best possible, groundcover values (Figure 3-10 left). These included supported areas and control areas as well as any parts of the Climate Landscape that was outside the study catchment. This process resulted in 420 spatial data files for:

- 88 reference areas,
- 27 control areas,
- 166 supported property (extension) areas, and,
- 139 incentives project areas (paddocks) within supported properties.

The 88 reference areas included all Climate Landscapes in the Upper Maranoa catchment. Of these, only 27 were used for comparative analyses as there were 27 Climate Landscapes intersected by supported properties and thus 27 derived control areas.

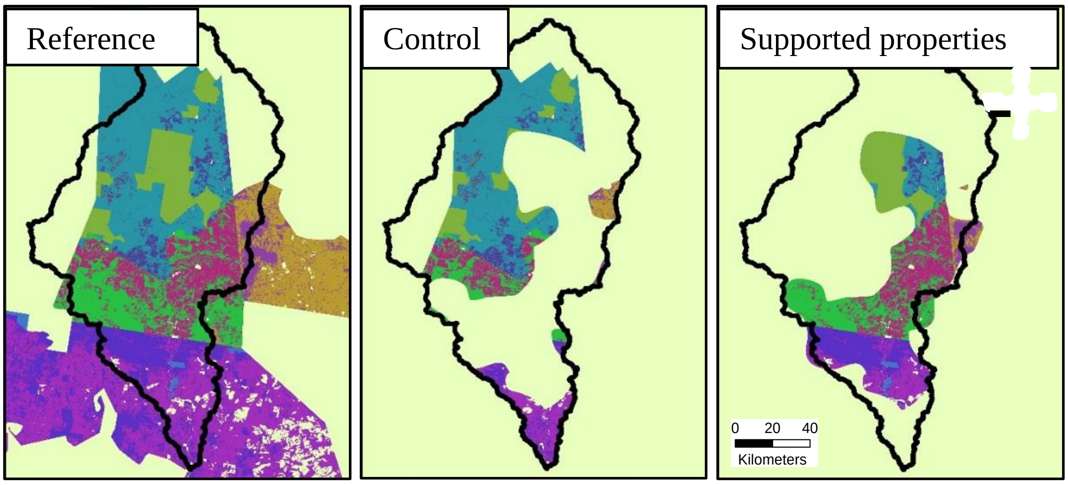

Figure 3-10: Climate Landscape areas used as reference, control and supported property areas
Note: Supported ("treated") area simplified for landholder privacy purposes.

3.6 Access and analyses of groundcover data

3.6.1 Data access

For each Climate Landscape within each supported property, incentives paddock, control and reference area, a shape file was produced. These 420 shape files were made available to Department of Environment and Science (DES) Remote Sensing staff. DES staff used these files to query the seasonal groundcover archives and create a ground cover data summary for each shapefile area. The flow chart in Figure 3-3 shows the ground cover data access and analyses processes. More information on this process and some early challenges are described in Appendix 3.1.

3.6.2 Groundcover Scores -adapted Dynamic Reference Cover Method

Each paddock, property and control area were contained within a Climate Landscape which served as a reference area. Pasture production capacity was assumed consistent across each (reference) Climate Landscape. Best possible groundcover in any Climate Landscape for a given season was assumed to be the 95% exceedance value for the reference (ref95). That is ,this was the % ground cover that was exceeded by only 5% of pixels in the reference area.

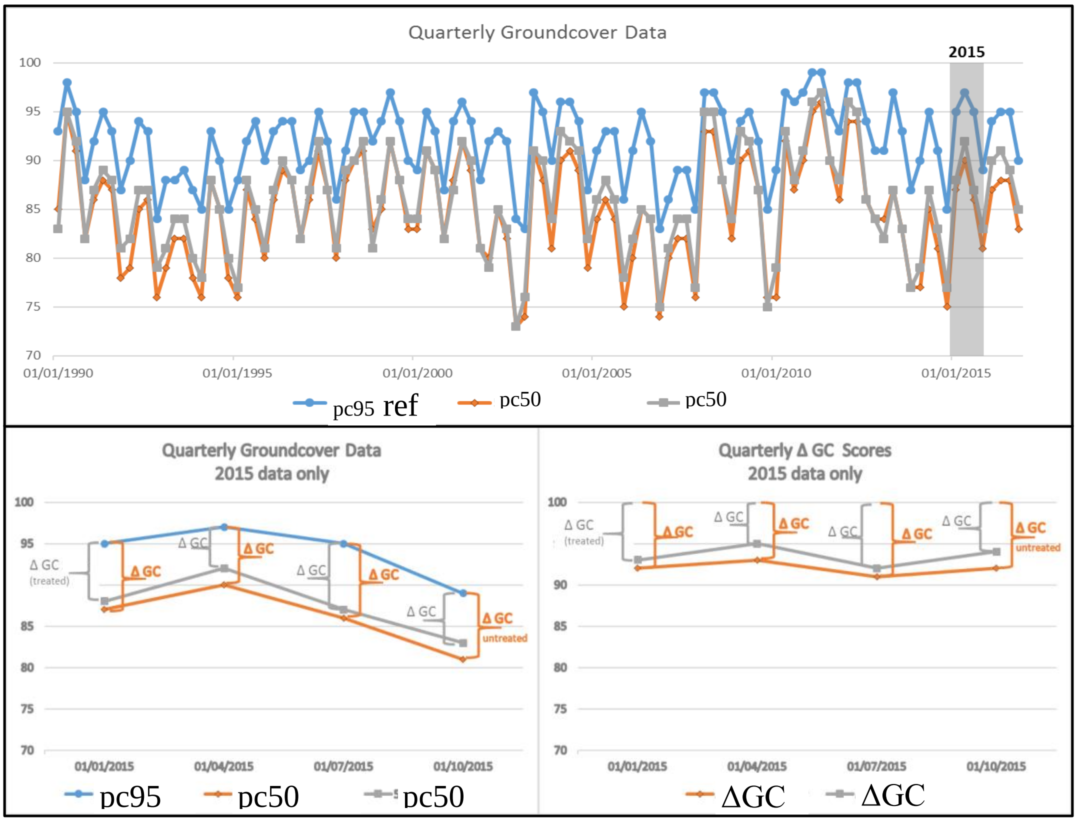

Figure 3-11: aDRCM Ground Cover score derivation
From seasonal median groundcover values for sample property area and control areas within the same reference Climate Landscape. Top: seasonal data for period of record; Bottom left: 2015 data; Bottom right: 2015 Scores

Groundcover scores (ΔGC) for a paddock, property or control were derived by comparing the median groundcover (pc50) with the ref95 value such that:

$\Delta GC = 100 - (ref95 - pc50)$ *Equation 1 (after Bastin et al. 2012)*

Figure 3-11 shows how this was applied to a sample property in the study catchment.

Ground cover scores were calculated using purpose written R Script *040_aDRCM groundcover scoring* (Appendix R) including the use of the ggplot2 package (Wickham 2009).

3.6.3 Method validation and application parameters

This study is assessing the impact of support on management and subsequent levels of groundcover affecting erosion risk and by implication the resulting sediment loads. Erosion risk is highest when groundcover is low and when rainfall is high (Silburn et al. 2011; Fraser & Stone 2016). From seasonal rainfall and cover data in the QMDBB, groundcover is lowest in summer and spring when rainfall is also highest (Figure 3-12). Spring is the end of the dry season with preceding cool, dry months resulting in minimal new pasture growth and ongoing utilisation. This is true of the study catchment which is classified as sub-tropical with moderately dry winters (Bureau of Meteorology 2005) and has its lowest recorded average ground cover in spring (76%) and summer (79%) (van den Berg, Trevithick & Tindall 2015). Northern Australia

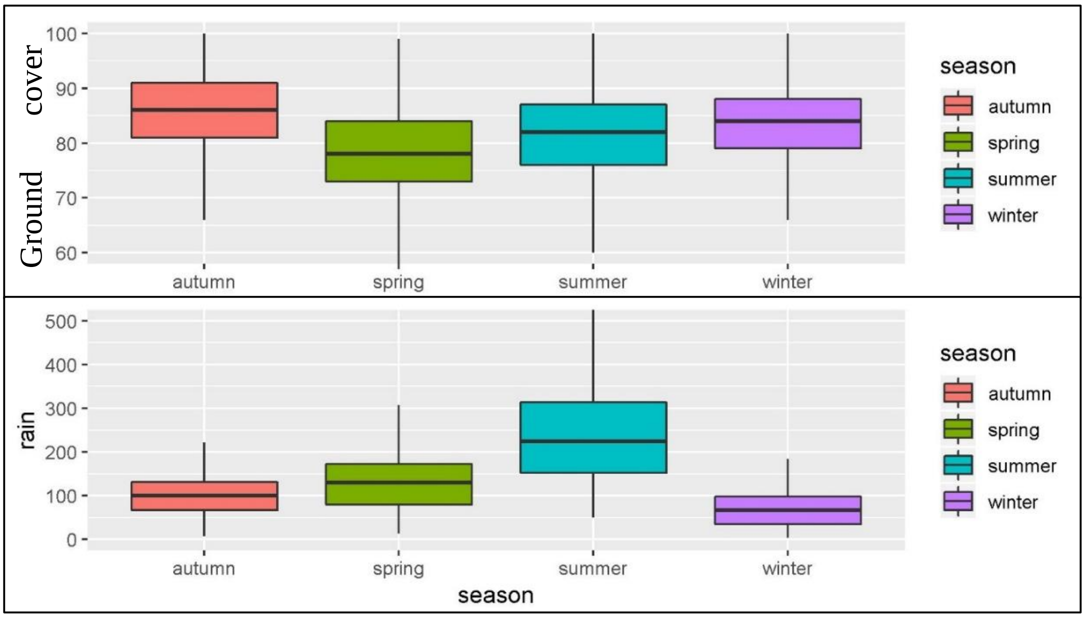

Figure 3-12: Seasonal median groundcover (pc50) and rain for the QMDBB

generally experiences low pasture productivity in winter and spring, with the main growth period in the summer and autumn from December to April (Brown et al. 2019).

With summer and spring identified as key seasons for consideration in evaluating erosion risk, Bastin et al.'s Dynamic Reference Cover Method (DRCM) was adapted to isolate management impact on cover from the influence of rainfall (Bastin et al. 2012; Bastin et al. 2014). The DRCM suggests that the deviation of cover in a landscape unit from the near best cover in that same landscape unit will give an indication of the management influence. This deviation (ΔGC) can be tracked over time with trends identified as ΔΔGC. That is, ΔΔGC represents the overall change in groundcover over time, across the seasonal effects. ΔΔGC can be compared with Δ reference (near best) cover to give an indication of whether ground cover is improving for reasons other than seasonal climatic factors, presuming therefore some influence of land and stock management.

Bastin et al. (2012 and 2014) found the management signal was strongest in spring and in dry years. They used a proximity grid to assess the reference cover but highlighted risks with this approach in broad landscapes with significant woody vegetation cover. This study used landscape areas defined by timbered or open grazing within Climate Zones to establish reference cover (see Figure 3-9). The adapted DRCM (aDRCM) uses 95% ground cover for a landscape as the reference (ref95). To have confidence in this approach requires that the raw GC value **is** correlated with climate and that the ΔGC **is not** correlated to climate.

In the Upper Maranoa pilot study catchment, DES Remote Sensing staff provided a groundcover data set for each of the 420 supported, control and reference areas in the study area. (Areas defined by spatial data files as described in section 3.5). Data sets each included 5, 20, 50, 80 and 95 percentiles of ground cover. The **5th percentile** is the ground cover value equalled or exceeded by **all but 5%** of pixels in the landscape (near worst ground cover). The **95th percentile** is the ground cover value equalled or exceeded by **all but 95%,** or, **by only 5%**, of pixels in the landscape (near best ground cover). The 5, 20, 50 and 80% values were subtracted from the reference 95% values and the difference subtracted from 100 to give ΔGC scores (D5, D20, D50 and D80).

To explore correlations between groundcover and rainfall, rainfall for 1 season (RF1 - season of groundcover observation only) through to 8 seasons (RF8 – total rainfall for season of observation plus preceding 7 seasons) were calculated. The expectation was that ground cover would correlate best to more than 1 year of cumulative rainfall,

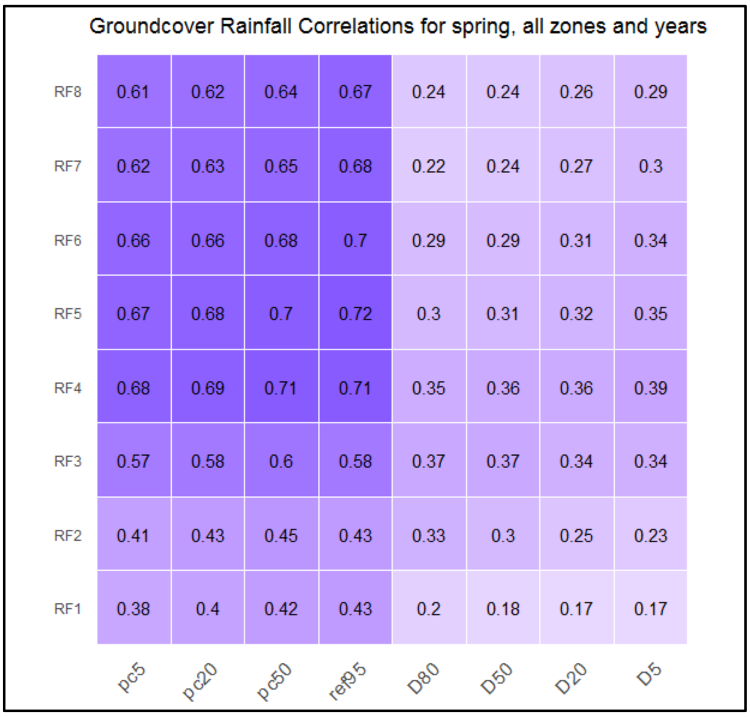

Figure 3-13: Heat map of Pearson's R for Rainfall v Groundcover
Rainfall (current season, RF1 back to including 7 preceding seasons, RF8) and various ground cover exceedences (pc) and ground cover scores (Dxx). Dxx 100-(ref95-pcxx).

however with moisture loss, there would be a limit to the effect of multiple years. Rainfalls were compared with groundcover % and with ΔGC scores for all seasons. Ground cover % exceedances generally had the strongest correlation with rainfall for the current season back to and including at least one summer (RF4-RF5 in pc columns in Figure 3-13).

To identify an indicator of management, data were reviewed to establish that: 1) % groundcover had a strong correlation with rainfall, and 2) ΔGC scores did not have a strong correlation with rainfall (thus confirming the significant removal of the climate signal from the ΔGC scores). Again, RF4 & RF5 showed the strongest contrast between % groundcover and ΔGC scores (pc and D columns in Figure 3-13).

The correlations and contrasts varied with different seasons, wet/dry/normal conditions and across Climate Zones. RF4 (rainfall for current and 3 preceding seasons) and D50 (100-(ref95 – median groundcover) were considered the most robust indicators of climatic conditions and of management signal respectively and were adopted as key indicators for the purpose of this study. See Appendix 4.1 for more results from the preliminary analyses including correlation heat maps by vegetation class, season and climate rating.

Correlations were calculated using purpose written R Script *050_Groundcover scores and climate data correlation anlyses* (Appendix R) including the use of reshape2 (Wickham 2007) and ggplot (Wickham 2009) packages.

3.6.4 Evaluation of NRM investment areas

ΔGC (50) scores were then adopted as a common "currency" to indicate whether or not there was a variation in residual management signal within and across Climate Landscapes. Comparisons were made:

- Between supported and unsupported properties (controls) in the Upper Maranoa catchment, individually and collectively (Research Objective 1), and,
- Between paddocks where incentive projects were implemented and control areas (Research Objective 1).

Analyses also considered the ground cover and the management signal across different landscapes, properties, seasons and climatic conditions.

Time series analyses were undertaken using R script *060_Groundcover scores time series and trend analyses* (Appendix R).

3.7 Landholder surveys to validate and explain results

From property information provided by QMDC, supported properties in the study area included 35 enterprises managing 57 properties. Managers of each enterprise were invited to participate in an interview and/or a survey. 29 enterprises responded and participated in interviews and 25 of these completed surveys with reference to 43 mapped property units.

Each enterprise was provided with preliminary findings of research for the catchment and for their own property. They were invited to complete a survey to rate and improve the analyses and to identify enhancers and inhibiters of improved grazing land management. They were also invited to provide any visual ground cover monitoring data that could be compared with remote sensing data.

The key purposes of the landholder surveys were:

- To reconcile groundcover data for each property with landholder's memories and/or with any available data.
- To gauge the validity of the groundcover scores through time. The intent was to determine if variations in groundcover scores aligned with property management circumstances and decisions.
- To gather data on perceptions of whether NRM extension activities enhanced grazing land management.
- To gather data on perceptions of whether NRM incentives projects enhanced grazing land management.
- To identify enablers and barriers to continuous improvement in grazing land management.

The survey and accompanying material (see Appendices 3.3) was designed to be self-explanatory so that surveys could be undertaken in an interview (preferred), by mail, or by email. The preference for interviews was to enable the researcher to understand the context in which the landholders were providing responses and to gain a better understanding of operational circumstances. That is also the mode that best enabled follow-up questions.

A pilot survey was undertaken with five enterprises covering 10 different property holdings. Minor changes were made to the surveys and to the accompanying material based on the feedback from the pilot surveys. These included minor changes to the wording of the survey and some changes in the colours and labels of maps and graphs in the property maps and ground cover reports.

All landholders were then invited to participate in the project through survey and/or interviews. A project information sheet was emailed to all participants for whom email addresses were available. Other landholders were called to establish interest levels and email addresses. Emails were followed up with phone calls to gauge interest and to schedule visits for interviews in August and September of 2018. For landholders who could not be contacted by phone or email, material was left in property letterboxes with a return address and contact information.

Interview and survey data and researcher journal notes were collated and depersonalised prior to inclusion as Appendices 4.3 to 4.5.

3.8 Trends in catchment groundcover, excluding climatic effects

Groundcover data were analysed across the entire study catchment through time to determine if there was a change in management signal. Periods assessed included the NRM investment period (2004-2017) and the preceding Landcare investment period (1990-2003). The approach used for these analyses was adapted from the ΔΔGC concept in the DRCM (Bastin et al. 2012; Bastin et al. 2014).

Although ΔGC scores remove some of the climate signal, Bastin et al. (2012) and this study has shown there is still a residual climate signal in the scores. The slope in the ΔGC, or the ΔΔGC, between two observation times could be compared with the slope in the reference observations, at the same two observation times to indicate whether management impact on ground cover was improving (Figure 3-14). While Bastin et al. (2012) had ungrazed enclosures as reference observations, this study used annual rainfall totals (RF4) as the reference. This was based on rainfall data availability and on the demonstrated strong correlation with GC and residual correlation with ΔGC scores (described in Sections 4.2 and 4.6). ΔGC scores and annual rainfall scores were standardised to allow them to be compared (Willett 1965).

Appendix 3.4 details how the data for trend analyses was determined and tested prior to the adoption of the following standardised data slope difference analyses.

Trends for 1990-2004 and 2004-2017 were calculated for both rf4 and ΔGC. These represented trends in climate (rainfall) and trends in groundcover scores with some

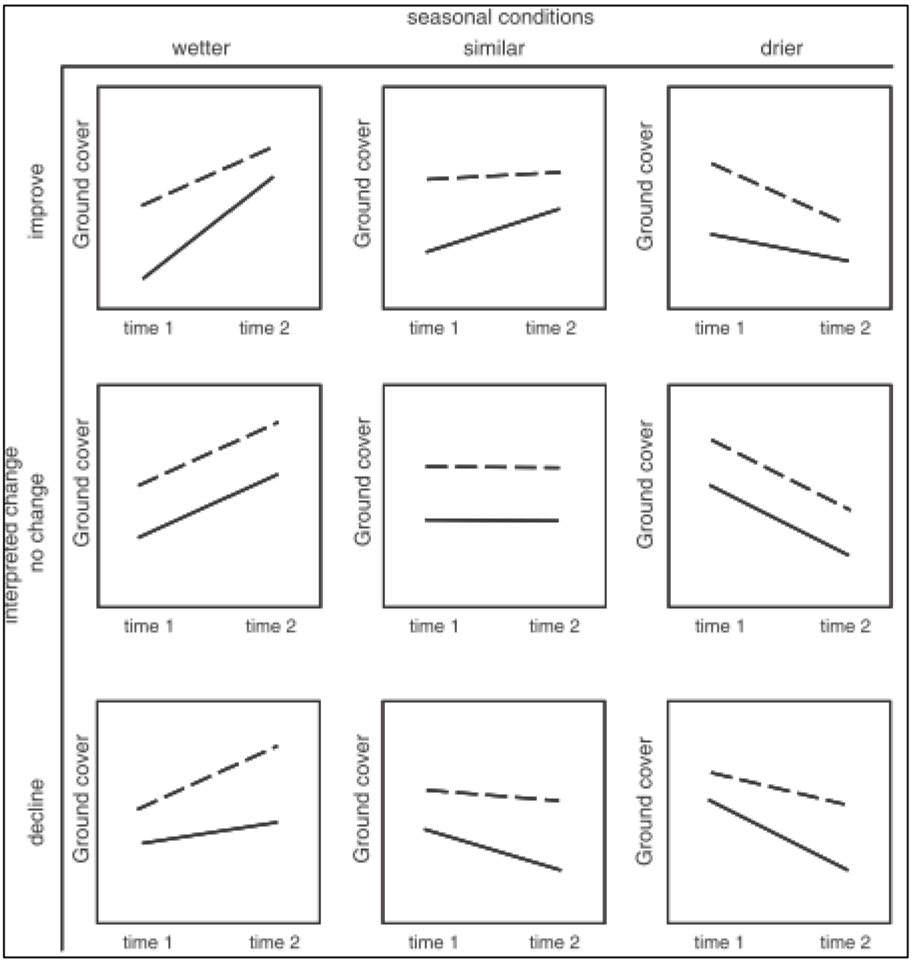

Figure 3-14: A schematic framework for interpreting change in ground cover [scores]
Change in ground cover scores between two dry periods is shown by the solid line in each plot. Change in reference is depicted with the dashed line. Columns represent seasonal conditions at the second time period relative to the first. Rows represent where management signal on ground cover improved, remained unchanged or declined. (adapted from Bastin et al. 2012, p. 449, Figure 5)

residual climate signal (see Figure 3-15). To allow these to be plotted together and compared, data were first tested to confirm data approximates normality with the Shapiro-Wilk test (Royston 1995; R Core Team 2018).

Shapiro-Wilk normality test for ΔGC - W = 0.97693, p-value = 0.7716

Shapiro-Wilk normality test rf4 - W = 0.94624, p-value = 0.1592
(Royston, 1995, suggests p-value < 0.05 for rejection of the null hypothesis – so the null hypothesis of normality was adopted for standardisation of data).

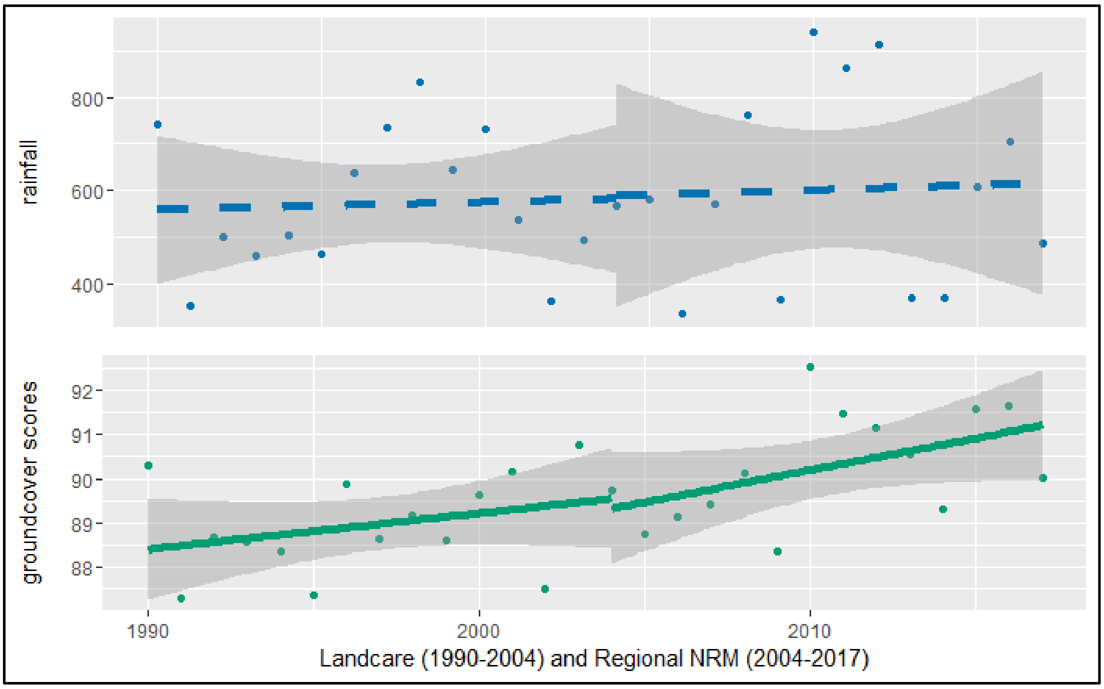

Figure 3-15: Rainfall and groundcover scores with trends for Landcare and Regional NRM periods.

Data were then standardised with:

(z) ΔGC = (ΔGC - mean ΔGC) – SD ΔGC Equation 2,
and,
(z) rf4 = (rf4 - mean rf4) – SD rf4 Equation 3

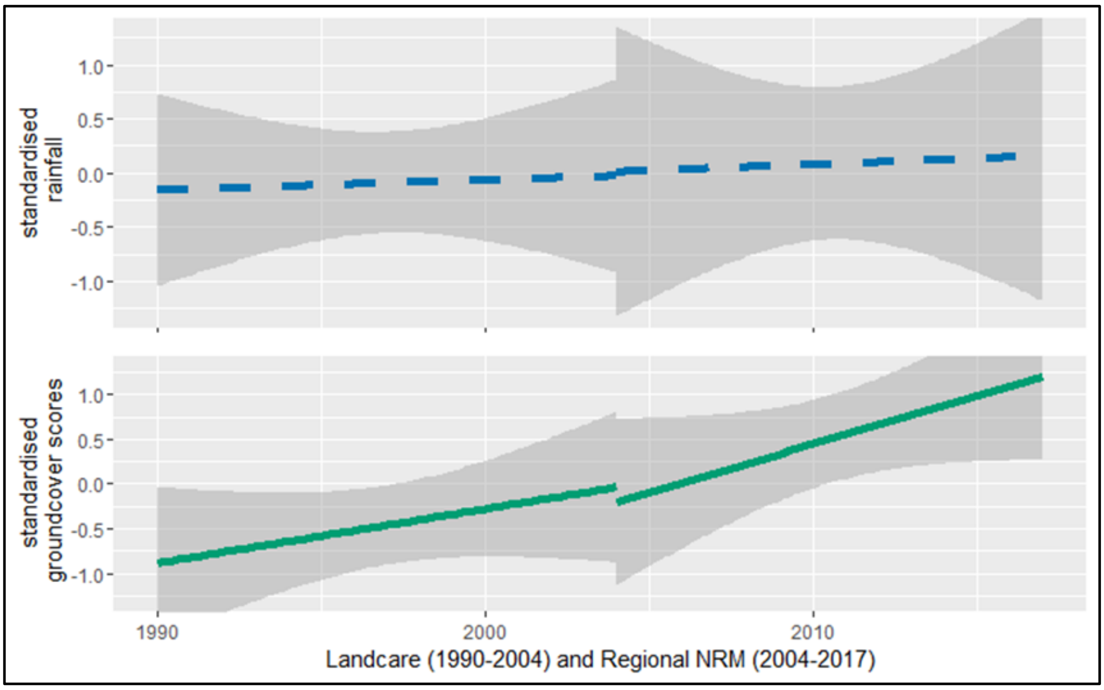

Figure 3-16: Standardised rainfall and groundcover score trends for Landcare and Regional NRM periods.

Trends in (z) ΔGC and (z) rf4 were determined with slopes representing the annual change in values averaged over each period (Figure 3-16). The difference in slopes ΔGCMS for each period represents ΔGC corrected for climate signal to reflect just the management signal.

That is:

(z)ΔGCMS slope = (z)ΔGC slope - (z) rf4 slope Equation 4

To get the annual change in ΔGC Management Signal (GCMS) then, it was necessary to multiply the corrected values by the standard deviations.

*GCMS = Corrected (z)ΔGCMS slope * sd(ΔGC) Equation 5*

The ground cover scores have a 1:1 linear relationship to Satellite Ground cover (from which they were derived) but a multiplier is applied to correct Visual Ground Cover data (Trevithick & Scarth 2013). Trevethick and Scarth describe the variations between ground cover estimates from satellite data and from visual assessments. They also provide data that confirms that visual estimates tend to give lower values that remote sensed estimates and provide data for adjustment of remote sensing data for use in C-factor estimates for catchment modelling (Lu et al. 2001). The multiplier was derived from Trevethick and Scarth, 2013, data in the 20-80% range of the median GC for all sites (75-83%).

vgc multiplier = coef of the liner model
(Visual.Ground.Cover ~ Satelite.Ground Cover 75-83%) Equation 6

And the visual ground cover management signal (vGCMS) was then derived.

*vGCMS = VGC multiplier * GCMS Equation 7*

The vGCMS was calculated separately for the Landcare Period (vGCMSlc) and for the NRM Investment period (vGCMSnrm).

As a result of these analyses, the interpretation framework for a qualitative assessment of the change in groundcover scores (Figure 3-14), has been adapted to enable quantification of the change in the management signal in ground cover over extended periods. This was achieved by measuring the divergence between ground cover scores and a climate reference through two extended study periods. Quantification of the ground cover management signal was a requirement for the use of a catchment model to evaluate implications for stream sediment load.

Trend analyses were undertaken using the purpose written R script *060_Groundcover scores time series and trend analyses* (Appendix R).

3.9 Synthesised ground cover data for catchment modelling

As outlined in Chapter 2, the value of increasing ground cover to reduce erosion is established internationally (Grudzinski et al. 2016), nationally (Osborn 1952; Bastin et al. 2012) and in southern inland Queensland (Loch 2000; Silburn et al. 2011) (Silburn et al., 1992; Loch, 2000). Links between soil loss and stream sediment loads are also well established (Wilkinson et al. 2014; Kroon et al. 2016) (Kroon et al., 2016; Wilkinson et al., 2014).

Models are well established as mechanisms to quantify soil loss and constituent movement through catchments associated with grazing land use (E.G. Waters et al. 2014; Liu et al. 2018; Fu et al. 2019). In the QMDB, including the Upper Maranoa study catchment, a *Source* catchment model has been established to quantify pollutant movements and to predict and evaluate impacts of management (Davidson 2018). This model was made available for this study with DNRME staff maintaining and running the model but with capacity for this study to supply spatial ground cover data for input into model run scenarios. The catchment modelling, therefore, was not done as part of the study but by external contributors. This study was provided with access to input seasonal ground cover raster data used for the Base model. Incremental adjustments to pixel values for grazing lands in the Upper Maranoa grazing lands were applied based on the management signal derived in Section 3.8. Adjusted raster files for three management scenarios and one best case scenario were then supplied to DNRME staff who re-ran the catchment model with each of the input scenario datasets. Model outputs were then provided for checking and interpretation as part of this study.

Soil loss in the Upper Maranoa is driven by several processes including, for grazing lands, hillslope erosion, gully erosion and streambank erosion (see Figure 3-17). For the purposes of this study, only hillslope erosion was considered. It is likely that groundcover due to management practices has some impact on gully and streambank erosion but that is not considered in this work.

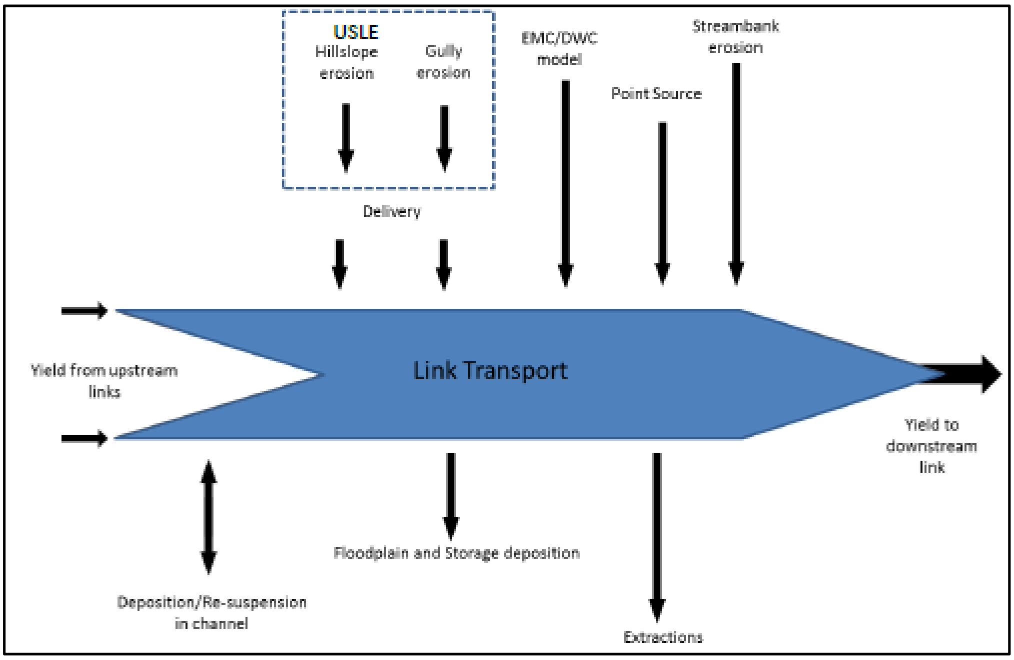

Figure 3-17:Source model sediment sources, sinks and outputs framework (Davidson 2018, p. 23 Figure 7).

The Source hillslope erosion model component is based on an adapted Revised Universal Soil Loss Equation (RUSLE) (Lu et al. 2001; Davidson 2018, p. 29). Davidson, 2018 used seasonal ground cover data from remote sensing at 30m*30m pixel size to run the dynamic hillslope sediment generation. The remote sensed data were adjusted to create “Visual Ground Cover” data (VGC) as required for the RUSLE (cf Trevithick & Scarth 2013).

The model was calibrated using the 36 year period from 1980 to 2015 (Davidson 2018). More recent data were made available, however, for model runs for this study with model runs using data for the period from 1986 to 2017 (perscomm Shawn Darr November 2018).

Data processes for the catchment modelling including indications of project activity and external (DNRME) contributions are presented as a flow chart in **Error! Reference source not found.**.

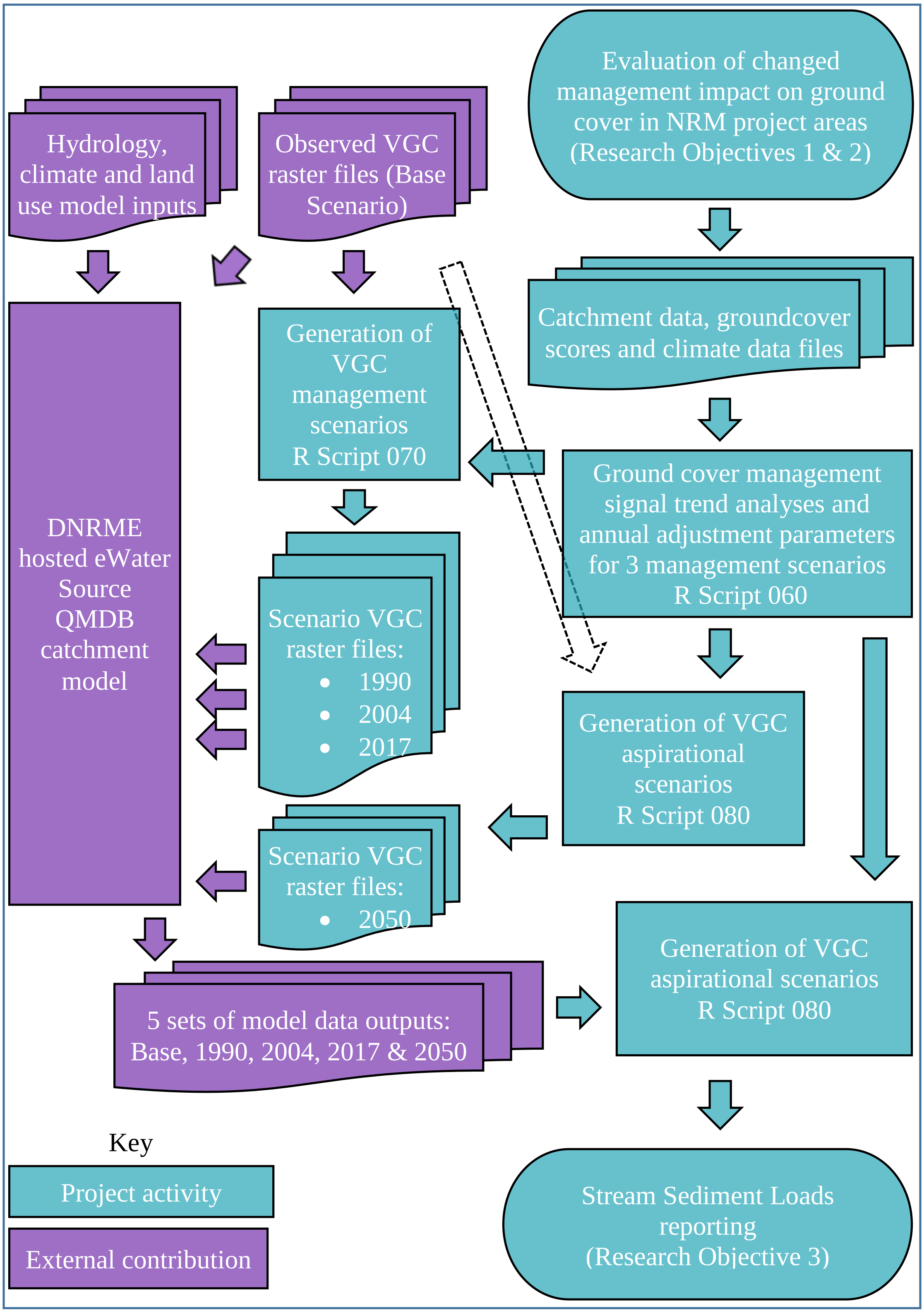

Figure 3-18: Flow chart for catchment modelling data processes

This **VGC data used for the base model** represents groundcover through the 1986-2017 model run **incorporating both climate and management signals (**Figure 3-19**)**.

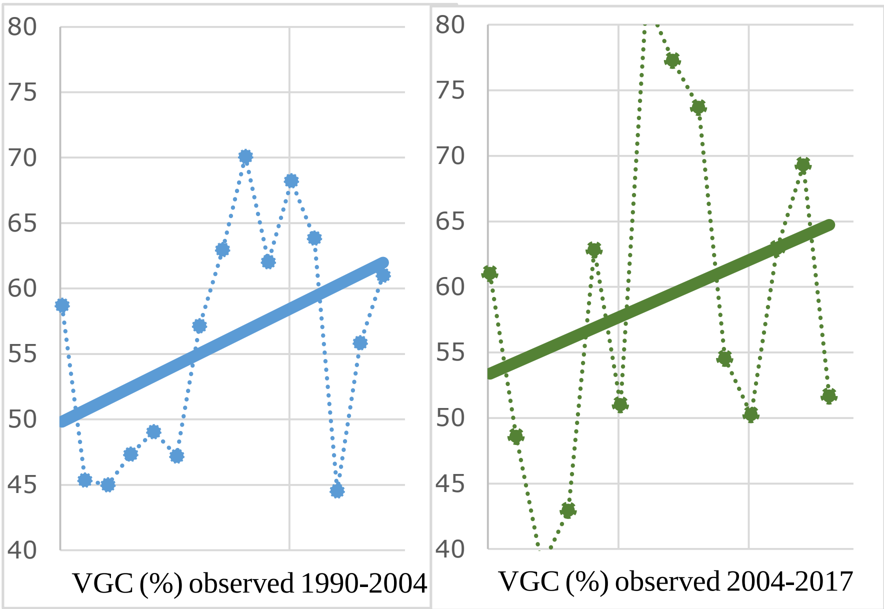

Figure 3-19: Visual Ground Cover (VGC) and trends for spring observations in the 1990-2004 (Landcare) and 2004-2017 (Regional NRM)

The trends in **groundcover management signal** (described in Section 3.8) were used to **adjust the ground cover** values to simulate effective static management standards to match those of:

- 1990 – at the start of the Landcare investment and also the beginning of reliable catchment wide groundcover data,
- 2004 – the start of the NRM period signified by the launch of the Regional NRM Plan, and,
- 2017 – the end of the assessment period.

The observed ground cover data occurred during a period of changing management and variable climate (Figure 3-20 (top)). From the processes described in section 3.8, estimates are available for the change in ground cover that has occurred due to management in the Landcare period and the Regional NRM period (Figure 3-20 (bottom)). So, for example, to estimate the ground cover that would have occurred if the 2017 management practices had been in place for the entire model period:

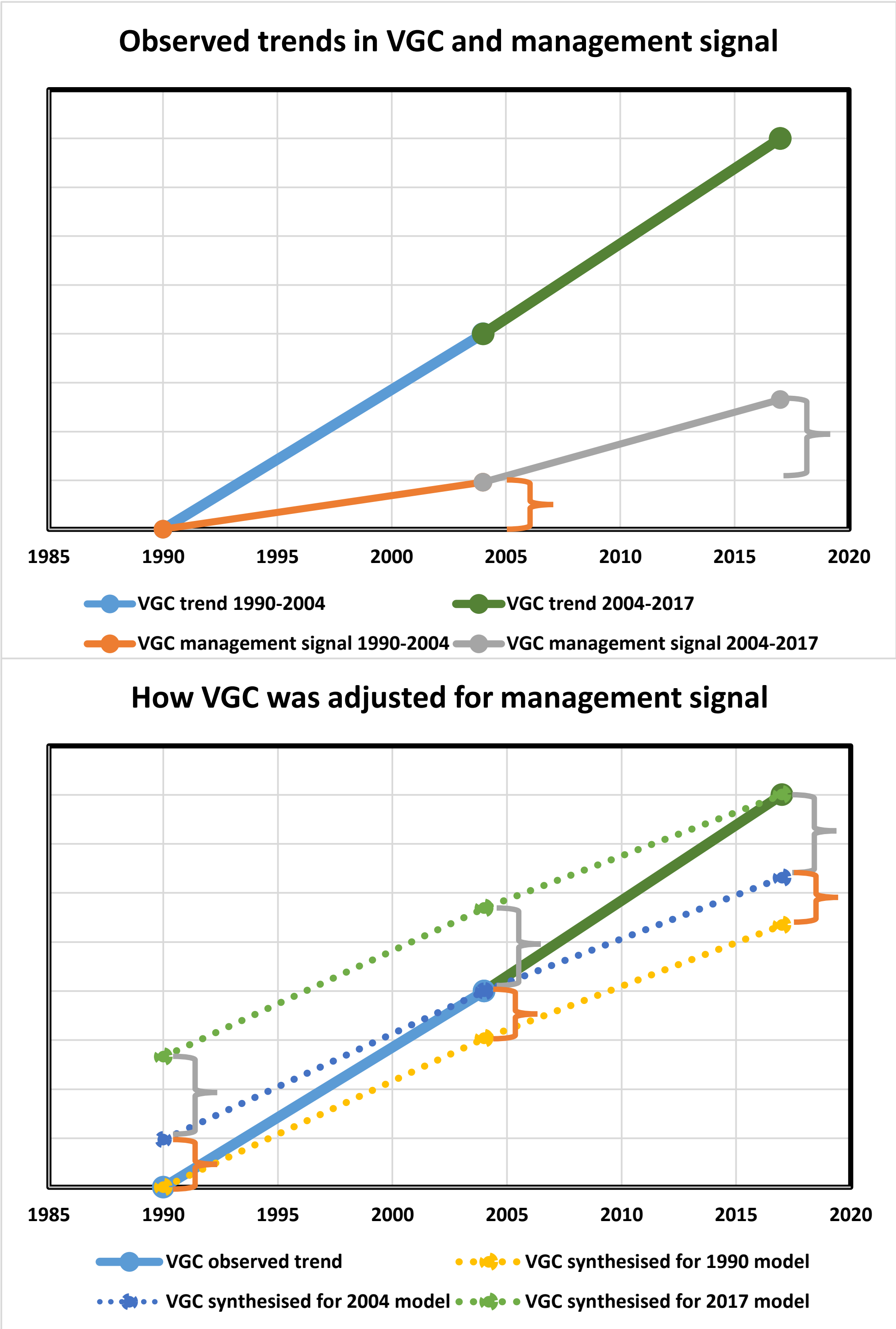

Figure 3-20: Observed VGC trends and management signal (top) and how VGC was adjusted for the management signal (bottom).

- Observed ground cover in 2017 is assumed to be the same as ground cover for a 2017 management model scenario,

- Between 2004 and 2017 ground cover was varying with climate but had an underlying increase due to the management signal in the Regional NRM period. To estimate the ground cover that would have occurred during this period, an amount was added to the observed ground cover with that amount based on the slope (annual increase) of the management signal trend calculated in Section 3.8. For the 2016 estimate, the annual increase amount was added to the observed ground cover value in each raster pixel in the Upper Maranoa catchment. For the year 2015, twice the annual increase amount was added to the observed cover values. And so on until the year 2004 when 13 times the annual increase amount was added to the observed cover values.
- Between 1990 and 2004 ground cover was varying with climate but also with an underlying increase due to the management signal from the Landcare period. To estimate the ground cover that would have occurred in 2003 if 2017 management was in place, the amount of the annual increase due to management in the Landcare period plus 13 times the increase from the NRM period (as used to estimate 2004 values) was added to the observed cover value. And so on back to 1990.
- For the model period before 1990 ground cover data was mostly synthesised from climate data (Davidson 2018). Adjustments to this data used the management signal derived for the Landcare period from 1990 to 2004.

3.9.1 2017 scenario

It is assumed that 2017 observed visual ground cover (oGC) = effective groundcover for 2017 management (GC17).

For years 2004-2017:

*GC17(yr) = oGC(yr) + vGCMSnrm * (2017 – yr)Equation 8*
*(with vGCMS from vGCMS = VGC multiplier * GCMS Equation 7)*

For years 1986-2003

*GC17(yr) = oGC(yr) + (vGCMSnrm * 13) + vGCMSlc * (2004 – yr) Equation 9*

3.9.2 2004 scenario

It is assumed that 2004 observed visual ground cover (oGC) = effective groundcover for 2004 management (GC04).

For years 2004-2017:

*GC04(yr) = oGC(yr) - vGCMSnrm * (yr - 2004)Equation 10*

For years 1986-2003

*GC04(yr) = oGC(yr) + vGCMSlc * (2004 – yr)Equation 11*

3.9.3 1990 scenario

It is assumed that the base model raster 1990 observed visual ground cover (oGC) = effective VGC for 1990 management (GC90).

For years 1986-1989

*GC90(yr) = oGC(yr) + vGCMSlc * (1990 – yr) Equation 12*

For years 1990-2004:

*GC90(yr) = oGC(yr) - vGCMSlc *(yr - 1990) Equation 13*

For years 2005-2017:

*GC90(yr) = oGC(yr) - (vGCMSlc * 14) - vGCMSnrm * (yr - 2004) Equation 14*

Each of the three management scenarios resulted in synthesised VGC data for the Upper Maranoa catchment representing groundcover values that would have occurred if management was constant through the period. The 1990 scenario, for example, provides VGC that would have been expected to occur through the 1986-2017 model period if management practices that were in place in 1990 had persisted through the whole period. The model was then run for the 1990, 2004 and 2017 scenarios with climate and other inputs unchanged to enable the quantification of stream sediment loads for each management scenario.

Groundcover data synthesis for these scenarios was achieved using the purpose written R script *070_UM_SourceRaster_scenarios_vgc_adjustments* (Appendix R).

3.9.4 2050 Aspirational groundcover scenario

A further groundcover dataset was developed for "Aspirational" management standards with aspirations to be achieved by 2050. Aspirational VGC values, or best achievable, were based on the 95% (best 5%) ground cover values for each grazing landscape unit in each season. 95% values were obtained from collated groundcover data output from R Script *040_aDRCM groundcover scoring.* For the 1986 to 1990 period where there was no available groundcover data, data were infilled using a correlation with rainfall for each Climate Landscape for the 1990-2017 period. Correlation parameters were applied to rainfall from the climate data archive output from R Script *030_Climate and groundcover data collation.* These calculations provided satellite pc95 groundcover values for each Climate Landscape in the Upper Maranoa catchment for each season for the model period of 1986 to 2017.

To establish an Aspirational Groundcover layer, the pc95 values were extracted for each Climate Landscape for each season. Pc95 (satellite derived gc) were mostly between 90 and 97% (20-80% range of pc95 values). Visual ground cover equivalents were calculated from Trevithick and Scarth, 2013, using Satellite observations 90-97%. From the linear model of satellite gc (90-97%) v visual gc:

$$vgc = 1.72 * gc - 79.9 \quad \text{Equation 15}$$

All pc95 satellite data were adjusted using Equation 15. Values were then applied by Climate Landscape for relevant pixels in VGC base model rasters for all grazing lands in the Upper Maranoa catchment. This resulted in 124 "2050 Aspirational" scenario rasters with adjusted VGC for Upper Maranoa grazing lands only.

R Scripts were used to adjust the Upper Maranoa grazing land pixels only in each of the 124 visual ground cover rasters and the rasters provided to DNRME staff to input into the Source QMDB catchment model. The visual ground cover layers were the only changes made to model inputs. This represents a significant step in addressing one of the 11 key challenges for catchment water quality modelling of "differentiating the effects of climate impacts from those associated with land use and management practices" (Fu et al. 2019).

The establishment of an aspirational ground cover layer enabled the comparison of results from the three management scenarios with best achievable outcomes. This means any outcomes from NRM investments can be interpreted against expectations and not just as an absolute change. Groundcover data synthesis for the aspirational ground cover scenario was achieved using the purpose written R script *080_UM_SourceRaster_Aspirational_vgc* (Appendix R).

3.10 Summary

This chapter described the methods used to determine and describe the study catchment and to map Climate Landscapes where pasture performance was expected to be homogeneous. NRM supported properties were mapped and split into Climate Landscapes components. Within these properties, incentive paddocks were identified where NRM incentives payments were made and improved groundcover was an anticipated outcome. Incentives paddocks were also split into Climate Landscapes components. Control areas were then established from parts of each Climate Landscape not in NRM supported property areas but still within the Upper Maranoa catchment. Reference areas were determined with these being all parts of each Climate Landscape that intercepted the Upper Maranoa catchment.

Spatial data for supported properties, incentives paddocks, control areas and reference areas were provided to DES staff. DES staff used the spatial data to query the seasonal groundcover archives to provide seasonal ground cover data summaries for each of the 420 spatial areas.

Data from reference areas were used to generate ground cover scores for each of the supported properties, incentives paddocks and control areas. Chapter 4 will present the findings of comparisons between ground cover scores at supported properties and controls, then at incentives paddocks and control areas. These results reflect the management signal in ground cover at supported areas and associated control areas. Chapter 4 will also present information obtained from landholder interviews to explain the ground cover score results and some data anomalies.

The last part of this chapter described the methods used to analyse catchment groundcover scores and climate data to quantify trends in the underlying management signal. Management signal information was applied to observed ground cover data to enable the eWater Catchment model to be run to estimate stream sediment loads under management practices that were prevalent in 1990, 2004 and 2017. A best achievable scenario was also developed and run. In Chapter 4, the model run results will be presented as stream sediment yield estimates and as differences between scenarios and as differences relative to aspirational (best achievable) loads.

Chapter 4 Results

4.1 Introduction

As described in Section 3.4, Climate Landscapes were identified and mapped across the Upper Maranoa study catchment. These Climate Landscapes were areas derived through the intersections of Climate Zones and land use vegetation classes where, excluding seasonal effects, pasture condition and ground cover should be reasonably homogeneous all other things being equal. Variations in groundcover within a Climate Landscapes would therefore likely be a response to variations in management. With the research objectives to determine if NRM extension and incentives activities led to improved management, these variations in groundcover were analysed. Analyses were performed to minimise the climate signal in the groundcover data and to compare resulting Groundcover Scores in NRM investment areas with control areas.

Seasonal groundcover data summaries were obtained for areas within each Climate Landscape that had, and had not, been supported with NRM activities (Section 3.5). Groundcover Scores were calculated using an adapted Dynamic Reference Cover Method (aDRCM described in Section 3.6). This chapter will present the results of analyses and of subsequent landholder interviews and surveys that enhance the understanding of the results. This chapter will also present results of further work undertaken to achieve the third research objective of estimating the reduction in soil loss and stream sediment loads due to changed management (explained in Sections 3.8 and 3.9). The characteristics of the groundcover summary datasets confirmed the suitability of the Climate Landscapes.

4.2 Removal of climate signal from ground cover data

Groundcover scores were computed for all supported properties and incentive paddocks, and for the combined supported property areas. Scores were also computed for control areas, these being areas of the same Climate Landscapes as supported properties/paddocks and contained within the Upper Maranoa catchment (See Chapter 3, Section 3.5).

Before comparing supported and unsupported areas to determine if there was a difference in the non-seasonal (management) signal, scores were compared with climate indicators to ensure climate signal was significantly removed by the adapted Dynamic Reference Cover Method (aDRCM).

Data were reviewed to establish that:

1. Groundcover had a strong correlation with climate, and
2. Delta GC scores did not have a strong correlation with climate (thus confirming the removal of the climate signal from the Delta GC scores).

Data were collated for all supported properties and all related control areas. Pearson's r was calculated to test the strength of the median ground cover data relationship with climate variables. Tests were also undertaken to test the strength of the (aDRCM) ground cover scores with the same climate variables.

For all data and all seasons, there was a moderate to strong relationship between median ground cover (pc50) and rainfall, and a weak negative correlation with maximum temperature and potential evapotranspiration (PET). The strongest correlation (r = 0.65) was with the previous 12 month rainfall. The ground cover scores (D50) all showed poor correlation with climate indicators confirming that the aDRCM removed a significant amount of the climate signal from the groundcover data. Figure 4-1 shows a correlation heat map showing strength of relationships between both ground cover and ground cover scores and climate variables.

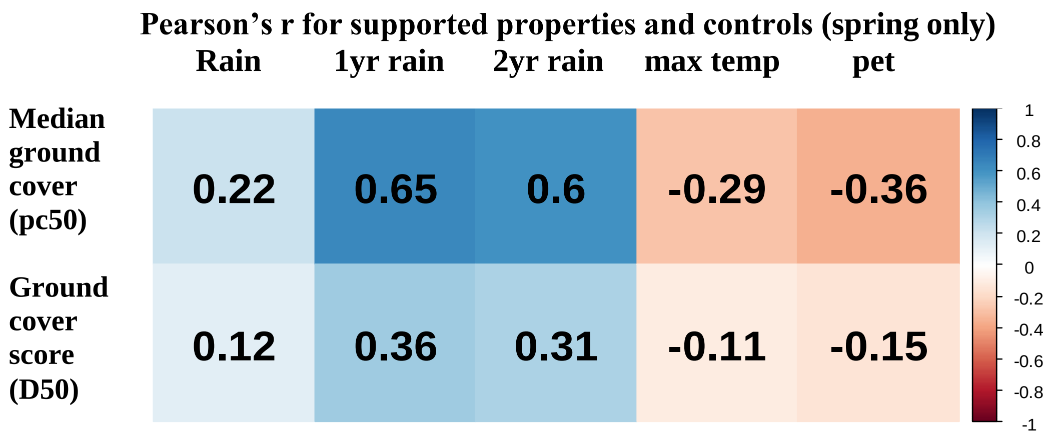

Figure 4-1: Correlation heat map for ground cover, scores and climate variables

Median ground cover for spring data showed stronger correlation with rainfall and a moderate negative correlation with maximum temperature and PET than other seasons.

Spring ground cover scores showed poor correlation with climate showing the more significant removal of the climate signal for spring data (see Figure 4-2). This was also observed by Bastin et al (2012) in the establishment of the DRCM. It should be noted, however, that a weak climate signal was still evident in the ground cover scores requiring comparison with a controls to evaluate relative impact of management in areas exposed to NRM extension or incentives.

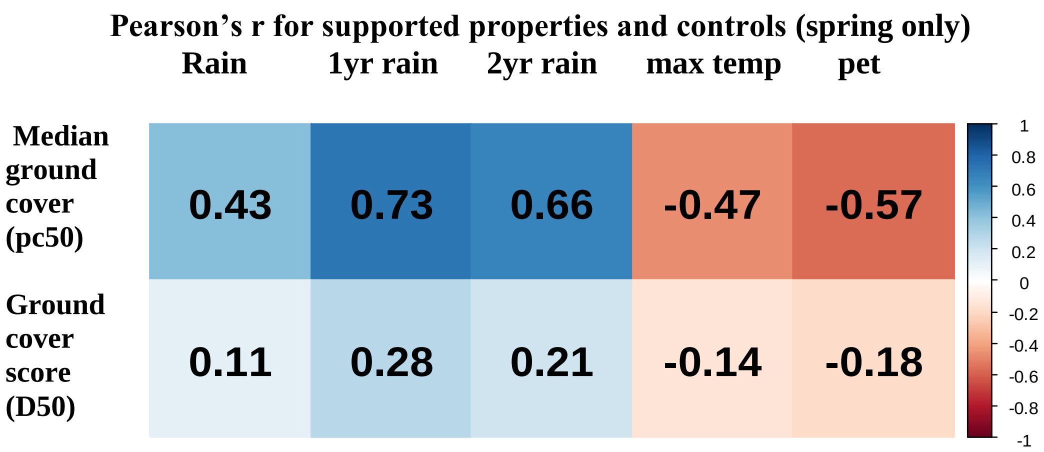

Figure 4-2: Correlation heat map for spring ground cover, scores and climate variables

Appendix 4.1 presents correlation heat map variations of Pearson's r for similar correlation tests with data grouped by different seasons, climatic conditions (wet, dry, normal) and different grazing land vegetation classes. Appendix 4.1 also includes confirmation of the assumptions for the Pearson's r test for spring data.

4.3 Evaluation of NRM investment areas

Across the catchment, there was a trend of increasing Groundcover Scores throughout the NRM period and preceding years for which remote sensing data were available. Scores for all properties supported by NRM programs showed a slight increasing trend mostly aligning to the trends in the control areas (Figure 4-3). This suggests either there was limited impact of the NRM investment on management, or other factors were also affecting management decisions.

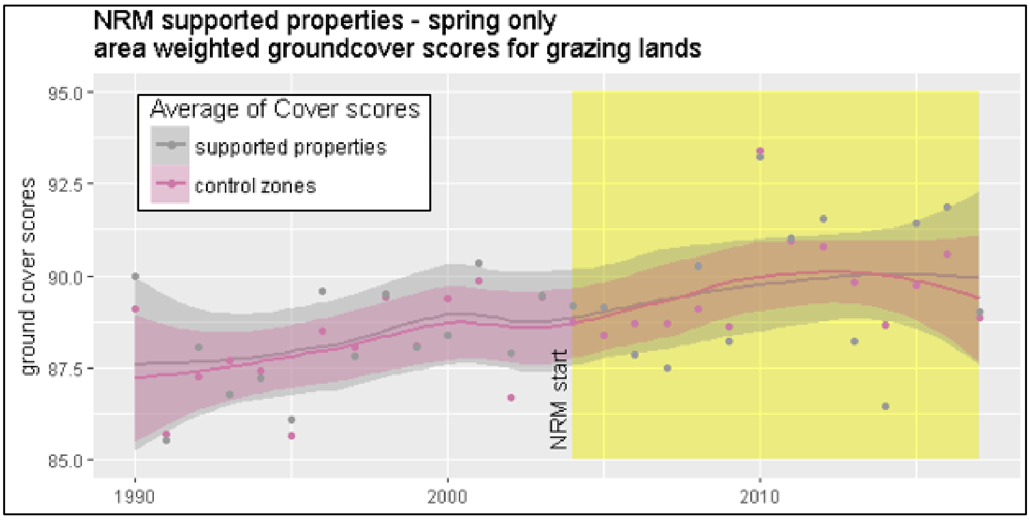

Figure 4-3: Ground cover scores for properties supported with NRM extension

Groundcover Scores for paddocks where incentives projects were implemented also showed slight increasing trends mostly aligning to the trends in the control areas (Figure 4-4). Again, this suggests either there was limited impact of the NRM incentives on management, or other factors were also affecting management decisions.

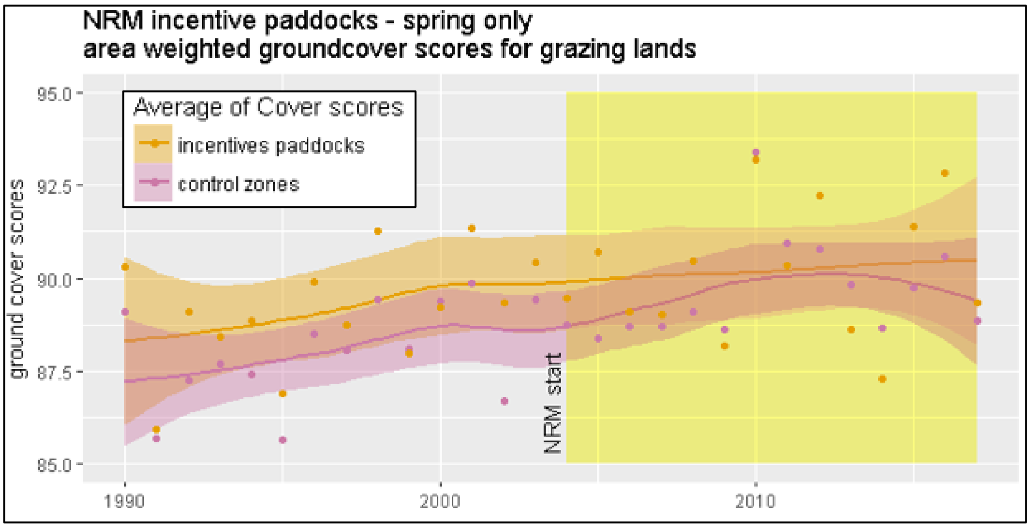

Figure 4-4: Ground cover scores for paddocks where incentives were paid

4.4 Scores for individual properties and paddocks

Individual properties and paddocks were also compared with control areas with a variety of results. Spring groundcover scores were plotted for properties alongside relevant control scores. Plots included all landuse areas (timbered grazing (tg), sparse timber (st), open grazing (og) and forestry (fo). Net scores were also calculated and plotted with these being area weighted averages of component scores. Net control scores were calculated separately for each property. Net scores were area weighted with the land use areas of the property area being evaluated.

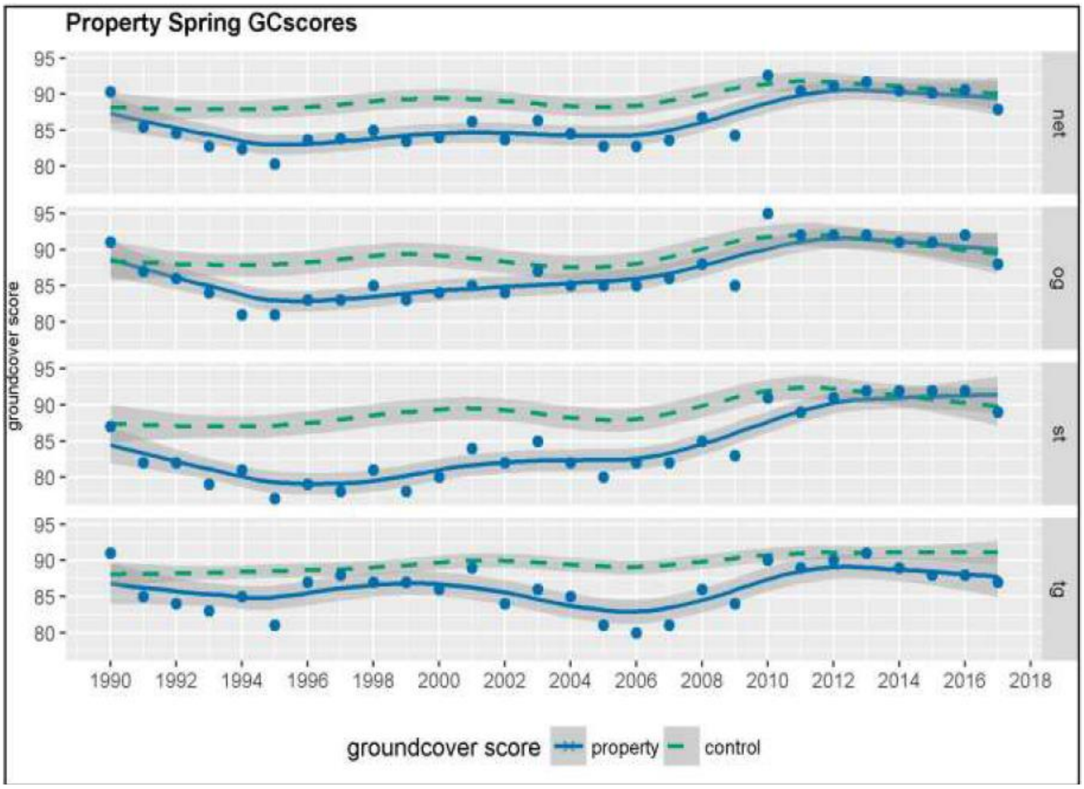

Figure 4-5: Improved Groundcover Scores for an NRM supported property
Scores showed improvement after 2008 when compared with ground cover scores for relative control areas in the same Climate Landscape. Plots show areas of timbered grazing (tg), sparse timber (st), open grazing (og) and net scores (area weighted average of component area scores).

Many supported properties showed apparent improvement in ground cover scores (for example, the property relating to Figure 4-5). There were, however, more supported properties that did not show improvement or even showed some decline in ground cover scores (E.G. property relating to Figure 4-6). Properties were evaluated based on the moving average ground cover scores compared to the control scores at the start and finish of the Landcare period (1990-2004) and the Regional NRM period (2004-

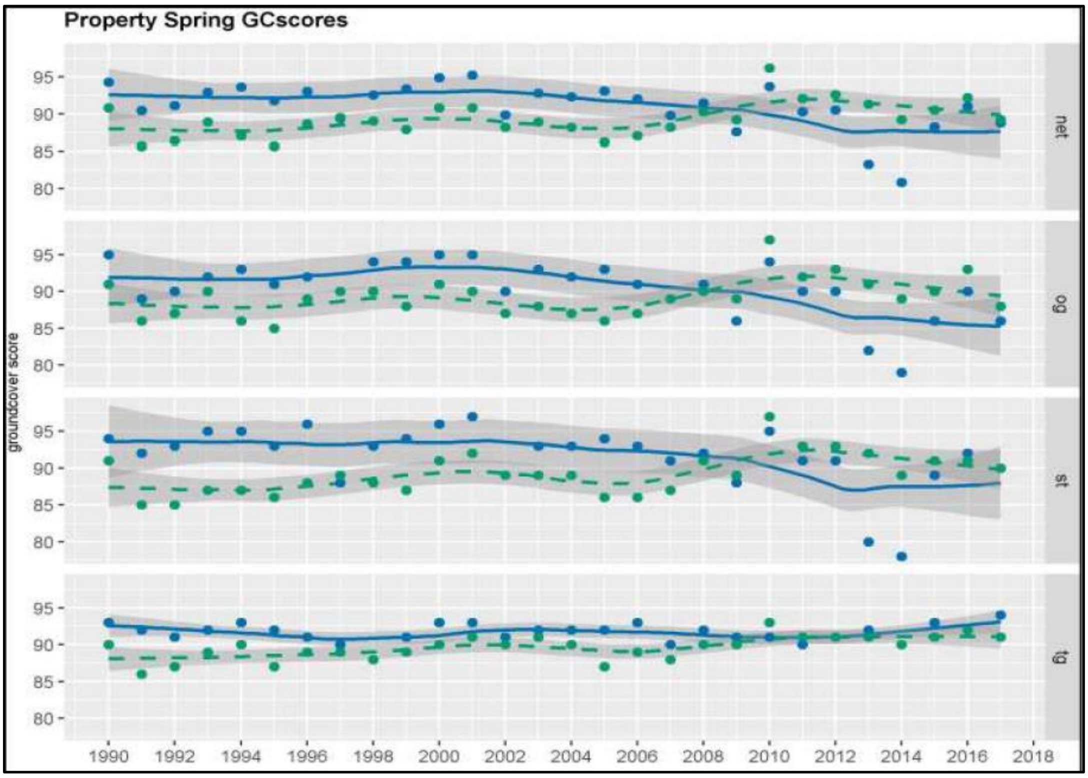

Figure 4-6: Declining Groundcover Scores for an NRM supported property
Property scores declined relative to control areas in the same Climate Landscape. Relative decline started in approximately 2008. Plots show areas of timbered grazing (tg), sparse timber (st), open grazing (og) and net scores (area weighted average of component area scores).

2017). During the Regional NRM period 12 properties showed improvement, 25 showed no change and 21 showed a decline in ground cover scores. Result summaries are presented in Table 4-1.

Table 4-1: Summary of outcomes from ground cover scores from extension properties

Trend in ground cover scores across properties mapped as having participated in extension programs

Outcome	1990-2004 all properties	2004-2017 all properties	2004-2017 properties WITH incentives projects	2004-2017 properties with NO incentives projects
Improved	20	12	9	3
No Change	28	25	13	12
Declined	10	21	9	12

Incentives paddocks were also evaluated to determine if there was any improvement in ground cover scores during the Landcare and Regional NRM periods (Table 4-2). For paddocks where incentives were paid and an improvement in ground cover was expected, 10 showed improvement (E.G. Figure 4-5), 10 showed no change and 11 showed a decline in ground cover scores during the Regional NRM period (see Figure 4-6). Reasons for this apparently neutral outcome are discussed in section 5.3 with reference to finding from landholder surveys. Appendices 4.2 and 4.3 show plots of net scores for all extension properties and incentives paddocks respectively.

Table 4-2: Summary of outcomes from ground cover scores for incentives paddocks

Incentives paddock outcomes	Landcare (1990-2004)	Regional NRM (2004-2017)
Improved	13	10
No Change	13	10
Declined	5	11

Correlations and trend analyses were performed using purpose written R Script *050_Groundcover scores and climate data correlation anlyses* (Appendix R).

4.5 Findings from landholder interviews and surveys

Landholders who had participated in NRM activities in the study catchment were invited to contribute to this study. Landholder participation was intended to:

- Compare observed conditions with the groundcover data for each property. The intent was for landholders to have the opportunity to compare the data with their own memories and/or with any available data.
- Relate management decisions to groundcover scores through time. The intent was to determine if variations in groundcover scores aligned with property management circumstances and decisions.
- To gather data on perceptions of whether NRM extension activities enhanced grazing land management.
- To gather data on perceptions of whether NRM incentives projects enhanced grazing land management.
- To identify enablers and barriers to continuous improvement in grazing land management.

From property information provided by QMDC, supported grazing properties in the study area included 35 enterprises managing 57 properties. Managers of each enterprise were invited to participate in an interview and/or a survey. Interest in the evaluation was strong with 29 enterprises participating in interviews and 25 of these completing surveys with reference to 43 property units (survey responses for 75% of properties).

Collated responses are included as Appendices 4.4-4.6. Landholder comments and research journal notes are paraphrased where appropriate to maintain landholder anonymity. This is a requirement of both the agreement with QMDC and the USQ Research Ethics approval.

Of the surveyed properties 90% were cattle only with the others being sheep or mixed land use (grazing and cropping or grazing cattle and sheep). 60% of surveyed properties had received incentives payments. Of the properties that received incentives, almost all indicated incentives projects had a major benefit for paddock management and some impact or major impact on whole property management.

Most survey responses indicated some to major benefit of information exchange and landholder networking from NRM program activities. Other listed benefits of activities included: property mapping, social networking and industry representative networking.

Most respondents indicated some to major negative impact on management from climate events and market conditions. Specific dates were not recorded but some dates mentioned included the mid 1990s, 2006-2008, 2014-2015 and the (2017-2018) period for climate. The 2011 live export ban was mentioned often with regard to market collapse. 21% of properties recorded changed ownership or managers as having a major impact on property management during the study period. 35% of properties recorded changes in family circumstances as having had major impact on management. In cases of succession planning, changed ownership and change in family circumstances both applied.

Most respondents indicated there were other issues that had some to major impact on management. 76% of respondents indicated vegetation and regrowth legislation (and instability of this legislation) was one of these other issues that impacted on property management. Numerous respondents also indicated native and feral animals and related management constraints were impacting on property management (17% recorded in surveys but most respondents at least mentioned this in passing during discussions).

Land managers for 12 out of 58 grazing properties indicated they had monitoring data that could be made available. Data has been accessed through a consultant subject to provisions of maintenance of anonymity of properties and persons. Some preliminary analyses have been performed on the data with further work required to provide detailed analyses. Visual ground cover observations showed some correlation with satellite data but the correlation was different to published data (Trevithick & Scarth 2013). The data from this study only had an r squared of 0.4 (correlation between satellite derived and visual observed ground cover %). Correlations were based on seasonal average satellite data from the point location from latitude and longitude indicated in visual observations. Field samples in fact involve transects of paddocks which may include a range of ground cover values. Visual observations are also taken on one day only and ground cover conditions may vary during the 3 month season for which corresponding satellite data is obtained. Further work is required to access monthly satellite data for more reasonable comparisons and also to confirm exact locations and extent of monitoring site data points with the consultant. This was beyond the scope of this study but permissions have been attained to use the data for further work. Appendix 4.7 provides more information on the preliminary analyses. Of note also was that in the analyses of individual property ground cover scores (Section 4.4 and Appendices 4.2 and 4.3) indicated properties that had available monitoring data had lower (better) average ratings for ground cover scores than the full set of properties supported with NRM extension activities. Possible reasons for this are discussed in section 5.7.7.

Some additional information provided by participating landholders included:

- Feedback on remote sensing data and ground cover scores included:
    - The general outcomes and trends from the remote sensing data are mostly consistent with monitoring data and memories.

    - Groundcover scores were mostly consistent with management decisions but there were anomalies in some years. 2014 and 2015 were mentioned by several landholders as years when groundcover scores were disproportionally low. In other years, low ground cover scores could be linked to dry years when landholders were maintaining a breeding herd or low market value stock that exceeded prevailing pasture production.

- With regard to NRM extension impact on land management:
    - NRM extension impact was seen to extend beyond mapped extension areas but, as outlined in section 1.4.4, the degree of impact outside mapped NRM participation areas was not able to be assessed in this study. Examples of how NRM activities encroached into control areas include:
        - Direct impact where participating landholders also own or manage land listed in control areas. Changed management resulting from information acquired from NRM activities was applied across all holdings, not just those mapped from QMDC stakeholder data.
        - Direct impact where family partnerships cover multiple properties and not all family members participated in NRM activities (so not all properties are on QMDC map records) but information was shared between all partners.
        - Partial impact where landholders participated in some extension activities but were not involved in mapping or incentives

activities where QMDC collected detailed property information used in this study to define supported properties.

        - Indirect impact where landholder industry and social networks lead to information exchange beyond properties listed as supported by NRM.
    - NRM activities are not the only contributors to changed grazing land management. Landholders in various ways indicated that their own innovations and initiatives, industry networks and social networks all contribute to evolving management practices within and outside areas directly influenced by NRM activities. This research had no control or measures of the extent to which these externalities have had impact on land management outcomes. This is a limitation of this research.
- With regard to incentive projects and their impact on ground cover:
    - Incentive project areas were often not consistent with landholders' recollections or records of funded projects.
    - An expectation of improved groundcover from some mapped incentives areas did not align with landholders' expectations. For example, mapped weed eradication projects (for Parthenium) may be expected to result in improved pasture composition but not necessarily in improved ground cover.

Two things should be noted in relation to these general findings:

1. Generalisations are inherently risky given there was no single representative or "normal enterprise" any more than there is a normal rainfall, and,

2. Generalisations reflect common responses but these were not unanimous. There were individual opinions and circumstances that contradicted general findings. For example:
    a. One landholder indicated that the 2002 drought was worse than the 2006 drought from his photo point records (confirmed from photos presented at the interview). Remote sensing records, however, indicated 2006 median groundcover was considerably lower than 2002. No explanation was offered for this anomaly.
    b. Several landholders questioned the low cover and the low cover scores for 2013 and 2014. A suggested explanation of this anomaly is discussed in Chapter 5 and Appendix 5.1.

4.6 Ground cover results used for catchment modelling

Research objectives 1 & 2 were to determine the impact of NRM extension and incentives on land management and ground cover. The third research objective was to determine the impact of NRM driven change on soil loss and stream sediment loads. This objective was to be achieved by use of a catchment model to quantify the impact of changed ground cover in NRM investment areas (extension and incentive areas) on soil loss and stream sediment loads.

From the results presented in sections 4.3 to 4.5, it was determined that:

1. Ground cover scores (averaged) showed improvement across the whole catchment with no clear difference between mapped NRM investment areas and other grazing lands in the catchment (mapped as control areas).
2. It was not NRM alone that contributed to improved ground cover in the mapped NRM investment areas, and,
3. True impact of NRM investment was not confined to mapped NRM investment areas but also included control areas.

The implications of these findings for research objectives 1 & 2 will be discussed in Chapter 5. What became apparent from these results, however was that modelling changes in soil loss and stream sediment loads based on ground cover for mapped NRM investment areas would not give a true indication of NRM investment outcomes. With NRM investment outcomes extending beyond the mapped extension and incentive areas it was decided that modelling would consider the impact of improved ground cover across the whole of the study catchment. It was also determined that modelling would include consideration of both the Regional NRM investment period (the focus of this study) and the preceding Landcare period. This enabled full utilisation of available remote sensing ground cover data, and, it would enable an alternate means of evaluating NRM with scope for comparing outcomes from the two different periods. It was conceded that this would mean outcomes could not be attributed solely to NRM investment. Instead, model results would indicate the degree to which NRM investment and other actions have contributed to outcomes.

4.7 Modelling changes in soil loss and stream sediment loads

From ground cover scores (Figure 4-3) it was determined that there was an increasing trend in ground cover scores in the study catchment throughout the period of remote sensing records.

Section 3.8 describes how trends were analysed to quantify the underlying Ground Cover Management Signal (GCMS). Also described in Section 3.8 was the requirement and process for adjusting the trends to equate to visual GCMS (vGCMS) for use in catchment modelling with a visual ground cover multiplier. The visual ground cover multiplier was determined to be 1.47. That is, data obtained from satellite observations of ground cover needs to be corrected to equate to visual or manually observed ground cover (Trevithick & Scarth 2013). The trend in GCMS calculated from ground cover scores determined in this study consequently needs to be corrected to quantify the equivalent trend in vGCMS. The vGCMS values are required to correct input data for the eWater Source catchment model used to calculate soil erosion “c” factors (Panagos et al. 2015; Davidson 2018).

For the 1990 to 2003 Landcare period the GCMS showed an increasing trend of 0.069 % per year. With the multiplier applied, this gave a **vGCMS of 0.102% per year.**

For the 2004 to 2017 Regional NRM period GCMS showed an increasing trend of 0.13 % per year. With the multiplier applied, this gave a **vGCMS of 0.191 % per year.**

4.7.1 Synthesised visual groundcover datasets for model scenarios

Using these vGCMS values, the observed VGC values used in the base model were adjusted to create simulated VGC datasets for 1990, 2004 and 2017 management scenarios. This meant, for example, that the 1990 VGC dataset included VGC values for the Upper Maranoa catchment that would have been observed if 1990 management practices had been used throughout the whole 1986 to 2017 model period.

The vGCMS for each period was used to determine annual adjustments to observed VGC values using Equations 8-15 in Chapter 3, Section 3.9. Table 4-3 shows the adjustments applied to raster pixels for grazing lands in the Upper Maranoa catchment to adjust the Base Model (observed) visual ground cover for grazing management for 1990, 2004 and 2017 scenarios. Section 3.9 also describes how the observed 95% (best 5%) ground cover values for each season in each Climate Landscape were used to establish and aspirational 2050 VGC dataset.

Table 4-3: Visual Groundcover corrections applied to Base Model raster data For 1990, 2004, and 2017 Land Management Scenarios

(a) Pre public access groundcover data

Scenario	Data Correction for Year			
	1986	1987	1988	1989
X1990	0.408	0.306	0.204	0.102
X2004	1.836	1.734	1.632	1.53
X2017	4.319	4.217	4.115	4.013

(b) Landcare Period

Scenario	Data Correction for Year													
	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003
X1990	0	-0.102	-0.204	-0.306	-0.408	-0.51	-0.612	-0.714	-0.816	-0.918	-1.02	-1.122	-1.224	-1.326
X2004	1.428	1.326	1.224	1.122	1.02	0.918	0.816	0.714	0.612	0.51	0.408	0.306	0.204	0.102
X2017	3.911	3.809	3.707	3.605	3.503	3.401	3.299	3.197	3.095	2.993	2.891	2.789	2.687	2.585

(c) NRM Investment Period

Scenario	Data Correction for Year													
	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
X1990	-1.428	-1.619	-1.81	-2.001	-2.192	-2.383	-2.574	-2.765	-2.956	-3.147	-3.338	-3.529	-3.72	-3.911
X2004	0	-0.191	-0.382	-0.573	-0.764	-0.955	-1.146	-1.337	-1.528	-1.719	-1.91	-2.101	-2.292	-2.483
X2017	2.483	2.292	2.101	1.91	1.719	1.528	1.337	1.146	0.955	0.764	0.573	0.382	0.191	0

4.7.2 Model results

Correction values described in the previous section were applied to Base model visual groundcover raster files by season and year for the Upper Maranoa grazing lands only and then merged back into the Condamine-Balonne scenes for each scenario. Model scenario labels were:

- Base – original model incorporating ground cover values derived from satellite data through the model period – incorporating changing grazing land management practices.
- X1990[3] – Base model data adapted for grazing lands in the Upper Maranoa to approximate ground cover assuming 1990 management practices.
- X2004 – Base model data adapted for grazing lands in the Upper Maranoa to approximate ground cover assuming 2004 management practices.
- X2017 – Base model data adapted for grazing lands in the Upper Maranoa to approximate ground cover assuming 2017 management practices.
- X2050 – Aspirational ground cover developed from Base model data adapted for grazing lands in the Upper Maranoa to reflect the best 5% of ground cover for each climate landscape.

The ground cover raster datasets developed for each of these scenarios were processed by DNRME staff to create RUSLE "c factor" data which was then input into the eWater Source model. The model was run by DNRME staff and results made available for analysis and interpretation. The model was run with the 1986 to 2017 climate data and constant landscape datasets apart from the groundcover generated c factor layers. The results, therefore, indicate the likely change in sediment loads for the different management scenarios given climate conditions observed in the 31 year period from 1986 to 2017.

[3] The "X" is inserted in model scenario identifications so the model interprets model names as text and not as a reporting year.

Results suggested a reduction in annual average sediment loads in the Upper Maranoa River of approximately 1,900 t/year due to changed management during the NRM period. This was in addition to reductions of 1,100 t/year due to changes during the preceding Landcare period. From the X2050 Scenario it was estimated that the greatest reduction in hillslope erosion contributions to sediment loads that could be achieved by improved grazing land management was 12,000 t/year. The likely impact on the exports from the whole Maranoa catchment due to changes in management in the Upper Maranoa were marginally less due to sediment sinks in the lower parts of the catchment. Result values are listed in Table 4-4 and also presented in Figure 4-7

Table 4-4: Total Annual Sediment Exports from the Maranoa Catchment

Total Annual Sediment Export (t)			**Reduction from 1990**		
Scenario	Upper Maranoa	Maranoa	Upper Maranoa		Maranoa
Base	95,435	144,825	t/year	%	%
X1990	96,582	145,895		0.0	0.0
X2004	95,438	144,824	1,144	1.2	0.7
X2017	93,572	143,076	3,010	3.1	1.9
X2050	84,530	134,530	12,052	12.5	7.8

The changed management during the Landcare period represents nearly 10% of total possible reductions in hillslope erosion. The changed management during the NRM period represents a further reduction of 15% of the total possible reductions. In total,

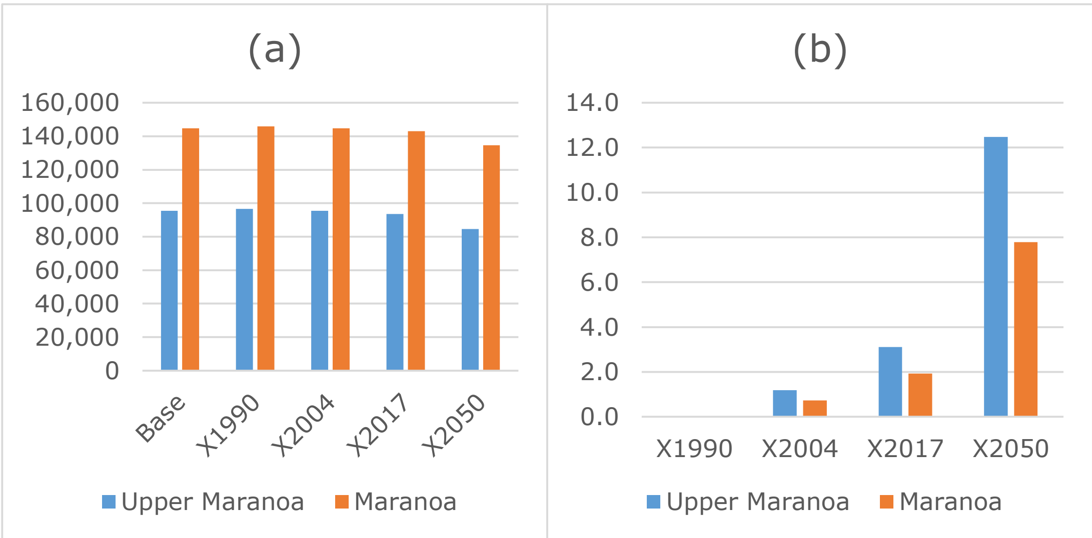

Figure 4-7: Modelled Catchment Sediment Exports in the Upper Maranoa and the whole Maranoa Catchment
With export in tonnes (a) and % Reduction (b)
Base=estimated actual; X1990=if managed as per 1990; X2004=if managed as per 2004; X2017=if managed as per 2017;and, X2050=aspirational management practices.

this means that during the 31 year model run period, changed management would result in 25% of Aspirational reductions in hillslope erosion in grazing lands of the Upper Maranoa catchment (Figure 4-8).

These are apparently modest reductions compared with total exports of 95,000 t/year for the Upper Maranoa and 145,000 t/year for the Maranoa catchment. The inclusion of the X2050 scenario, however, puts the reductions into perspective against what could reasonably be achieved with changes in grazing land management. These aspirational values were established independently of the assumptions used for the other management scenarios as they were derived from the near best observed ground cover in each Climate Landscape in each season.

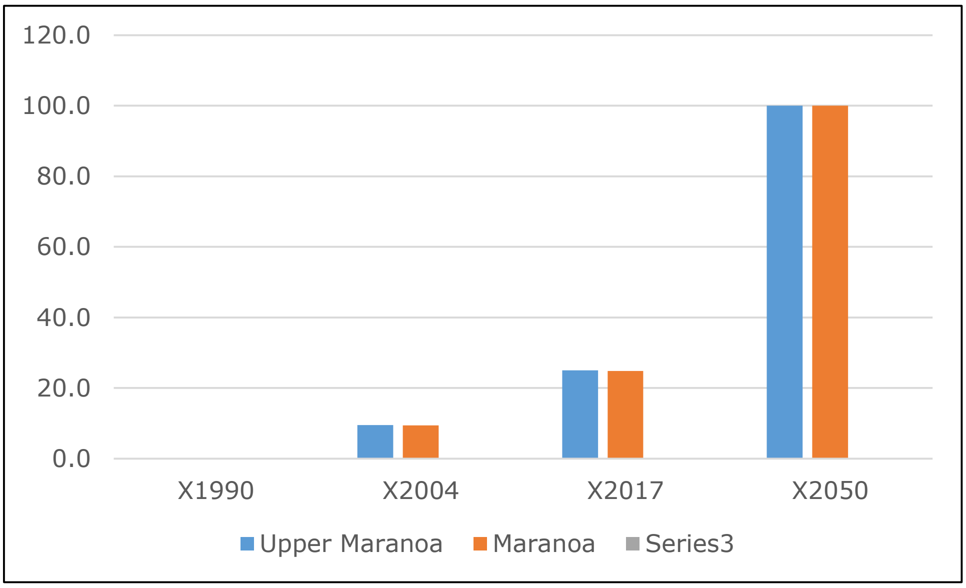

Figure 4-8: Progress towards Aspirational Hillslope Erosion for the Maranoa Catchment (%)
X1990(benchmark)=if managed as per 1990;X2004=if managed as per 2004; X2017=if managed as per 2017;and, X2050=aspirational management

4.8 Summary

The adapted Dynamic Reference Cover Method (aDRCM) was successfully applied to minimise the climate signal on groundcover data. aDRCM derived Groundcover Scores were used to compare areas that were known to have been supported with NRM investment. There was no clear difference in Groundcover Scores for supported properties and unsupported areas in the Upper Maranoa study catchment. Similarly, smaller paddock areas where NRM incentives payments had been paid showed no clear difference in Groundcover Scores than other parts of the catchment. Supported and unsupported areas across the study catchment showed an increasing trend in Groundcover Scores.

Responses to landholder interviews and surveys mostly aligned with satellite groundcover data dynamics. Responses also mostly confirmed the validity of aDRCM derived Groundcover Scores. Landholders indicated, however, that mapped NRM extension and incentives areas did not include all beneficiaries of NRM investment. Landholders also indicated that improvements in management, even in NRM investment areas, could not be attributed to NRM investment alone.

Catchment modelling indicated that the improvements in land management and ground cover could have resulted in a reduction in sediment loads in the Upper Maranoa River of approximately 1,900 t/year. When improvements in the Landcare period were combined with improvements during the NRM investment period, 25% of the possible reductions in soil loss and stream sediment loads from hillslope erosion have been achieved.

Chapter 5 will present some discussion of these results to identify strengths and weaknesses in the research methods and in conclusions regarding NRM investment outcomes.

Chapter 5 Outcomes and learnings from results

5.1 Introduction

Chapter 4 presented results of groundcover analyses in the Upper Maranoa catchment. Results were also presented on subsequent modelled estimates of the impact changed management had on groundcover and on stream sediment loads.

In this chapter the results will be explained in terms of the research question and objectives. Consideration will also be given to implications for NRM investment and sustainable grazing. Additional explanation will be provided of findings from landholder interviews within and beyond the research objectives. Finally, some suggestions will be made about further development and use of data and methods from this study to assess and support sustainable landscape management.

This study set out to determine the impact of NRM investment on grazing land management and on intended "intermediate outcomes" of improved ground cover, and subsequent "final outcomes" of reduced soil loss and stream sediment loads. Intermediate outcomes were evaluated by analyses of remote sensing data for the Upper Maranoa study catchment to determine if:

1. Ground cover increased across "properties" participating in extension programs in grazing lands, and,
2. Ground cover increased at incentive project "paddock" sites in grazing lands.

Then, final outcomes were evaluated with the application of catchment modelling to:

3. Estimate changes in soil loss and stream sediment loads due to changes in ground cover in grazing lands within the study catchment.

5.2 NRM intermediate outcomes - extension

An adapted Dynamic Reference Cover Method (aDRCM) (after Bastin et al. 2012; Bastin et al. 2014) was used to provide ground cover scores for supported properties and for nominated control areas in the study catchment. These ground cover scores removed most of the climate signal from remote sensing data to suggest a management signal for supported areas and controls. There was no clear distinction between trends in the management signal on groundcover for direct beneficiaries of NRM extension support and other properties in the study catchment (Figure 5-1, left). Landholder feedback suggested that NRM support beneficiaries extended well beyond the mapped support areas provided by the NRM body.

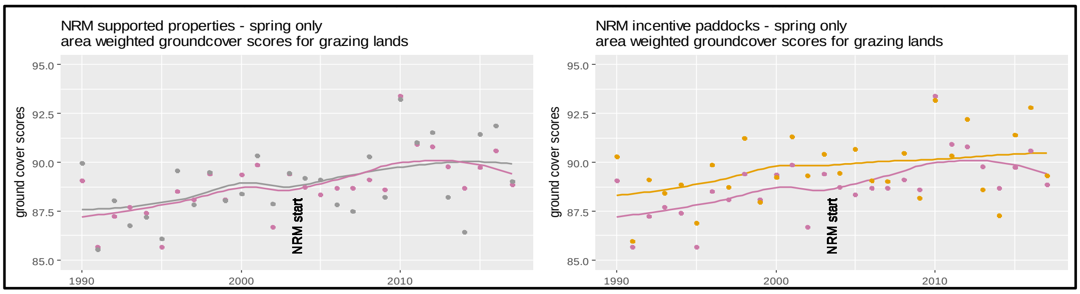

Figure 5-1: Moving averages of Groundcover Scores
Control areas (pink), supported properties (grey) and incentives paddocks (orange).

Ground cover similarity between supported and unsupported (control) areas across the catchment plus the landholder indications that impacts of support extended across significant portions of the control areas, meant the validity of the control area was unclear. It is likely that NRM extension impacted on many of the mapped control areas as well as the mapped extension areas. From landholder interviews, across the catchment it was also indicated that changes in understanding and management of grazing systems was influenced by NRM programs PLUS other drivers. This concurs with findings from other studies where conservative or sustainable agriculture is expanding due to financial, social and environmental drivers (Friedrich, Derpsch & Kassam 2012) and relies on a variety of communication and support mechanisms (Lubell, Niles & Hoffman 2014; Larsen et al. 2018). This has challenged those evaluating the outcomes of extension programs including public NRM programs (Coutts, Koutsouris & Davis 2019). Notably, this study has demonstrated an intermediate outcome which has been a gap in NRM program evaluation (Australian

National Audit Office 2008) but has not been able to quantify links with individual activities or outputs.

The conclusion is that Regional NRM extension activities have contributed to improved groundcover but that the degree to which improvements can be attributed to these NRM activities is not quantifiable from results of this study.

5.3 NRM intermediate outcomes - incentives

Ground cover scores were also established for paddock areas that were subject to NRM incentive project funding. All of these areas were contained within properties that had participated in extension programs. There was no clear distinction between trends in groundcover scores in combined incentives areas and other parts of supported properties (Figure 5-1, (right and left respectively)). Similarly, combined incentives areas scores showed no clear variation from control areas (Figure 5-1, right). (Note: Control values show an increase in the moving average due to the single high value in 2010 when all areas in the catchment showed similar high values due to the very wet conditions. The high volatility of the incentives scores is due to the small areas in incentives projects which show fluctuations more clearly that the larger control areas where averaging across broader landscapes dampens the variations.)

When evaluated at the property scale, again there is no strong indication of incentives areas having improved ground cover scores. This could be interpreted to mean incentives had no impact on grazing land management. There were indications from landholders, however, that incentives had helped with broader property management. This was borne out in the ground cover results with properties that had received incentives performing better than areas that had not received incentives (Chapter 4, Table 4-1).

An example of how this happened is where one landholder indicated that incentives were received for riparian fencing and off stream watering but that this was part of a broader re configuration of paddocks across the property to better manage grazing. In that same example property, riparian fencing outcomes were expected to include reduced stream bank erosion and improved aquatic ecosystem health (Waters & Webb 2007; González et al. 2017). Neither of these outcomes were assessed as part of this study. A number of landholders also indicated that the availability of incentives was itself a catalyst for participation in NRM extension activities. The indications in the survey comments that incentives enhance property management and participation in NRM extension programs may be subject to bias as respondents had a vested interest. Landholders also indicated some anomalies in recorded paddock data where some incentivised works were not mapped and some mapped works would not have been expected to lead to improved groundcover.

This highlights the ongoing challenge of promoting sustainable NRM based on demonstrated outcomes with change driven by many drivers ((Friedrich, Derpsch & Kassam 2012)), knowledge pathways (Larsen et al. 2018) and gradual uptake (Liu, Bruins & Heberling 2018). The interaction of information, incentives and regulation requires ongoing review and tailoring to local circumstances (Liu, Bruins & Heberling 2018; Yasué & Kirkpatrick 2018). Incentives can only ever be part of a suite of tools NRM groups can use to support and promote sustainable agriculture, but they do remain an important part of the toolkit (Comerford & Binney 2004).

In conclusion, incentives have contributed to property management within and outside paddocks mapped in project reporting. Incentives may have also improved the participation rate in NRM extension activities. In these two ways, incentives have contributed to improved groundcover but the degree to which improvements can be attributed to incentives projects is not quantifiable from the results of this study.

5.4 NRM outcomes - changes in soil loss and stream sediment loads

From the trends in groundcover due to management, ground cover datasets were synthesised to simulate ground cove that would have been observed if:

1. The observed climate for the 1986-2017 model period was unchanged, and,
2. Management was constant throughout the model period with scenarios:
    a. X1990 – assuming 1990 management practices were maintained through the model period,
    b. X2004 - assuming 2004 management practices were maintained through the model period,

c. X2017 - assuming 2017 management practices were maintained through the model period, and,

d. X2050 (Aspirational) – the best achievable ground cover for climate during the model period.

Datasets developed in this study were provided to DNRME who executed the Source QMDB catchment model (Davidson 2018) for each scenario and provided output data for interpretation in this study. Differences in model outputs for the different scenarios represent changes in catchment sediment export due to changes in management between the years represented in the different scenarios.

Model estimates of annual sediment export from the Upper Maranoa catchment were:

- 1990 management practices - 96,582 tonnes per year,
- 2004 management practices - 95,438 tonnes per year,
- 2017 management practices - 93,572 tonnes per year, and,
- 2050 aspirational management practices - 84,530 tonnes per year.

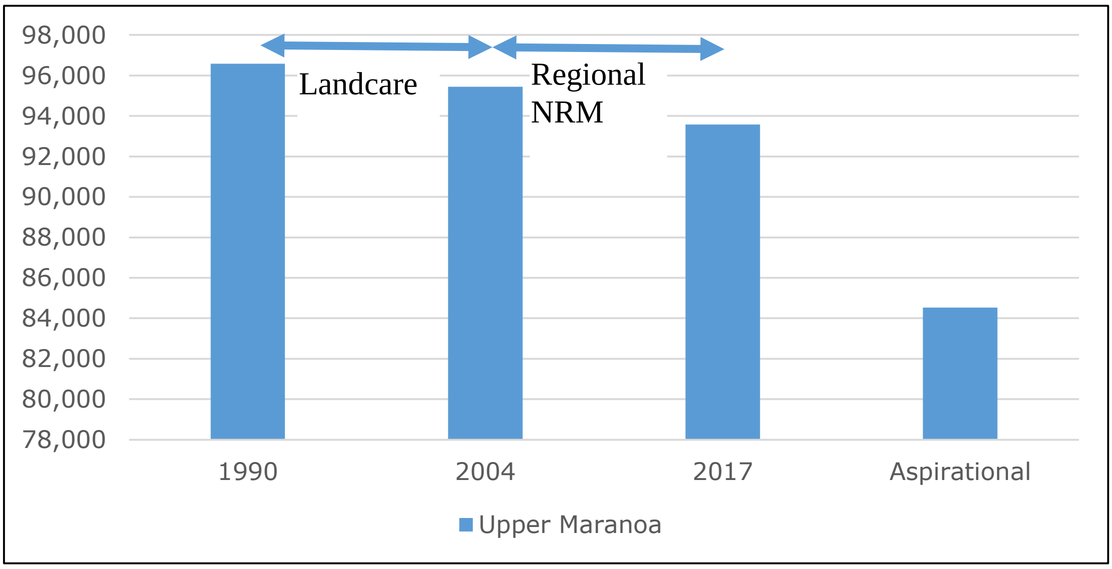

Figure 5-2: Sediment Exports (t/year) for the Upper Maranoa Catchment for different management scenarios.
Based on synthesised groudcover layers representing land management practices in 1990, 2004, 2017 and Aspirational or Best Case.

These results (Figure 5-2) indicate a reduction in annual average sediment loads in the Upper Maranoa River of approximately 1,900 t/year due to changed management during the Regional NRM period. This was in addition to reductions of 1,100 t/year due to changes during the preceding Landcare period. From the Aspirational model run, it was estimated that the greatest reduction in hillslope erosion contributions to sediment loads that could be achieved by improved grazing land management was 12,000 t/year.

The use of catchment modelling to quantify final outcomes from observed intermediate outcomes is effective and proven (Cook et al. 2009; Waters et al. 2014; Fu et al. 2019). A significant challenge for NRM evaluation has been building the capacity of stakeholders to calibrate, build and run complex and resource hungry models (Waters & Johansen 2016). In some cases this has led to groups of NRM bodies combining resources for evaluation (Carroll et al. 2013). The eWater Source model used in this study was made available by the hosting organisation who built the model to support state and commonwealth water regulations (Waters & Johansen 2016). This approach provides a more stable and auditable evaluation framework than previous evaluations in the QMDB (Waters & Webb 2007; Rattray 2009; Webb 2012). The modelling approach also mitigates the limitations on evaluation due to the time required for changes in management to impact on measurable landscape features (Emma & Rob 2016; Greiner 2016).

It is important to consider that these figures are for stream sediment loads due to hillslope erosion only. For the Upper Maranoa catchment these reductions represent just over 1% reduction in total stream sediment loads during the Landcare period and almost 2% additional reduction during the Regional NRM period. The greatest plausible reduction in stream sediment loads for the Upper Maranoa due to management impact on hillslope erosion is estimated at 12%.

In relative terms, model outcomes indicate improvements in grazing land management during the Landcare period may have achieved 10% of possible reductions in hillslope erosion. During the Regional NRM investment period a further (greater) 15% reduction may have been achieved. This means that using 1990 management practices as the benchmark, there has most likely been 25% progress towards the 2050 Aspirational goal.

The inclusion of the Aspirational scenario, puts the reductions into perspective against what could reasonably be achieved with changes in grazing land management. The methods used to develop the aspirational values could be translated across to other grazing lands in the QMDBB using datasets developed in or adapted from this study. As indicated in Section 5.1, this process may contribute to the establishment of groundcover measures associated with local Water Quality Guidelines (Department of Environment and Resource Management 2009).

Modelling results indicate that progress has been made towards the intended NRM final outcomes of reduced soil loss and stream sediment loads.

5.5 Regional NRM investment contributions to Outcomes

Ground cover scores showed an improving trend across the study catchment through both the Landcare and the Regional NRM periods. From the comparison of groundcover scores in supported and control areas, however, there was no clear indication that supported properties showed any greater improvement in land management than unsupported properties. Similarly, paddocks where incentives projects were implemented showed no greater improvement in groundcover scores than mapped control areas.

From landholder interviews it was determined that control areas were also affected by NRM investment activities such that these areas were not true controls. Incentives paddocks were identified as being part of broader property management changes and were, in some instances, not accurately mapped to identify NRM incentives areas where an improvement in groundcover could be expected. Several landholders did indicate that the availability of incentives was an important catalyst for landholder participation in NRM activities. They also frequently indicated that Landcare and Regional NRM activities had contributed to improved knowledge and management. Also, they proposed that other industry and social networks, and activities had contributed to improved knowledge and management.

This feedback from the landholders about the inexact records and application of NRM activities and funds confirms the challenges highlighted in Chapter 2, Section 2.4, regarding NRM evaluation. In particular, that evaluation of NRM is particularly challenging as it is encompasses diverse policy objectives and numerous projects and stakeholders (Verbeek et al. 2016, p. 383). And that this has been very evident in Australian NRM with the evolution of funding programs (Hajkowicz 2009; see Figure 1; Vella et al. 2015). Despite the complexities, however, this study has demonstrated at least partial achievement of intermediate outcomes and final outcomes that were previously difficult to demonstrate (Australian National Audit Office 2008).

From the trends in groundcover scores (corrected for climate trends) it was apparent that improvements in ground cover scores were greater during the NRM investment period than in the preceding Landcare period. This indicates that the Regional NRM investment did contribute to improved grazing land management (intermediate outcomes). NRM investment, however, was not the only contributor to these outcomes as indicated by landholders and confirmed by (lesser) improvements in the Landcare period – prior to Regional NRM investment.

From the Source modelling results it was also evident that there could have been reductions in stream sediment loads during the Regional NRM investment period (final outcomes) but also (lesser) reductions in the preceding Landcare period. Improved grazing land management has contributed to the reduced soil loss and reduced stream sediment load outcomes.

In summary, Regional NRM investment has contributed to intermediate outcomes and to final outcomes but the degree to which outcomes can be attributed to Regional NRM activities is not quantifiable from results of this study.

5.6 The aDRCM as an evaluation method

The adapted Dynamic Reference Cover Method (aDRCM) used to remove climate signal from seasonal groundcover data showed significant value.

5.6.1 Successful application for this study

Climate Landscapes showed good correlations between groundcover and climate signals. All data together showed some correlation between median groundcover and four season rainfall with a Pearson correlation coefficient (r) of 0.65. The aDRCM derived ground cover score, showed significant removal of this climate signal with an r of 0.33. Spring ground cover correlation with rainfall had r of 0.72 and ground cover scores showed even more significant removal of this climate signal with an r of 0.27.

Initial review of groundcover scores confirmed the findings (and inferences) of Bastin et al. (2012) that the removal of the climate signal was most significant in spring and in open grazing areas. This study, however, was also able to establish significant removal of the climate signal in wet years and in timbered grazing areas which were highlighted as gaps in the DRCM (Bastin et al. 2012).

Using the aDRCM it was possible to gain some qualitative indications of trends in management impact on groundcover through time and on management impacts on groundcover across different landscapes and management units. In particular, it was possible to provide some indication of how particular properties were performing compared with norms for a broader catchment.

5.6.2 Observations from collated data

Additional observations of how climate related to median ground cover and to ground cover scores included:

- Four seasons' rainfall had consistently higher correlation with ground cover than current season rainfall and only slightly higher correlation with pc50 than eight season's rainfall. Numerous variations of one to eight seasons of climate data were trialled but the use of four seasons rainfall (being the current season and the three preceding seasons for any given ground cover value) is suggested as a parsimonious model for future applications.
- Maximum temperature and potential evapotranspiration both had consistently negative correlation with ground cover and this signal was reduced in ground cover scores. The signal was not as strong as the rainfall signal, however, so was not investigated any further in this study.
- Potential evapotranspiration (pet) did show a moderate negative correlation with median ground cover in autumn (r=-0.63) and spring (r=-0.57) but not so in summer (r=-0.27) or winter (r=-0.29). As indicated previously, this relationship was not investigated further in this study but it may have

implications in other studies. Of additional interest in this dynamic was that the autumn association with potential evapotranspiration was not mirrored in temperatures but the spring association for pet and maximum temperatures was very similar.

- Ground cover scores developed from other than 50% (median) ground cover percentiles showed some value in the removal of climate signal from ground cover. Given the erosion risk and the infiltration capacity implications (cf Fraser & Stone 2016), management signal impact on 20% ground cover may have value for other landscape resilience studies.
- Further to the previous point, the removal of the management signal using 5% groundcover percentiles was less than for other percentiles. This suggests that the aDRCM may not be ideally suited to identification of extreme erosion risk areas. A suggestion is that the 5% groundcover levels may include a signal from fixed infrastructure, active erosion and water point related bare ground that does not respond directly to routine grazing management changes.
- Although spring ground cover scores showed significant removal of the climate signal, timbered and non-timbered areas still showed differing characteristics in the time series ground cover score plots (e.g. Figure 4-5 to 4-7). Generally timbered areas showed less volatility than open grazing areas. This reiterates concerns of Bastin et al. (2012) about the use of the DRCM in timbered areas. In this study, the impact of this variability between timbered and open grazing areas was tempered with a variable weighting of control scores. That is, control scores were calculated from timbered and open control areas scores with area weightings based on the proportional area of timbered and open grazing areas in the test area (not the control areas). In that way if an

extension area or incentives area that was being assessed had was dominated by, for example, open grazing areas it was being compared with a control dataset that was also dominated by open grazing areas.

See Appendix 4.1 for correlation heat maps of Pearson’s r for ground cover and ground cover scores in different years, seasons and grazing land use filters.

5.6.3 Further application of the aDRCM

Groundcover data similarities plus feedback from landholders indicated sparse timber and open grazing areas performed similarly and the boundaries between them are likely to vary with successive regrowth clearing events. Timbered grazing areas and forestry areas were mostly similar in groundcover results characteristics and landholder feedback was that grazing management did not change between these different tenures. Landholders also indicated that some former forestry areas are now freehold and that the freeholding process is not complete (cf Department of Agriculture and Fisheries 2016).

For future work, **landscapes could be combined to two classes of open grazing (fpc 0-10%) and timbered grazing (fpc > 10% including forestry areas).**

Some caution should be used in assigning and assessing forestry land based on a static vegetation layer as used in this study. Logging events in these areas are likely to have (occasional) significant impact on carrying capacity, ground cover and erosion risk with these being independent of grazing management practices. This impact may be exaggerated in the immediate future with some feedback indicating significant clearing (liquidation of natural assets) by the Queensland Government where former forestry areas are being freeholded and government rights vested in timber have a sunset clause.

Further investigation would be required before using the aDRCM in Mulga lands where Mulga is cleared or partially cleared for stock feeding in drought (Metcalfe et al. 2018). In these conditions a static grazing land class approach may not be appropriate as areas of Mulga would actually alternate between open and timbered grazing states.

Although this study subsequently focussed on the Upper Maranoa catchment only, the climate landscape zoning was undertaken across the Queensland Murray-Darling and Bulloo Basins (with a buffer). The dataset and method are available for further use. **A possible application of this dataset would be in the derivation of local water quality guidelines across the QMDB** with consideration of these guidelines being supported by climate zoning for grazing lands within existing broader water quality type zones (Department of Environment and Heritage Protection 2015). In the development of Water Quality Objectives, ground cover in grazing lands was identified as important (Newham M et al. 2018) summarised and scored across the water quality type zones (van den Berg, Trevithick & Tindall 2015). The variation between groundcover data characteristics within this study area confirm the van den Berg et al. (2015), suggestion that the water quality type zone reporting is not appropriate for local scale assessments (p2). The methods used in this study to identify Climate Landscapes reflect local scales that could be incorporated into water quality zone and broader regional reporting. Consideration should be given, however, to combining open grazing with sparely timbered areas and combining timbered grazing and forestry areas.

5.7 Learnings from Landholders

5.7.1 Ambiguities in defining NRM beneficiaries

Numerous landholders indicated that regional and property scale mapping did not accurately define the extent of areas exposed to NRM extension or incentives.

With regard to supported properties, all properties mapped were confirmed to have received NRM support. Support was also provided to other landholders, however, through direct and indirect mechanisms. Direct mechanisms included properties managed by landholders that were not mapped in NRM activities reports. Reasons for the gaps in mapping included purchase of properties after NRM mapping exercises and family partnerships represented in NRM activities with only some partners/properties participating in NRM activities but learnings being shared and implemented across all properties. Indirect mechanisms included the sharing of information and ideas from NRM activities occurring in industry and social contexts including people outside mapped property areas.

This is an extra dimension to the challenges of evaluating NRM programs. Within NRM areas it has been highlighted that other initiatives and programs are influencing management besides NRM (eg Verbeek et al. 2016 and the following Section 5.7.2). Those anomalies can bring into question the efficacy of NRM investment within a defined area due to other potential contributors to outcomes. This study highlights that the interaction of activities can also go the other way where NRM activities can contribute to outcomes outside the NRM reported areas.

5.7.2 Non Regional NRM activities also influencing management

Just as NRM activities and support from Regional NRM groups (including QMDC) extended beyond the mapped area, new information and support for mapped areas was not confined to QMDC activities. Industry groups (E.G. Meat & Livestock Australia described in Mayberry et al. 2019), education and training, intergenerational information exchange and social networks were at times suggested in landholder interviews as additional drivers for changed grazing land management. This is not a new finding but a reiteration of previous realisations (Pannell et al. 2006; Bosomworth et al. 2018). It should be noted that some of these drivers have also been supported by the $10 Billion NRM Australian NRM funding (cf Chapter 1, Figure 1 citing Hajkowicz 2009; Vella et al. 2015) but were not the focus of this study. Some of these interrelated drivers that were at least partly funded by the Australian governments' NRM investment included Landcare (Love, Coral 2012), industry groups (Meat & Livestock Australia Limited 2011) and Government agencies.

5.7.3 Outliers in ground cover scores

Several landholders questioned the very low groundcover scores in 2013 and 2014 (following the big flood in 2012) despite there being no significant changes in management. Further investigation revealed that this was likely due to pasture mortality following the flood due to water logging and also possibly due to high temperatures (See Appendix 5.1 for details of this investigation).

5.7.4 Clearing of regrowth - routine

The periodic clearing of regrowth is a routine element of grazing land management (Whish, Pahl & Bray 2016). Ground cover and groundcover scores decline immediately following a regrowth event. This was more significant on properties where regrowth was followed by dry seasons. Due to the inconsistent impact of regrowth on groundcover scores, caution should be exercised in using individual property or paddock results for evaluation of management impact on groundcover. It is suggested, however, that this issue will average out in routine conditions allowing more confidence in the use of groundcover scores to evaluate collective changes in ground cover due to management across multiple properties. To resolve this issue at property scale consideration would need to be given to incorporating a dynamic vegetation layer into groundcover evaluations.

5.7.5 Clearing of regrowth – non-routine

The regrowth impact on groundcover scores was also more significant on properties that indicated they had cleared more area or cleared sooner than planned when State Government was debating changes to vegetation regulations. Changes could have resulted in areas of significant regrowth being reclassified as (protected) remnant vegetation. This legislation was introduced into parliament in 2016 but was defeated. It was reintroduced and passed in 2018 (Vegetation Management and Other Legislation Amendment Bill 2018). Several landholders indicated in casual conversations outside interviews that this legislation has, and is likely to, result in more frequent clearing of regrowth. It is suggested that this could have ongoing negative consequences for production, biodiversity, carbon sequestration, soil loss and stream sediment loads (England 2018).

5.7.6 Vegetation policy considerations

A concept that evolved out of conversations with landholders was that the Murray-Darling Basin Plan (Basin Plan) buyback approach for water (Grafton & Ann Wheeler 2018) should be applied to vegetation regulations in Queensland. That is, if particular areas are identified as having high environmental value then a voluntary buyback approach be used. This approach requires that Government compensate producers for lost production potential from land previously cleared for grazing or cropping but now deemed to be ineligible for (re) clearing. This approach is not without complications including costs for Government as real values of natural assets are established alongside production value of the same assets (Wittwer 2011). As with the Basin Plan, there may be capacity to also pursue policy options with mutual (production and environmental) benefits (Wittwer & Dixon 2013).

A suggested approach for mutually beneficial management is a cyclical clearing approach with consideration of multiple environmental and production benefits including: carbon sequestration; biodiversity; soil health; ground cover; stock carrying capacity and native species' populations (supported by data and recommendations of Whish, Pahl & Bray 2016; England 2018). This approach is what has been referred to as Agri-Environment schemes (Ansell, Gibson & Salt 2016). Some graziers interviewed in this study were already implementing this approach in unregulated areas with the growing realisation of the value of woody vegetation in grazing landscapes (cf Tongway, Sparrow & Friedel 2003; McKeon et al. 2008).

5.7.7 Ground cover monitoring

In section 4.5 it was indicated that properties for which ground cover monitoring data was available showed better average ground cover scores than other properties. This suggests monitoring is associated with better management. Data from this study would require more follow up work including conversations with landholders to confirm these findings and explore the association. At face value, however it confirms the literature that suggests monitoring is critical to adaptive management and dealing with climate variability and climate change (McCollum et al. 2017). This suggests both on-ground monitoring and landholder access to remote sensing data reported at property scale (eg Long Paddock website described in Stone et al. 2019) should be considered as part of ongoing support for sustainable grazing landscapes.

5.8 Quantifying trends in ground cover management signal

The Groundcover Scores derived with the aDRCM significantly reduced the climate signal but a weak climate signal was still evident in Pearson correlation coefficients and in time series moving average plots. The additional step of standardising Groundcover Scores and rainfall data and thus correcting trends (ΔΔGC referred to in Bastin et al. 2014) for climate provided a quantitative assessment of trends in groundcover data. This approach could conceivably be used to assess or compare data across a range of landscapes during designated periods within the range of available remote sensing derived seasonal groundcover data (from 1990 onwards).

Bastin et al (2012 & 2014) in the development of the DRCM suggest trend analyses should be applied in successive dry periods only. The aDRCM showed reasonable removal of climate signal for all years using the spring seasons only. The trend analyses in this study for both the Landcare period and the NRM investment period happened to start and finish in dry years with wet periods in between. In this situation, the aDRCM partly complied with the DRCM qualitative evaluation recommendations. The validity of the approach was strengthened by the ground cover/climate correlation dynamics (see Appendices 3.4 and 4.1). The trend in the ground cover management signal for non-wet years (with no correlation with climate indicators) agreed with the signal for all years after it had been corrected for remaining climate signal. This provided a management signal trend that could be used for all years and thus for catchment model inputs.

If the aDRCM was to be applied over shorter periods or in periods that did not start and finish in dry years, more work may be required to confirm the suitability of the method. Consideration could be given to applying the method during drying phases (as used by Barnetson et al. 2017). This approach would, however, require access to groundcover data at monthly rather than seasonal resolution.

This study has also assumed that the management signal indicated by the spring ground cover scores represents all seasons. This assumption was not validated. A possible future refinement of the method would be to run separate management signal trend analyse for separate seasons.

5.9 Groundcover and hillslope erosion in the NRM context

Hillslope erosion, the focus of this study, represents only 13% of total sediment exports from the Maranoa catchment. Other sources of sediment are gullies (60%), streambanks (24%) and channels (remobilisation 2%) (Davidson 2018, p. 51, Table 15). NRM supported activities that have contributed to other forms of erosion are not considered in this study.

Increased groundcover quantified in this study would reduce the likelihood of new gullies forming or of accelerated stream bank erosion (Fraser & Stone 2016; Nouwakpo et al. 2016). Increased groundcover is likely to also reduce damage in areas of active erosion in gullies or stream banks due to reduced runoff and flow intensity (Bartley et al. 2006; Silburn et al. 2011). These secondary benefits of increased ground cover are not included in estimations of reductions in stream sediment load in this study.

Some gully erosion mitigation has been done on properties visited and this was a consequence of NRM extension activities. For example, NRM supported track maintenance field days resulted in one landholder reconfiguring his track “whoa boy” drains. This action included remediation of some early stage gullying which means it has led to reduced soil loss and stream sediment load. Again, these actions would have reduced stream sediment loads but these reductions are not included in load reductions quantified in this study.

Just as groundcover and hillslope erosion is not the full story for stream sediment loads, erosion is not the full story for sustainable NRM (Emma & Rob 2016; Whish, Pahl & Bray 2016). Other NRM themes, which are not assessed in this study, were addressed in activities in the Upper Maranoa study catchment (Queensland Murray-Darling Committee 2012) . These include support for terrestrial and aquatic biodiversity, weed and pest management, social capacity building and cultural heritage awareness activities. These all combine with erosion management to contribute to sustainable landscape management (Ansell, Gibson & Salt 2016).

The Upper Maranoa catchment is itself nested in the Maranoa catchment the Condamine-Balonne catchment and the Murray-Darling Basin. The modest contribution of improved grazing management in the Upper Maranoa links to outcomes for the wider basin (Queensland Murray-Darling Committee 2015b; Newham M et al. 2018). Although the significance may be modest it is important to acknowledge and share the good news that these outcomes demonstrate capacity to achieve positive outcomes from targeted NRM investment (Liu, Bruins & Heberling 2018).

5.10 Summary

From the results presented in Chapter 4, this study provides evidence of changes in management and subsequent increases in ground cover across the catchment. Building on that evidence, there has been some progress towards the NRM intended outcome of reduced soil loss and stream sediment loads.

From the groundcover data analyses and related landholder feedback, however, it is not clear to what extent NRM investment has led to these outcomes as there were a number of other contributors to improved grazing land management.

Methods used to evaluate the management signal in groundcover data offer opportunities for further use of remote sensing data to evaluate grazing land management and related support programs. Translation of the methods used in this study should be informed by the discussion in this chapter, but also by the underpinning work by Bastin et al (2012 & 2014) and possibly the work of Barnetson et al (2017).

Information obtained in the landholder interviews as part of this study offer insights into how NRM and other activities are contributing to improved knowledge and grazing management. Landholders also provide information on limitations of data and research methods. They also provide ideas that are documented here on possible variations to vegetation management that could lead to better outcomes for production and for the environment.

The ground cover, soil loss and stream sediment loads considered in this study show benefits of a small slice of the NRM investment. Chapter 6 will summarise the results with a focus on the research objectives of this study.

Chapter 6 Conclusions

6.1 Introduction

This Chapter will summarise the findings of this study against the research aims and objectives. Some brief points will then be made on the evaluation methods and observations to enhance result interpretation and to inform future work.

6.2 Research aims and objectives

This study of grazing lands in the Upper Maranoa catchment was undertaken to evaluate NRM Investment. The study considered groundcover as an indicator of NRM investment outcomes during the period of available data from 1990 to 2017. This included two key NRM investment periods which have been referred to in this study as the Landcare period and the Regional NRM investment period. Regional NRM investment was the focus of the study but inclusion of the Landcare period suited the evaluation method and added value to the results.

6.2.1 Research aim

The aim of the research was to determine whether or not Regional NRM program activities and outputs have led to the achievement of intermediate outcomes and final outcomes. In particular the aim is to determine if NRM investments have influenced grazing land management with benefits for impacted environments.

From the catchment model results based on remote sensing ground cover and underlying trends, soil loss and stream sediment load may have been reduced in the Upper Maranoa study catchment. This can be attributed to modest improvements in ground cover due to management. Regional NRM investment was found to have contributed to these positive outcomes but the degree to which Regional NRM investment contributed to outcomes could not be ascertained in this study.

6.2.2 Research question

To achieve the aim of the research, the intention was to answer the question:

> *What was the impact of NRM investment on grazing land management and subsequently on ground cover, soil loss and stream sediment loads in the Upper Maranoa study catchment?*

Although ground cover showed some improvement with associated reduced soil loss and stream sediment loads, the degree to which NRM investment has contributed to this improvement is not clear. Two key factors made it difficult to isolate the NRM signal in the improved management and ground cover:

1. The NRM investment footprint was not clear or complete. Some landholders, including extended family partners, were managing land outside the listed participating properties which compromised the control for comparative purposes. Not all incentive projects were recorded on NRM reporting databases and not all recorded projects could be expected to result in improved groundcover.
2. Landholders all indicated that NRM activities alone were not contributing to ongoing improvements in grazing land management. Industry bodies, social networks and "learning from experience" all worked in tandem with NRM extension and incentives programs.

The research question was not definitively answered despite the research aim having been met.

6.2.3 Research objectives

In pursuing an answer to the research question, 3 particular research objectives were pursued.

> *Research Objective 1 – To analyse available remote sensing and groundcover monitoring data to determine whether ground cover scores increased across "properties" participating in extension programs in grazing lands.*

Ground cover increased when averaged across properties listed as participating in extension programs. The increase was not universal across supported properties, however, with some properties showing a decline in ground cover scores. Improvements were not confined to listed properties with groundcover scores across the study catchment showing similar trends to those of supported properties.

Research Objective 2 – To analyse available remote sensing and groundcover monitoring data to determine whether ground cover increased at incentive project "paddock" sites in grazing lands.

Ground cover increased when averaged across paddock areas mapped as having been supported from Regional NRM incentives with anticipated benefits for ground cover. The was no clear indication that ground cover scores in incentive paddocks performed any better than elsewhere on associated properties or on other properties in the study catchment.

Research Objective 3 – To Estimate changes in soil loss and stream sediment loads due to changes in ground cover in grazing lands within the study catchment.

The project was successful in estimating changes in soil loss and stream sediment loads due to changes in ground cover in grazing lands within the study catchment. As indicated previously, however, improvements to ground cover with associated reduced soil loss and stream sediment loads cannot be attributed solely to NRM activities. Remote sensing data and landholder interviews indicated improvements were not due solely to Regional NRM investment but included numerous industry and social contributions.

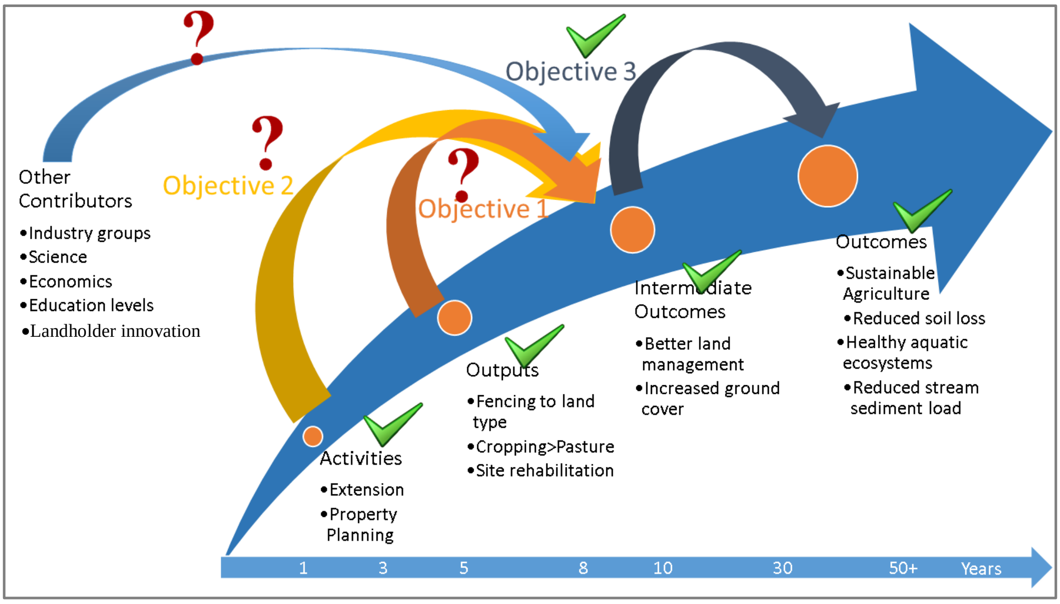

Figure 6-1: Research Objectives evaluating NRM Outcomes (adapted from Australian National Audit Office 2008)

From the above summary, the research aim was met. The research question was partly answered. Research Objectives 1 and 2 were partly answered and Objective 3 was met (see Figure 6-1).

Regional NRM activities and outputs have contributed to intermediate outcomes, but the degree to which they contributed was not quantifiable in the findings of this study. Intermediate outcomes have contributed to final outcomes. This has occurred during the Regional NRM period and to a lesser extent during the previous Landcare period.

6.3 adapted Dynamic Reference Cover Method (aDRCM)

The adaptation of the DRCM (Bastin et al. 2012; Bastin et al. 2014) allowed comparison of ground cover scores to indicate relative differences in management signal across properties and groups of properties. The adaptations included the use of defined landscape zones to establish reference data rather than the proximity based approach of the DRCM. The adaptations also separated timbered and non-timbered areas allowing the use of the method in landscapes with significant timber cover. A further benefit of the adapted approach was the use of 95% and 50% summary data formats from standard VegMachine reports to establish ground cover scores (Beutel et al. 2005 and inpress, 2019). This approach means the method can potentially be used by a range of stakeholders to obtain qualitative comparisons of management signal between selected properties.

This study has triggered adaptations of the VegMachine products with future enhancements likely to include the option of "no subsampling" and the use of raster data to interrogate VegMachine with complex spatial datasets.

The distinction between open grazing and sparse timber that was used in this study was shown to have limited or no value as it picked up a lot of "fringing" timber areas along variable boundaries of regrowth management areas.

The Foliage Projective Cover (fpc) criteria of greater than 10% used for timbered grazing areas was appropriate for this study and was based on "woodlands" and "forests" in NVIS and SLATS literature (NVIS Technical Working Group 2017; Queensland Department of Environment and Science 2018 and inpress, 2019). Consideration should be given, however, to the use of 15% and above as the threshold for woody vegetation to align with, for example, Long Paddock Forage landholder support products (The State of Queensland (DES) 2019).

The distinction between Forestry areas and other timbered grazing areas applied in this study proved unnecessary. All landholders interviewed who had Forestry leases indicated there was no significant difference in grazing management practices for Forestry leases and other timbered grazing areas. It was also indicated that some former Forestry leases have been “freeholded” albeit with some rights vested in timber retained by the State for a period (Department of Agriculture and Fisheries 2016).

6.4 Ground cover score trend analysis

Trend analyses were done on ground cover scores after they were merged with an area weighted average. This allowed a comparison of ground cover scores for the Regional NRM period (2004-2017) and for the preceding Landcare period (1990-2003). There was a slight increasing trend for both periods which confirmed visual assessments of groundcover scores used previously in qualitative assessments (Section 6.2). When compared with rainfall data trends, however, the relative increase in groundcover scores was greater in the Regional NRM period. Scores were standardised before trend comparisons were made.

This approach was reasonable given the extended (13 year) duration of data for each of the two compared periods. Both periods also had dry years near the start and finish possibly providing greater consistency between the two periods. The relative trends (i.e. trends in groundcover scores relative to the climate trends) were adopted as the management signal underlying the observed groundcover.

For shorter duration study periods or for periods that finish in a different climate phase to their start a variation of the standardised data trend comparison may be more appropriate. Such a variation could be modelled in the approach used in Barnetson et al (2017) where recession phases only of time series ground cover data were used (Barnetson et al. 2017). In this approach, the divergence (or otherwise) of data from comparative sites were analysed to determine relative management signals.

6.5 Model data synthesis

With trend information available for the management signal in observed groundcover data, it was possible to review historic remote sensing data for a number of management scenarios. Before undertaking this exercise, however, the trend in remote sensing groundcover estimates needed to be adjusted to equate to Visual Ground Cover (VGC). Seasonal VGC data is used to establish RUSLE c factors used in the eWater Source catchment model (Trevithick & Scarth 2013).

With VGC equivalent management signal trends available, historic (base model) VGC raster data were adjusted to infer the vgc that would likely have occurred for:

- A 1990 scenario assuming management practices used in 1990 were maintained for the entire model period (1986-2017).
- A 2004 scenario assuming management practices used in 2004 (end of Landcare period and start of NRM period) were maintained for the entire model period.
- A 2017 scenario assuming management practices used in 2017 (end of NRM study period) were maintained for the entire model period.
- And, a 2050 “Aspirational scenario based on pc95 reference scores for each climate landscape for each season in were maintained for the entire model period.

Adjusted/synthesised raster files for each scenario were made available to DNRME staff to process through the Condamine-Balonne model (ref Davidson 2018).

Model results imply that the NRM outcomes of reduced soil loss and reduced sediment load have been achieved to some degree. Approximately 10% of the possible hillslope erosion reduction was achieve in the Landcare period and a further 15% in the Regional NRM period (Figure 6-1, Objective 3).

6.6 Enablers for improved grazing land management

29 landholder interviews were taken with surveys completed for 43 different properties (some enterprises managed more than one property). Most indicated NRM extension

and incentive programs had some impact or major impact on their operations with benefits including:

- Information provided at workshops and field days,
- Information exchange with other landholders at workshops and field days, and,
- Property mapping support.

Those who received incentives payments indicated the incentives had a major impact on management of individual paddocks and some impact or major impact on whole of property management.

6.7 Inhibitors for improved grazing land management

Over 75% of responses listed vegetation legislation or instability of vegetation legislation as a significant inhibitor for ongoing grazing land management. In some cases it could be implied that instability in vegetation legislation was detrimental to management practices and land condition. For example several landholders indicated that they had cleared regrowth sooner rather than later due to the possibility that some older regrowth may be "locked up". There was strong support for changes in vegetation mapping to follow the Murray-Darling Basin Plan approach where changes to rights vested in a natural resource should be purchased by the governments rather than resumed.

Other issues with at least some effect on management and on efforts to improve management included climate, markets, changed ownership or ownership succession associated with changed family circumstances.

Climate and market fluctuations were mostly accepted as "par for the course" but timing of poor seasons or poor markets impacted on cash flow when trying to implement changed practices. This was a significant issue in relation to NRM incentives support with often short time frames and short notice of available incentive funds for activities that also required landholder time or cash contributions.

6.8 Significance of this study

This study has achieved the aim to determine if NRM investments have influenced grazing land management with benefits for impacted environments. Benefits have been confirmed in the study catchment during the Regional NRM period and in the preceding Landcare investment period.

This study had also developed and tested an adapted Dynamic Reference Cover Method (aDRCM) to reduce the climate signal from ground cover data and thus evaluate trends in the management signal on ground cover at property and at wider program scale. This enhanced method can be applied to grazing lands which include areas of significant woody vegetation.

This study has also established a method for incorporating the management signal trends in ground cover into the eWater Source modelling environment to quantify impacts on stream sediment load estimates. Included in this process was the development of an "aspirational" ground cover layer for the catchment established from seasonal "near best" ground cover values in each homogenous landscape area.

In the process of the study a number of enablers and barriers to improved grazing land management were identified for consideration in ongoing NRM.

6.9 Summary

Regional NRM has helped grazing land managers in the Upper Maranoa catchment to improve land management. Improved management has led to modest improvements in ground cover and reductions in hillslope erosion and stream sediment loads. The degree to which Regional NRM contributed to improved practices, reduced soil loss and reduced stream sediment load is not clear. Other initiatives from landholders and industry groups have also contributed to changes.

The aDRCM was useful for comparing properties and groups of properties for qualitative assessment of trends in the management signal on ground cover. Trend analyses of aDRCM derived ground cover scores provides a novel approach to the use of remote sensing data to contribute to catchment model assessments of the benefits of changed land management practices. The aDRCM could be further explored with more detailed study of the dynamics of groundcover through varying climate conditions across a range of temporal scales.

This work has bridged the world class operations of Australian graziers, remote sensing scientists, catchment modelling experts and natural resource management professionals. It has also highlighted at least some success from state and commonwealth initiatives delivered through Regional NRM groups to support and promote sustainable land management practices. It has highlighted the range of challenges and other initiatives that are part of the continuous improvement that is occurring in our grazing industry.

Graziers have achieved a lot in terms of improved management of production landscapes. More can still be achieved to manage ground cover and associated hillslope erosion. Stability of vegetation management for production and environmental sustainability has capacity to contribute to better management of ground cover and hillslope erosion. Gully erosion and stream bank erosion works could also make significant contributions to reduced stream sediment loads.

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Appendices

Appendix 1.1 Australian Governments NRM investment

Table 1.1.1: NRM investment from Hajkowicz 2009, pp472-475

Program	**National Soil Conservation Program**	**NLP**	**NHT1**	**NHT2+NAP**	**CfoC**
year started		1990	1996	2000	2007
year ended		1996	2000	2007	2013
$M		360	1300	2600	2250
$/year		60	325	371	375

Table 1.1.2: NRM investment from Vella et al 2015 p383

Program	**Growing awareness of NRM issues**	**(NLP)**	**NLP**	**(NHT)**	**NHT2 /NAP**	**CfoC**	**CfoC2 /(new) NLP**
start	1930	1983	1992	1996	2002	2008	2013
end	1983	1992	2003	2002	2008	2013	2018
$M		132.6	596	1500	3150	2000	2000
Average $/year		15	54	250	525	400	400

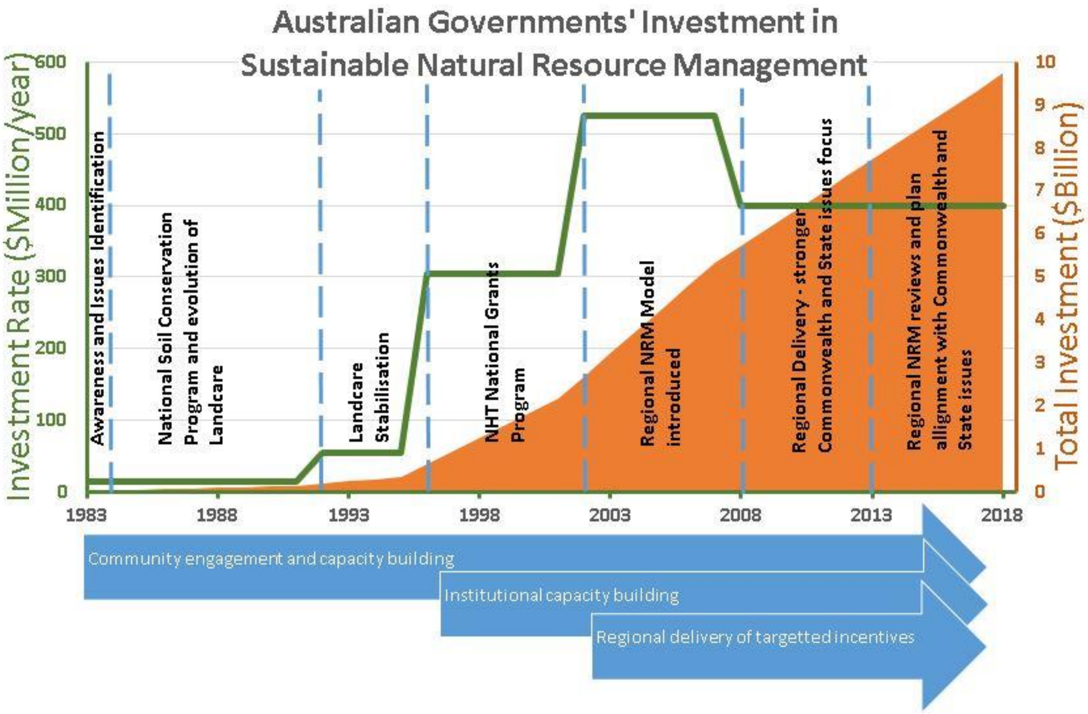

Figure 1.1.1: NRM investment chronology

Table 1.1.3: Annual and cumulative NRM investment

	Compiled from Tables 1 and 2		
Year	Investment ($Million/year)	Cummulative Investment ($Billion)	Phases (Vella)
1983	15	0.015	1
1984	15	0.03	1
1985	15	0.045	1
1986	15	0.06	1
1987	15	0.075	1
1988	15	0.09	1
1989	15	0.105	1
1990	15	0.12	1
1991	15	0.135	1
1992	54	0.189	2
1993	54	0.243	2
1994	54	0.297	2
1995	54	0.351	2
1996	304	0.655	3
1997	304	0.959	3
1998	304	1.263	3
1999	304	1.567	3
2000	304	1.871	3
2001	304	2.175	3
2002	525	2.7	4
2003	525	3.225	4
2004	525	3.75	4
2005	525	4.275	4
2006	525	4.8	4
2007	525	5.325	4
2008	400	5.725	5
2009	400	6.125	5
2010	400	6.525	5
2011	400	6.925	5
2012	400	7.325	5
2013	400	7.725	6
2014	400	8.125	6
2015	400	8.525	6
2016	400	8.925	6
2017	400	9.325	6
2018	400	9.725	6

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Appendix 3.1 Bulloo Downs ripping sites groundcover evaluation

In the early stages of the Upper Maranoa study, data became available from a previous study that was considered suitable for an independent testing of the adapted Dynamic Reference Cover Method (aDRCM) to be used in the Uppe Maranoa study.

In the 2000s a number of sites on Bulloo Downs were ripped to effect reductions in rabbit numbers (Berman et al., 2011). A review of groundcover has been undertaken to determine if there was any measurable effect of rabbit treatment on groundcover in ripped and unripped (control) areas.

An adapted Dynamic Reference Control Method (aDRCM) (after Bastin et al., 2012; Bastin et al., 2014) was used to assess groundcover scores in each of 4 ripped sites and in the 4 corresponding control sites.

No clear response was seen in groundcover following the 2001 rabbit warren ripping activities. Some improvement in groundcover scores was observed in the broader Bulloo IBRA sub region from 2006-2010. It is not clear if this can be attributed to the 2003 ripping of warrens within proximity to permanent waterholes.

Method

Bastin et al proposed a Dynamic Reference Cover Method (DRCM) where the near best ground cover value (% total groundcover) within proximity to a study cell could be adopted as an Aspirational or best achievable groundcover value. The difference between this aspirational value and an observed value could be used as a groundcover

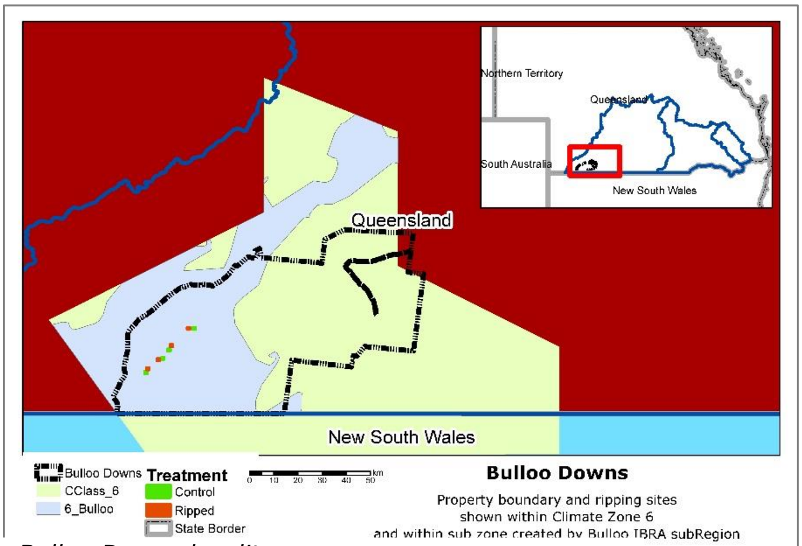


Figure 3.1.1: Bulloo Downs locality

score. Groundcover scores could be compared between an area where a known change in management occurred and an untreated control area to determine the effect of the change in management on groundcover (Bastin et al, 2012 & 2014).

In this study an adapted DRCM (aDRCM) was used. The aDRCM used a reference area based on climate (and landform) rather than on proximity to the study area. That is, the aDRCM climate and IBRA zoning was used to identify "landscape zones" where groundcover results could be regarded as reasonable homogeneous. Groundcover scores were originally derived using a reference "zone 6" which was determined from cluster analyses of climate data across the Queensland Murray-Darling and Bulloo Basins (Webb, 2019 unpublished). Variations in high cover values across the zone compared with ripped and control sites highlighted that the climate zoning alone was not sufficient for establishing reference (homogenous) groundcover zones. IBRA subregions (Department of the Environment, 2012) were overlaid over the climate zones to add broad landform information to the zoning process (see Figure 3.1.1). The "zone 6/Bulloo IBRA subregion" derived through this process provided much more credible groundcover reference data.

Within each zone the 95% groundcover value (the groundcover value exceeded by 5% of pixels in the zone) was adopted as the Aspirational ground cover reference. The difference between that reference value and the median groundcover value for a study area in a given season was calculated and subtracted from 100 to give a Δ50 or D50 groundcover score. The study area has less than 2% timber cover (see Figure 3.1.2) so

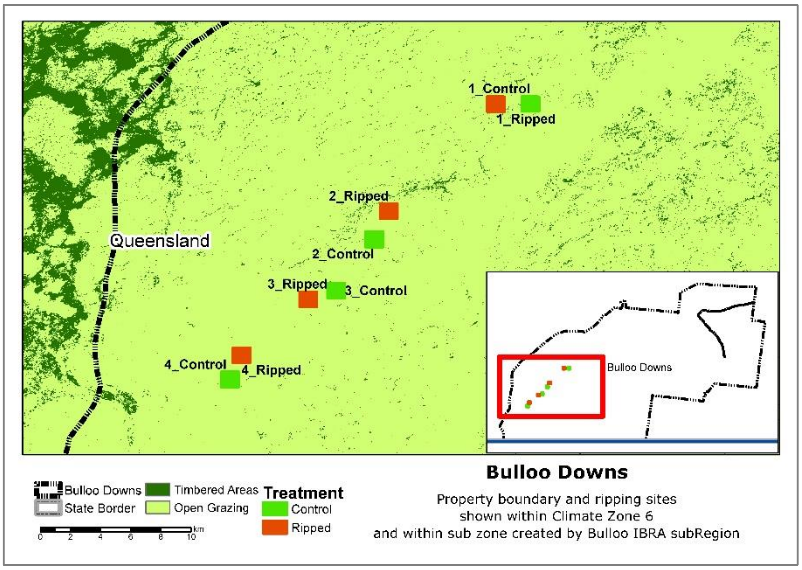


Figure 3.1.2: Bulloo Downs ripping sites

the 5% Aspirational criteria ensures timbered areas do not affect reference values (cf Bastin et al., 2012).

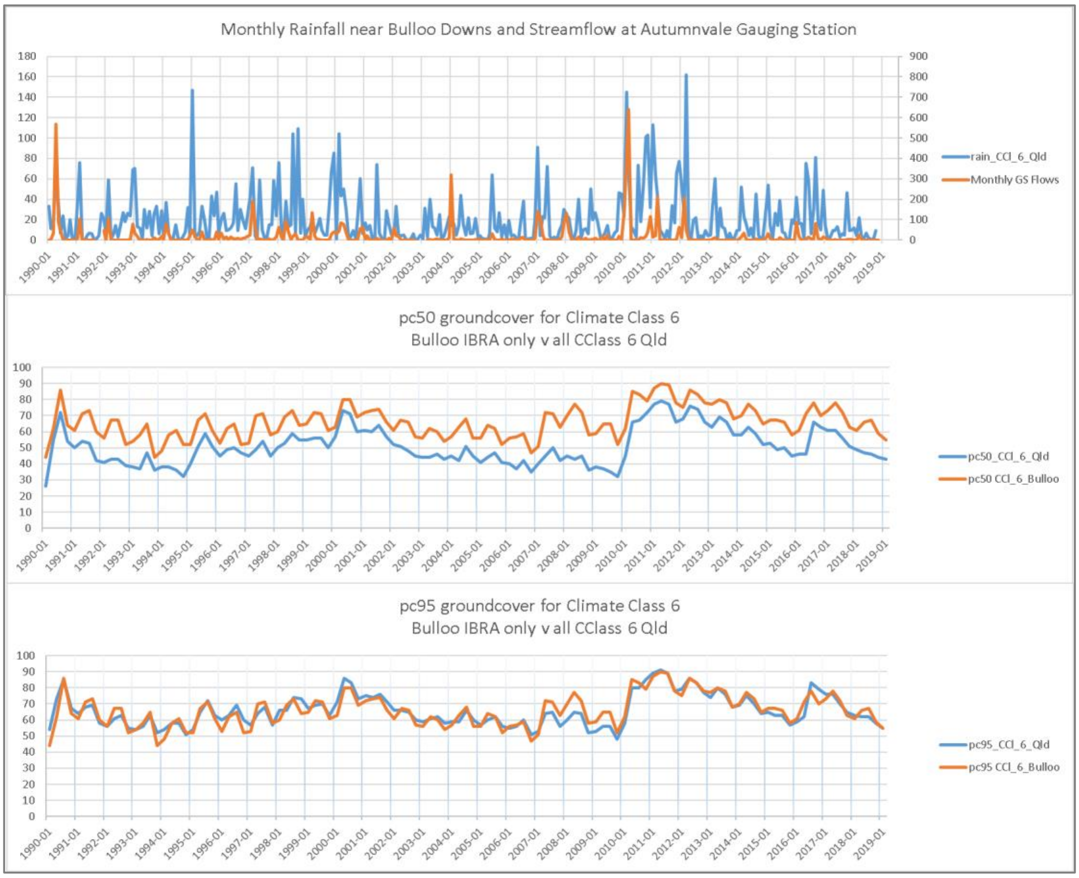


Figure 3.1.3: Time series data for climate class zone 6 and the Bulloo IBRA sub region

Results

Initial concerns about the suitability of a reference zone based on climate data cluster zones only was confirmed. Median (pc50) ground cover for the Climate Class zone 6 was significantly different to that of only the Bulloo IBRA subregion within zone 6 (see Figure 3.1.3, middle). The Bulloo IBRA subregion is an area that is subject to floodplain inundation due to flooding from the Bulloo River. The variations in groundcover can be explained at least in part by the rainfall and streamflow data relating to the Bulloo area (Figure 3.1.3, top). When rainfall is complemented by flow events the Bulloo IBRA region records greater increases in ground cover than does the broader climate cluster 6 region which also includes ridges (E.G. 1997 and 2004). Conversely, when rainfall occurs with no significant flow event the broader region records a greater increase in groundcover (E.G. 2000 and 2016). These variations are not as strong but are still apparent in the pc95 reference cover values (Figure 3.1.3, bottom).

Groundcover scores were comparable between each pair of sites (control and ripped). No clear change in groundcover at ripped sites could be attributed to the reduced number of rabbit warrens after 2001. Total rabbit numbers were very low from 2001 to at least 2007 for a transect that represented the property including both ripped and control sites (Berman et al., 2011, Figure 6). No change in groundcover scores could be attributed to this reduction in rabbit numbers across the study area. Groundcover for each of the paired sites varied seasonally and annually (See Figure 4) with no clear trend.

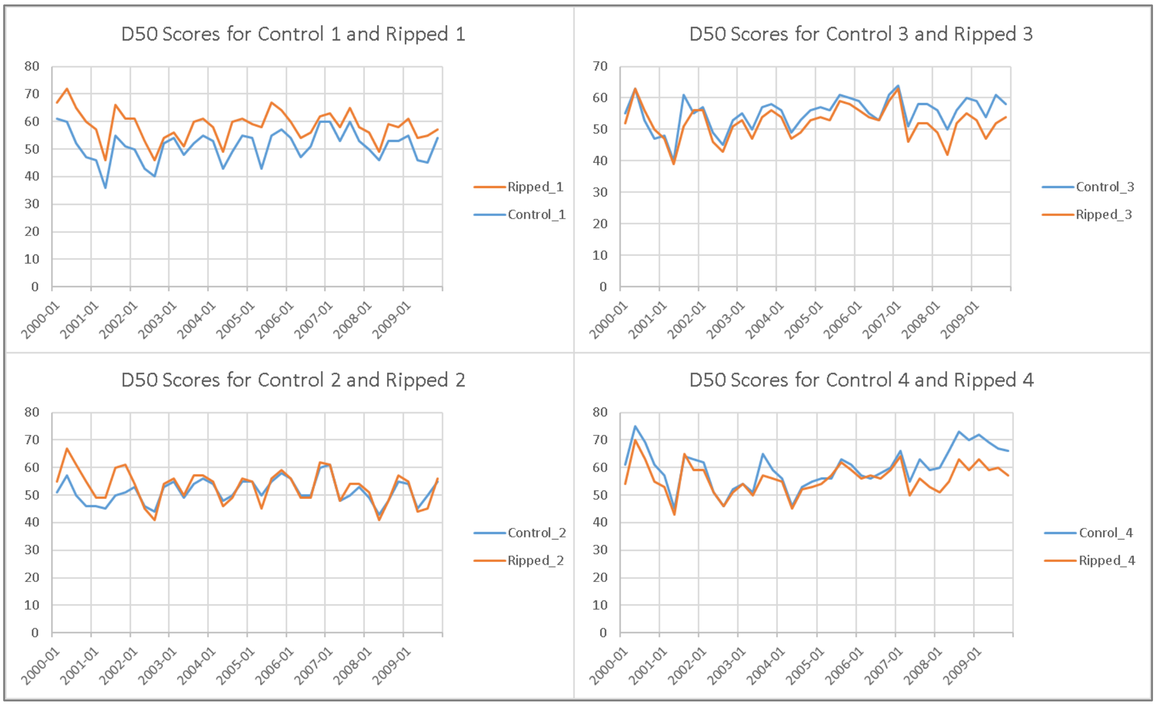


Figure 3.1.4: Groundcover scores at paired sites for the 2000s

Bastin et al. (2012) suggest the management signal in groundcover scores is best ascertained with spring groundcover scores in dry years. When this filter was applied there was a positive trend in groundcover scores for the 2000s when Berman et al’s study was undertaken. This improving trend showed in both the ripped and the control areas suggesting that the ripping event was only part of the improved management (Figure 5). The trend is only slightly positive (1-2% GC unit per year) but is contrary to the broader reference zone which showed a 1%/year decline. Berman et al indicate that the landholder in fact undertook further rabbit warren ripping from 2003 across parts of the property within proximity to permanent water. It is likely that a lot of this work and impact was in close proximity to the study sites but this needs to be investigated to confirm.

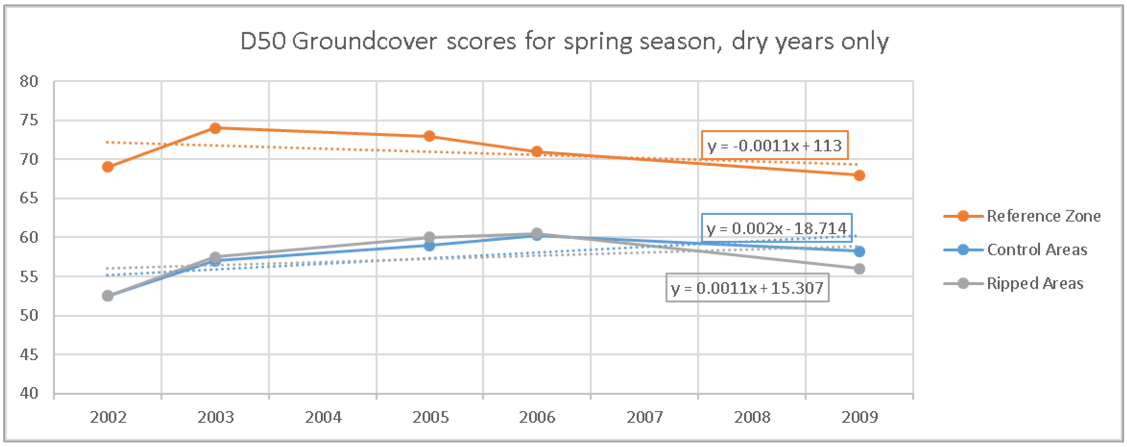


Figure 3.1.5: Groundcover scores and trends during rabbit warren study period

The trend was also apparent before and after the treatment period indicating that rabbit treatment associated with the study was not the only management action contributing to modest improvements in groundcover scores (see Figure6, middle). Additional

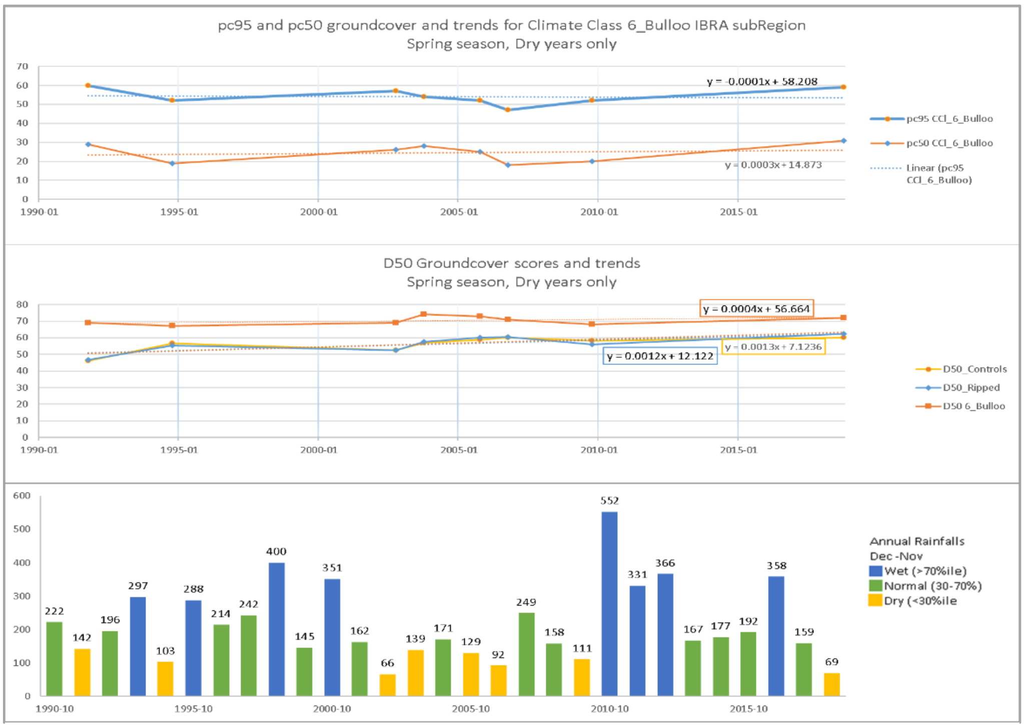


Figure 3.1.6: Groundcover scores and trends for all available remote sensing data. Includes: groundcover values (top), groundcover scores (middle) and annual rainfall values 1990-2018

property management information would be required to further explore what management actions have led to the ongoing improvements in groundcover scores.

Conclusions

Rabbit Warren ripping activities in 2001 had a demonstrated impact on rabbit populations. Together with subsequent treatments in 2003, there seams to have been a positive impact on groundcover. This impact is not confined to the ripped areas with control areas showing similar improvements. The aDRCM was useful as a tool to compare groundcover across different areas with similar climate and landscape features. In particular, groundcover scores derived from the aDRCM for spring season in dry years shows value in assessing management impact on groundcover with significant removal of the climate signal.

The addition of the IBRA subRegions to the data used to identify homogeneous seasonal groundcover zones was proved in this study to be necessary to give some confidence in the use of the aDRCM.

More detailed study of ripping done by land managers and of other management actions during the period of available remote sensing data is recommended. Such a study could explore the benefits of rabbit treatments, stocking rates and (post 2012) nature refuge management.

References

Bastin, G., Denham, R., Scarth, P., Sparrow, A., & Chewings, V. (2014). Remotely-sensed analysis of ground-cover change in Queensland's rangelands, 1988–2005. *The Rangeland Journal, 36*(2), 191-204. doi: http://dx.doi.org/10.1071/RJ13127

Bastin, G., Scarth, P., Chewings, V., Sparrow, A., Denham, R., Schmidt, M., . . . Abbott, B. (2012). Separating grazing and rainfall effects at regional scale using remote sensing imagery: A dynamic reference-cover method. *Remote Sensing of Environment, 121*, 443-457.

Berman, D., Brennan, M., & Elsworth, P. (2011). How can warren destruction by ripping control European wild rabbits (<i>Oryctolagus cuniculus</i>) on large properties in the Australian arid zone? *Wildlife Research, 38*(1), 77-88.

Department of the Environment. (2012). *Interim Biogeographic Regionalisation for Australia (Subregions - States and Territories) v. 7 (IBRA) [subregions and codes]*. Retrieved from http://www.environment.gov.au/system/files/pages/090951b9-b859-43af-9386-a4586faf03b1/files/subregions-list.xlsx

Appendix 3.2 Groundcover data access

Climate Landscapes and associated supported, control and reference areas were initially determined using polygon data to create shapefiles. This was to suit the VegMachine interface which required shapefiles as inputs for groundcover seasonal analyses (Beutel et al., 2016). This approach was determined to be inappropriate for a number of reasons:

- Polygon data became difficult to manage due to file sizes and the introduction of multiple "slivers" with minor variations in some of the boundaries on input data files.
- The size of some of the more complex shapefiles was beyond the capacity of VegMachine.
- VegMachine uses a subsampling methodology to create seasonal groundcover data summaries for input areas. This subsampling process was not precise enough for this study.

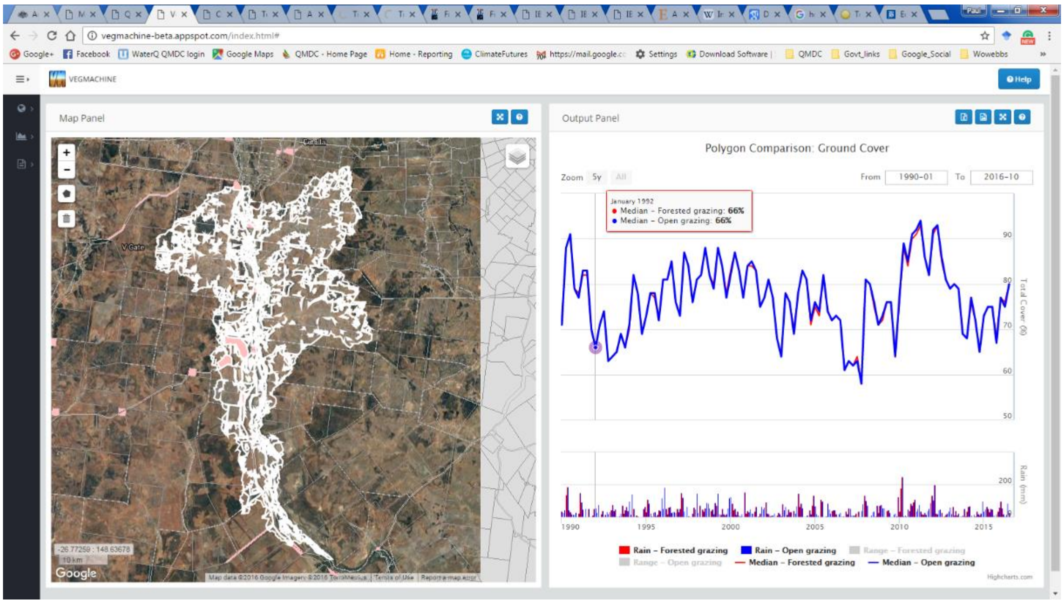


Figure 3.2.1: VegMachine map and groundcover plot for timbered (Forested) and non-timbered (Open) grazing in a Maranoa sub-catchment

Regarding item 3 above, early work for this study used VegMachine to access data for two polygons of interconnected timbered and non-timbered grazing areas. The extent of each polygon was similar with one polygon defining timbered areas within that extent and the other polygon defining non-timbered grazing areas within the same extent.

VegMachine seasonal ground cover summaries for each polygon were very similar (Figure 3.2.1). This was not expected as smaller polygons within the same extent but including defined timbered or non-timbered grazing areas showed clear differences in seasonal ground cover dynamics (Figure 3.2.2).

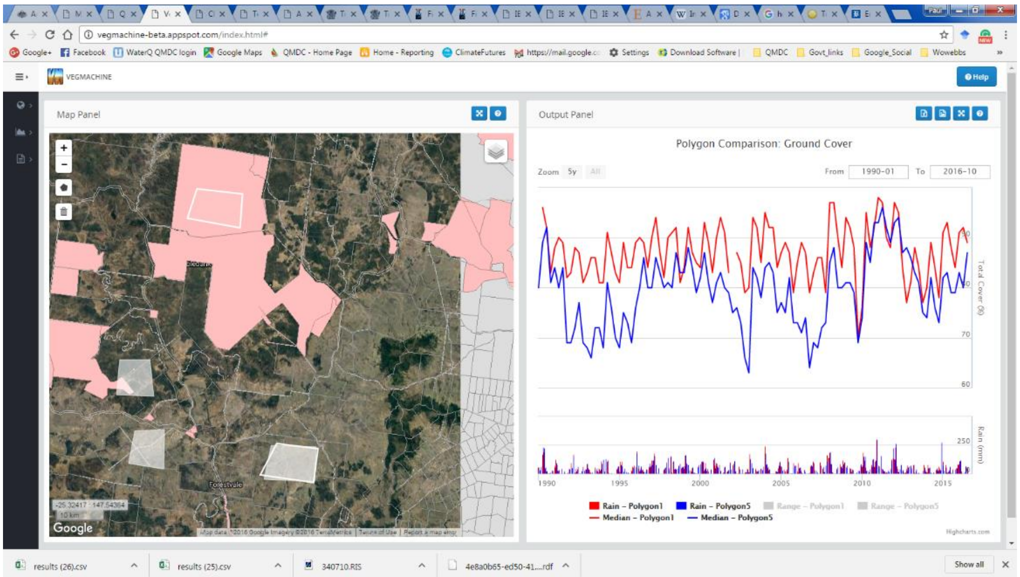


Figure 3.2.2: Two polygons in timbered (Polygon 1)and non-timbered Polygon 5) areas within the Maranoa sub-catchment show less variability in timbered area and significantly lower troughs in non timbered area.

This anomaly was highlighted with Queensland Department of Environment and Science (DES) Remote Sensing Unit (Joint Remote Sensing Research Program, 2018). DES ran independent tests on similar data. It was found that the similar results in overlapping timbered and non-timbered areas were not correct. VegMachine outputs were confirmed to show similar results for large timbered (forested) and non-timbered (open) grazing areas whilst true results showed significant variations between seasonal ground cover in the same timbered and non-timbered areas (perscomm Terry Beutel, 29th November 2016 – Figure 3.2.3).

Data were reprocessed in raster file format which better suited the large datasets and aligned with the native data format of the underpinning vegetation layers used in this study project. Project related spatial data files were created for each of the supported (property or paddock), control (unsupported properties in the same Climate Landscape) and reference (Climate Landscape) areas. The Queensland Government

Remote Sensing group developed and executed a script to query groundcover data archives for each of these (330) project related spatial data files provided to them for this study. 330 seasonal groundcover data files were then provided by the Remote Sensing group for analyses in this study.

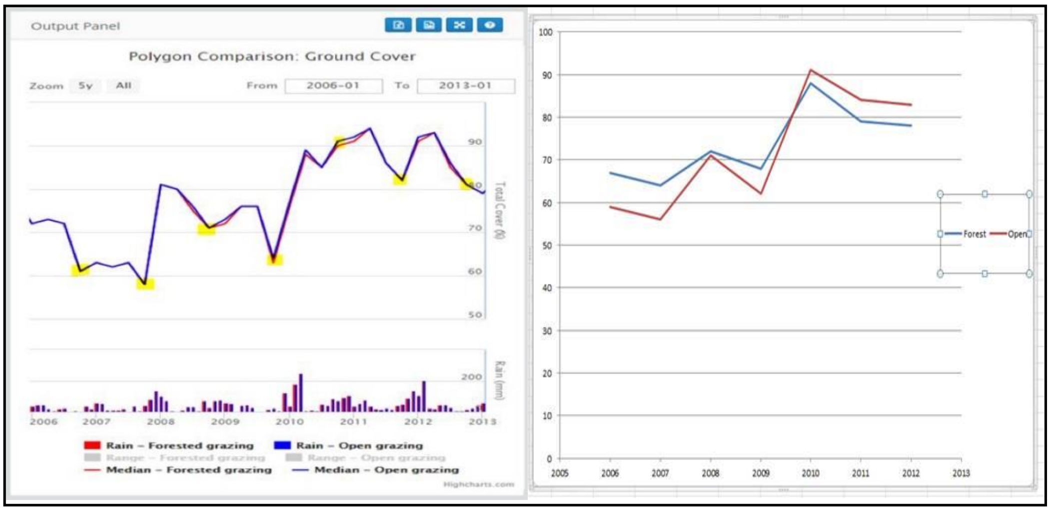


Figure 3.2.3: Ground cover comparisons for polygons with forested and open grazing with data obtained from VegMachine seasonal summaries (left) and from raw data analyses (right). Spring results from VegMachine (highlighted yellow) were similar while spring results from raw data (all points on the right) show significant variation between forested and open grazing areas. Analyses and plots provided by Terry Beutel (perscomm, 29th November 2016).

To facilitate data access and analyses, spatial data files for each area were labelled with a "scilapp" code comprising:

- s – a two digit Study identifier (um for all files in this Upper Maranoa study),
- c – a two digit climate cluster number (from 01 to 52),
- i – a five character IBRA sub region code,
- l – a two character Land use code (open grazing(og), sparse timber (st), timbered grazing (tg) or forestry (fo)),
- a – three character Activity code (reference (ref), control (con), or supported (scp),
- p – a three digit Property ID (000 for reference and control), and,
- p- a three digit Paddock (project) ID (000 for reference, control or for whole

For example, the file named “um_24_BBS13_og_ref_000_000.*” was for the area in the Upper Maranoa, in Climate Cluster 24, and IBRA subregion BBS13, with Open Grazing land use and this was a reference area.

Analyses undertaken in this study included:

- Collation of ground cover data and independent SILO climate data with Climate Landscape definitions.
- Assigning of reference data for each project area and use of the reference data and project area data to create seasonal ground cover scores for each project area.
- Summarising and plotting results with a range of merges and filters to test improved management hypotheses.

Due to the problems with the use of VegMachine, it was not used in this study. It is a public data access interface, however, and it was desirable in this study to make processes repeatable for related work. For this reason, data formats and processing methods used in this study were the same as would be used with VegMachine. This means that with ongoing development of VegMachine to address sub-sampling and complex data file issues, the methods used in this study will align with the use of VegMachine to access free, available groundcover data for future works.

References

Beutel, T., Trevithick, R., & Scarth, P. (2016). *The VegMachine Guide*. Brisbane: Department of Science Information, Technology and Innovation Retrieved from http://vegmachine-beta.appspot.com/assets/help/VegMachine_Guide_July_2016.pdf

Joint Remote Sensing Research Program. (2018). *Fractional ground cover for Australia derived from USGS Landsat images*: Made available by Queensland Department of Environment and Science under Creative Commons Licence (https://creativecommons.org/licenses/by/4.0/legalcode)

Appendix 3.3 Landholder information pack, sample property report and survey form

[Letterbox covernote left at sites where landholder could not be contacted]

Hello,

Ground cover on your patch - opportunity to participate in NRM evaluation project in the Upper Maranoa catchment area.

I am sorry I have been unable to schedule a meeting with you by phone or email from contact information provided by the Queensland Murray-Darling Committee (QMDC).

QMDC is supporting research to assess the benefits of public investment in Natural Resource Management (NRM). As a participant in Sub-Catchment Planning and other projects associated with Landcare, your property is part of an area being assessed.

Attached is a project information sheet from myself as a QMDC employee and a University of Southern Queensland researcher.

Also attached for your reference is a map of your property (separate plots for different tenures if applicable). With reference to this property there is also a 3 page groundcover levels report – with the first page showing results across the whole Upper Maranoa catchment and the following pages showing results for your property. Although these reports have been developed from public access remote sensing data, the property location for individual reports will not be made available to governments, QMDC or the public.

I would be happy to talk with you about this project and the results for your property. I can be contacted by phone or email – details below. I will be out in the catchment from Monday 1st October till Saturday 6th October and would be happy to meet with you to discuss the project if we can arrange a suitable time.

I have also attached a project survey form. If you wish to contribute to this project by filling in the survey and including any notes, ideas or concerns that would be greatly appreciated.

In response to common queries from other landholders, I have included a two page guide for products available from the Queensland Government remote sensing team on the Forage website.

Any feedback is welcome but I appreciate that this is a difficult time so responses may be limited. I hope and pray you have some good seasons coming.

Yours Sincerely,

Paul Webb

Program Leader, Water and Wetlands, Queensland Murray-Darling Committee Inc.
& PhD Candidate, School of Agricultural, Computational & Environmental Sciences, University of Southern Queensland.

Mob: 0429644421
Fax: 07 4632 8062
Email: Paul.Webb@usq.edu.au

Mail to:
Confidential – Paul Webb
c/o QMDC
PO Box 6243
Toowoomba Qld 4350

Queensland Murray-Darling Committee
and the
University of Southern Queensland

Participant Information for Research Project Survey

Project Details

Title of Project: **The role of NRM incentives in sustainable agricultural landscapes**

USQ Human Research Ethics Approval No H16REA214

Research Team Contact Details

Principal Investigator Details

Paul Webb (QMDC employee and USQ researcher)

Email: Paul.Webb@usq.edu.au

Mobile: 0429644421

Supervisor Details

Professor Geoff Cockfield

Email: Geoff.Cockfield@usq.edu.au

Telephone: (07) 4631 1246 Mobile: 0439 146 909

Description

This project is being undertaken as part of a PhD Project with the University of Southern Queensland (USQ) in partnership with the Queensland Murray-Darling Committee (QMDC).

The purpose of this project is to examine how regional NRM projects designed to support landholders have affected grazing systems. In particular, grazing properties supported by the QMDC and Landcare from 2004 to 2017 are being evaluated in relation to changes in ground cover relative to climatic conditions.

I have seasonal groundcover data for your property from publicly accessible remote sensing (satellite) data and this can be compared with other properties in close proximity. There is now an opportunity for you to view and comment on these data and to provide information or other data that will help improve my understanding of conditions and outcomes.

Participation

If you choose to participate, you will be supplied with maps and preliminary groundcover analyses for your property. With reference to this material, you will be asked to complete a survey that will take approximately 30-60 minutes of your time.

I will ask you to review and comment on the mapping with respect to property boundaries, management areas and ownership for the 2004-2017 study period. Then there will be survey questions about your property and activities and issues during the study period.

It is preferred that participation in the survey is by face to face interview at a time that suites you. If this does not suite or cannot be scheduled, you will have the choice of participating by Skype, by phone or by email exchange.

Your participation in this project is voluntary. If you decide to take part and later change your mind, you are free to withdraw from the project at any stage. If you do wish to withdraw from this project, please contact the Research Team (contact details at the top of this form).

Your decision whether you take part or to take part and then withdraw, will in no way impact your current or future relationship with QMDC or USQ.

Expected Benefits

Through this project I will provide you with maps and historic groundcover data which will enable you to review groundcover on your property and to consider management implications. Access to these maps will also give you insight into what information is publicly available in relation to your property and the surrounding region. Your participation, along with that of other landholders, will also help NRM organizations such as QMDC to target programs that better support both production and resource protection.

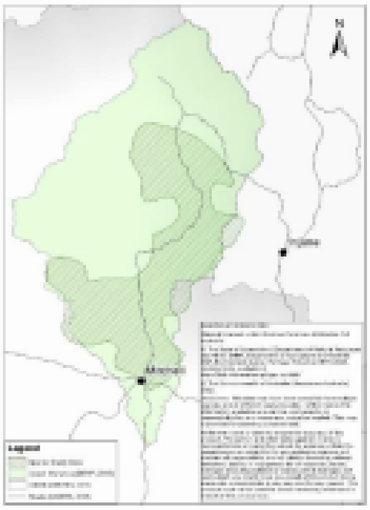
There are no anticipated risks beyond normal dayto-day living associated with your participation in this project.

Risks

All comments and responses will be treated confidentially unless required by law.

Privacy and Confidentiality

Any data collected as a part of this project will be stored securely to protect privacy. Project data made available to the public, to QMDC or to USQ will be "depersonalised" before being made available and will be removed from USQ systems at the completion of the project.



Upper Maranoa Catchment study area

Data may be made available in confidence during the project period to persons with related expertise to ensure data and analyses meet academic standards.

The return of the completed survey will be accepted as an indication of your consent to participate in this project.

Consent to Participate

Questions or Further Information about the Project

To indicate your willingness to participate or to request further information about this project please contact Paul Webb (email Paul.Webb@usq.edu.au, or Mob 0429644421).

Concerns or Complaints Regarding the Conduct of the Project

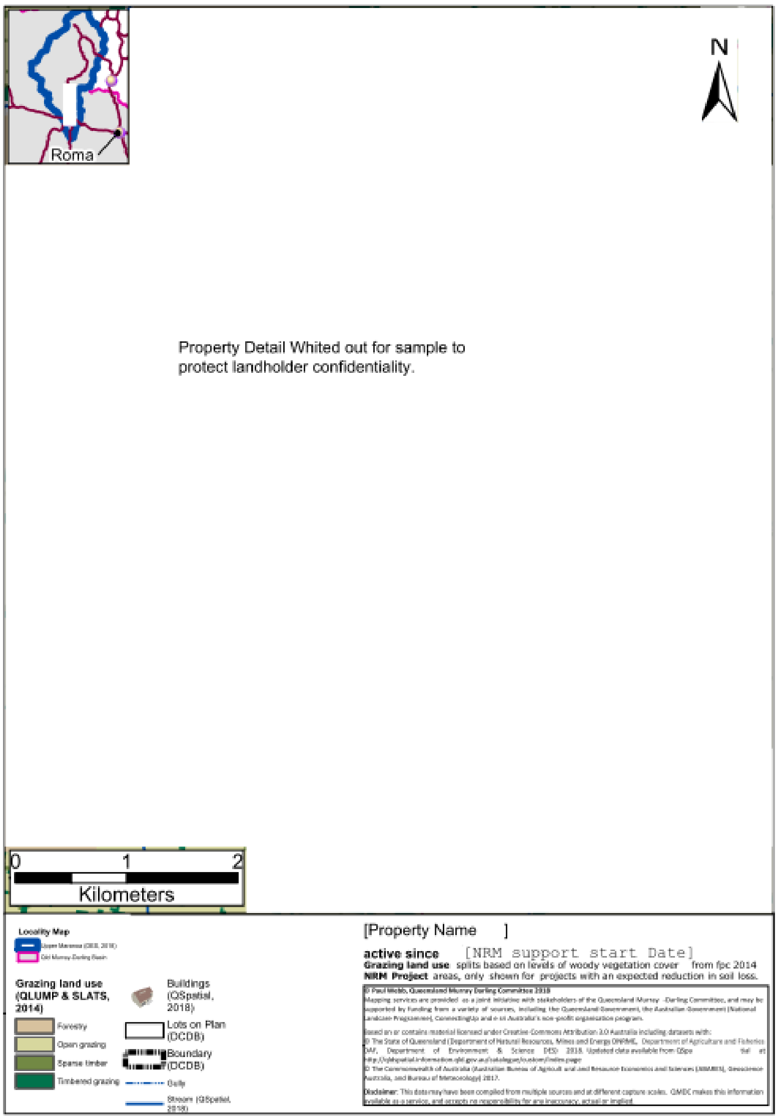
If you have any concerns or complaints about the ethical conduct of the project, you may contact either:

- The Queensland Murray-Darling Committee, Regional Coordinator Information Management, Roxane Blackley on (07) 46376200 of email roxaneb@qmdc.org.au, or,
- The University of Southern Queensland Ethics Coordinator on (07) 4631 2690 or email ethics@usq.edu.au. The Ethics Coordinator is not connected with the research project and can facilitate a resolution to your concern in an unbiased manner.

Thank you for taking the time to help with this research project. Please keep this sheet for your information.

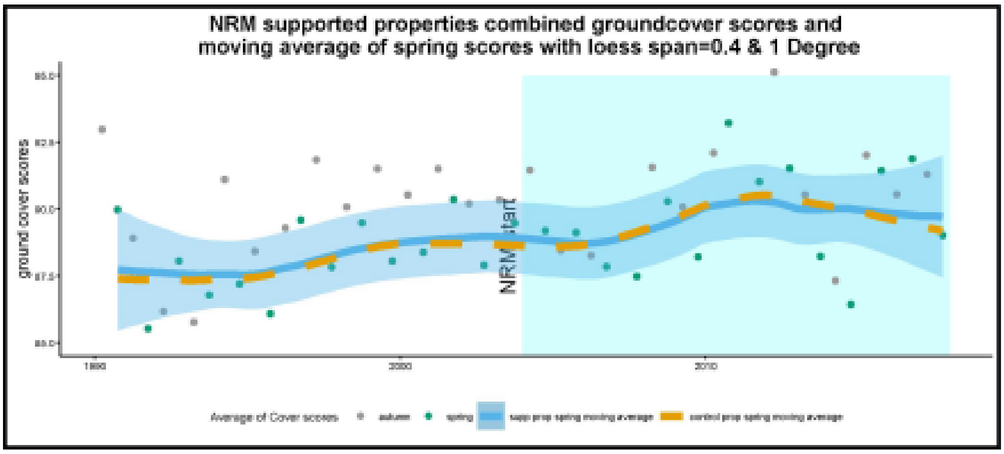
Page 2 of 2

Property Map



Groundcover levels improving in the Upper Maranoa River catchment

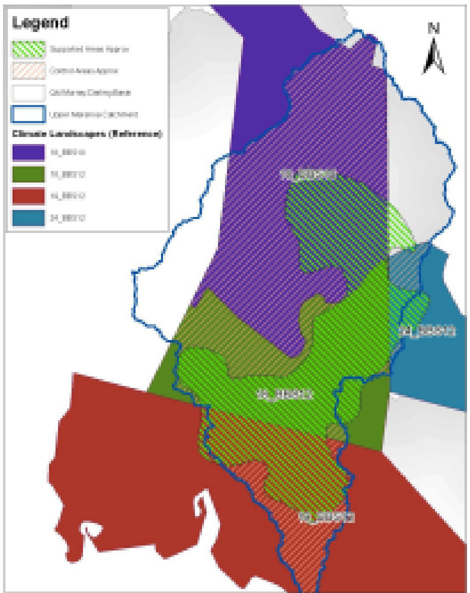
Preliminary findings of research indicate that groundcover levels are increasing slightly in grazing lands of the Upper Maranoa River catchment. Remote sensing data shows that despite some highs and lows, there is an underlying increasing trend in groundcover for the 1990 to 2017 period. Results vary significantly within the catchment and across property boundaries. An adapted Dynamic Reference Cover Method (aDRCM) was used to isolate the climate signal from remote sensing groundcover data. The aDRCM scores were then used to evaluate the underlying trends in groundcover. Properties supported by Natural Resource Management (NRM) extension programs were also assessed. Results showed very little difference between ground cover scores for supported properties and other (control) properties in the study area. There was some indication, however, that ground cover is holding up better in the current dry period for supported properties.



Within supported areas, there were a range of results including some significant improvements in groundcover and some apparent declines in ground cover. Over the page is a draft "Groundcover Report" with groundcover estimates for an individual property. These results are for discussion purposes with the land manager . The property has not been identified in this document to protect the privacy of the landholder. A property map will be presented to the landholder with this document to enable discussion about the results and about the influence of NRM support and other events on ground cover and grazing land management.

Each property was assigned to a "Climate Landscape" based on historic climate data and landscape characteristics. Spring ground cover estimates for open grazing, sparsely timbered and timbered grazing areas were obtained for each property. These were compared with a reference groundcover for the climate landscape to establish seasonal groundcover scores. Groundcover scores for the supported property was then compared with groundcover scores for unsupported properties that were within the Upper Maranoa Catchment and in the same climate landscape.

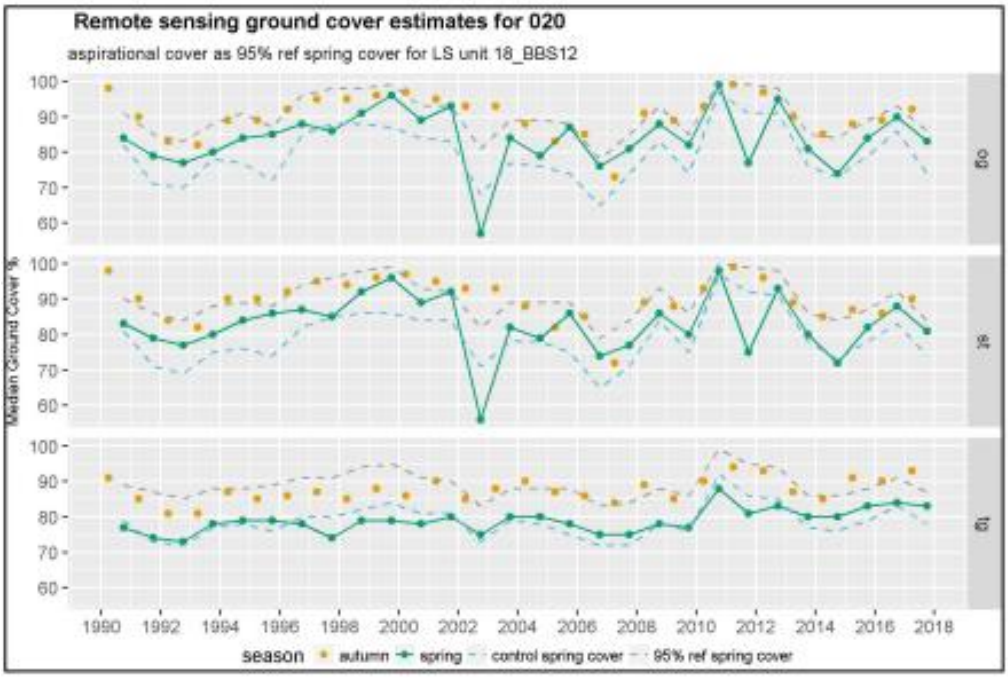
Seasonal groundcover estimates have been provided by DES Remote Sensing group from Landsat imagery. Estimates are available for all seasons from 1990 to 2017.



Climate Landscapes used to evaluate groundcover for supported and unsupported (control) properties in the Upper Maranoa Catchment

Property Groundcover Report

These analyses focus on spring groundcover values which have been shown to be better indicators of management and of erosion risk. Median spring groundcover estimates for the property are shown below as green dots joined by a green line. Cover estimates for autumn is included as dots only as a reference . The dashed blue line shows the median spring groundcover estimates for areas within the Maranoa catchment and in the same climate landscape as this property that did not receive support from NRM programs. The grey dashed line is the 95% reference cover estimate (% cover for the best 5% of pixels) for the climate landscape.



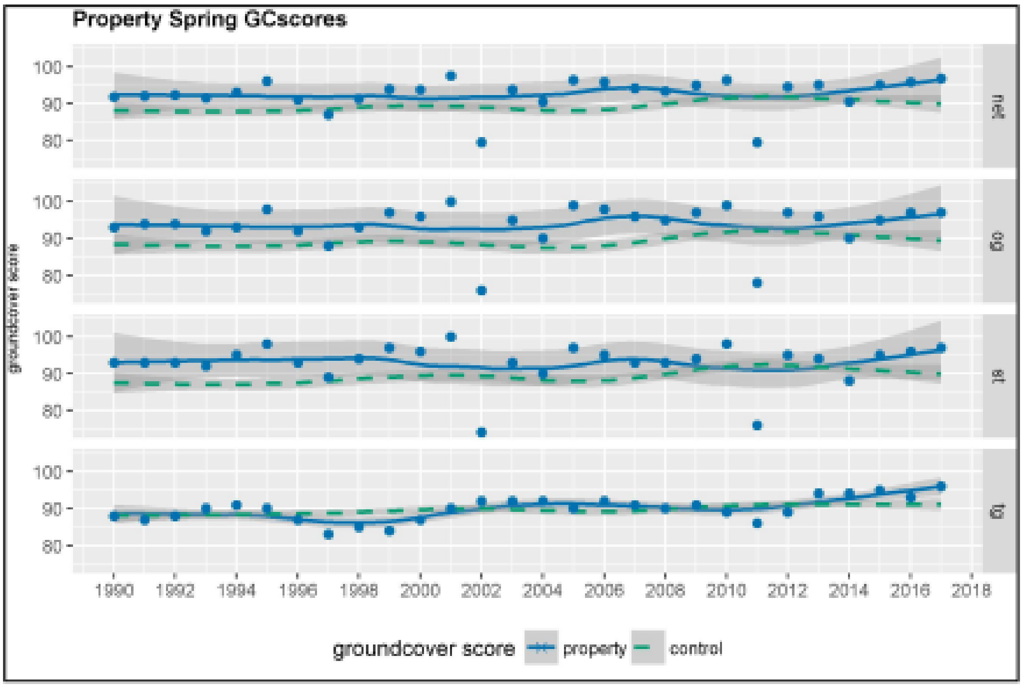
Groundcover scores were established for each spring season by comparing the median ground cover with the aspirational (95% reference) groundcover for the same season. Scores were offset by 100 to ensure they were in a range of 0 to 100.

GC score = 100 - (95%ref cover—median cover)

Ground cover summaries and scores were initially calculated separately for units of open grazing (og), sparse timber (st) and timbered grazing areas (tg). For forestry leases (fo) there was no separation. Net scores were than calculated by combining scores for units with unit areas. For forestry leases the net score is the same as the GC score.

Property spring groundcover scores are plotted over the page with (LOESS) moving averages for the study property and for unsupported (control) properties in the same climate landscape unit.

Net score = (score*area (og) + score*area (st) + score*area (tg))/ Total area

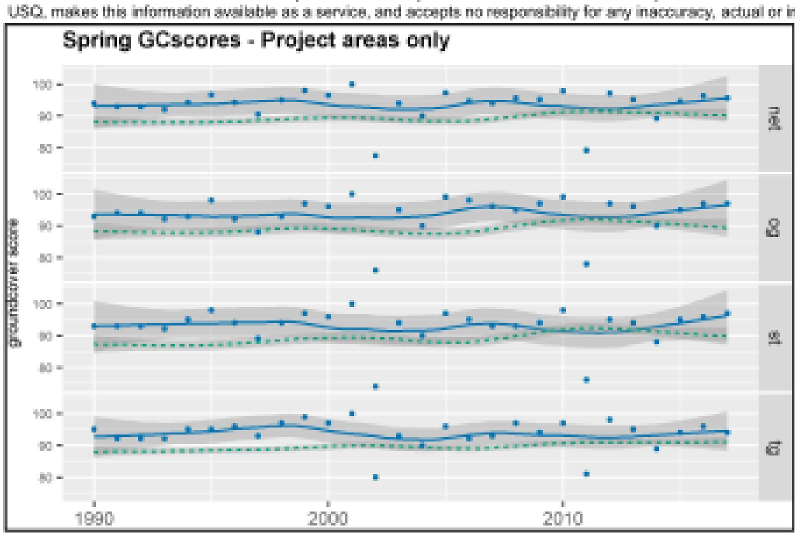


Where properties had paddocks where incentives were paid for projects with an expected reduction in erosion, scores are also plotted for incentive project areas at the bottom of the page.

This work is part of a research project supported by QMDC and USQ. Project data has been made available on the strict proviso that individual results cannot be made public in any manner by which the individual landholder can be associated with the results. Hence the use of numbers instead of property names in this document.

The research is using data and technical support from the Queensland Government (Q Spatial and DES Remote Sensing group). The analyses are adapted from a Dynamic Reference Cover Method developed by Gary Basting, Peter Scarth and others from 2012-2014.

Disclaimer: This data have been compiled from multiple sources and at different capture scales. The author, along with QMDC and USQ, makes this information available as a service, and accepts no responsibility for any inaccuracy, actual or implied.



QMDC Land Manager Survey

Thank you for participating in this survey. With this survey, you should have received a research project information sheet explaining the project and how information you provide will be used. You should also have received maps of your property and graphs of ground cover estimates for the same property and for surrounding properties in a similar climate zone.

The following questions are intended to determine whether information and support from the Queensland Murray-Darling Committee (QMDC) has influenced the management of your property and particularly whether it has resulted in improved ground cover. Support from QMDC in your area has been through Sub-Catchment Planning and other programs delivered in partnership with Mitchell Landcare since 2004. It is assumed that the Land Manager/s for the property are the persons responding to this survey. Land Manager/s are the person or persons who are the primary decision makers for the property operations.

Property and Land Manager information

Before starting the main part of the survey, I want to check that I have the correct project and property details.

Property Name:		**Lot/Plan no/s:**	
Land Manager/s:		**Postal Address:**	
Phone No:		**Email:**	

Is the property information above correct?

If No, please provide corrected information below:

___

___

___

Property Management

Primary land use on the property. Please ☒ Mark the most correct option:

☐ Cattle grazing ☐ Sheep grazing ☐ Cropping ☐ Cropping and grazing

☐ Other (please describe) ____________________

Support from QMDC and Mitchell Landcare since 2004

	Yes	No	N/A or can't say
Has your property participated in "Sub-Catchment Planning" with QMDC and Mitchell Landcare? (If Yes) Approx 1st Year ______	☐	☐	☐
Have you received any incentives for works on the property? (Works may include activities such as fencing, water points, rehabilitation, planting pasture or soil conservation works)	☐	☐	☐
Have you received other incentives or support from QMDC or Mitchell Landcare for other activities since 2004? (These may include ALMS or EMS planning or auditing, or, grazing or business management training.)	☐	☐	☐

Benefits from activities supported by QMDC and Mitchell Landcare since 2004

	1 Not at all	2 Very little	3 Some impact	4 Major impact	N/A or can't say
Has information provided at QMDC and Mitchell Landcare events since 2004 enhanced your knowledge and management of your grazing enterprise?	☐	☐	☐	☐	☐
Has information exchange with other landholders at QMDC and Mitchell Landcare events since 2004 enhanced your knowledge and management of your grazing enterprise?	☐	☐	☐	☐	☐
Have subsidised works contributed to improved management of paddocks in which works occurred?	☐	☐	☐	☐	☐
Have subsidised works contributed to improved management of your property as a whole?	☐	☐	☐	☐	☐
Have there been any other benefits from QMDC and Mitchell Landcare activities since 2004?	☐	☐	☐	☐	☐

Inhibitors to benefits from activities supported by QMDC and Mitchell Landcare since 2004

Have any of the following external events prevented the land management benefits from activities supported by QMDC and Mitchell Landcare since 2004?	1 Not at all	2 Very little	3 Some impact	4 Major impact	N/A or can't say
Extreme climate events?	☐	☐	☐	☐	☐
Market conditions?	☐	☐	☐	☐	☐
Change of property manager/s?	☐	☐	☐	☐	☐
Change of family circumstances?	☐	☐	☐	☐	☐
Other?	☐	☐	☐	☐	☐

Feedback on mapping and remote sensing data

The following questions relate to the maps and graphs of ground cover estimates for your property that were sent out with this survey.

Please note that ground cover estimates provided were derived from satellite imagery of moderate (30m) spatial resolution. These values are often about 20% higher than visual observations using methods such as Stocktake or Grasscheck.

	Yes	No	N/A or can't say
Do highs and lows in ground cover graphs for your property align with your records or memories of recent droughts and wet years?	☐	☐	☐
Do any differences between ground cover on your property and on neighboring properties in the same climate zone reflect management decisions you or they made at particular times?	☐	☐	☐
Do you have recorded ground cover data that you are willing to make available to check and improve remote sensing ground cover estimates?	☐	☐	☐

Further Property Management Information

The following questions are optional but responses will help in the interpretation of previous responses and of property groundcover data.

What is the relationship between the current land manager/s and the owner or leaseholder? ☐ Same person/s ☐ Close relation ☐ Employee

Number of primary decision makers involved in the farm business for the property? ____________________

What are the approximate ages of the primary decision-makers? ____________________

Can you tell me a little about the background of the primary decision-makers, considering their involvement with farming and this property in particular? ____
____
____
____

Has clearing of native vegetation (not regrowth) occurred on more than 5% of the property area since 2004? ☐ Yes ☐ No ☐ Unknown

(If yes) Approx Ha or % property area cleared since 2004: __________

Thank you for completing this survey. Please return it to:
Paul Webb, c|o QMDC, PO Box 6243, Toowoomba Q 4350.
Or email to Paul.Webb@usq.edu.au
Phone enquiries – Mob 0429644421

Appendix 3.4 Trend data selection

Groundcover data was analysed across the entire study catchment through time to determine if there was a change in management signal. Periods assessed included the NRM investment period (2004-2017) and the preceding Landcare investment period (1990-2003). The approach used for these analyses was adapted from the ΔΔGC concept in the DRCM (Bastin et al., 2012; Bastin et al., 2014).

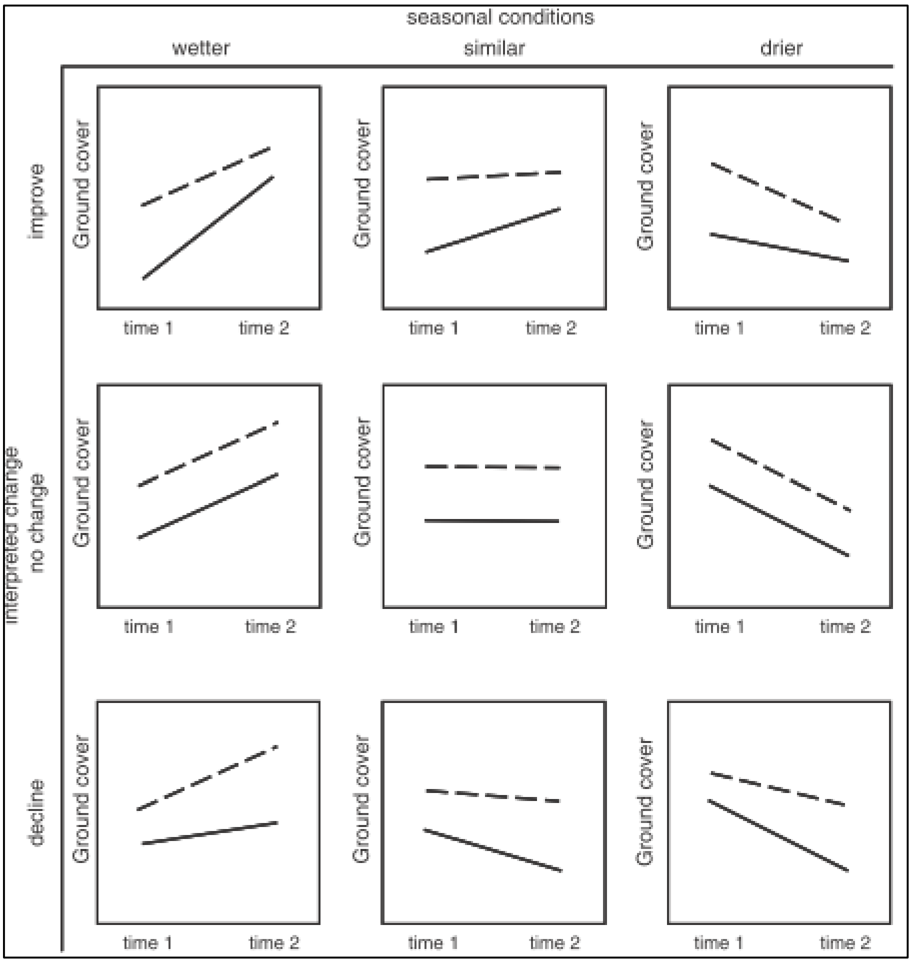


Figure 3.4.1: A schematic framework for interpreting change in ground cover [scores].
Change in ground cover scores between two dry periods is shown by the solid line in eacht plot. Change in reference is depicted with the dashed line. Columns represent seasonal conditions at the second time period relevant to the first. Rows represent where management signal on ground cover improved, remained unchanged of declined (adapted from Bastin et al, 2012 p449 Figure 5).

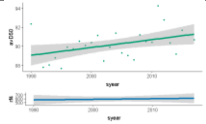
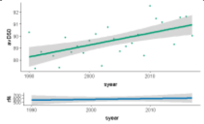
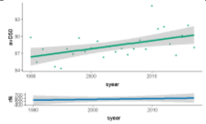
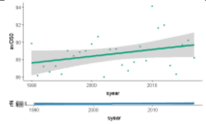
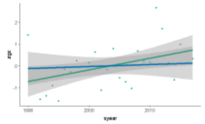
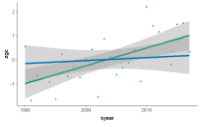
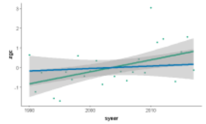
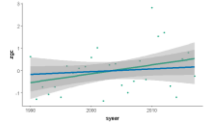
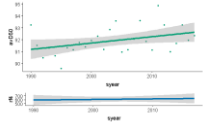
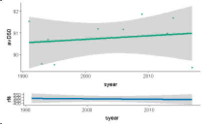
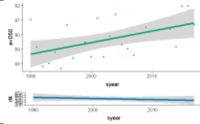
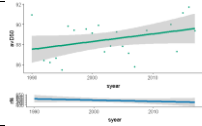
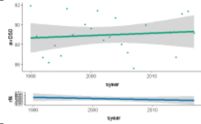
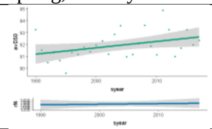
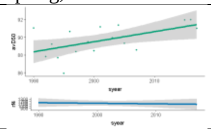
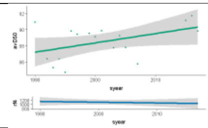
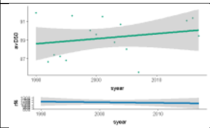
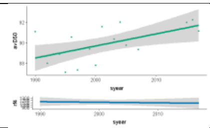
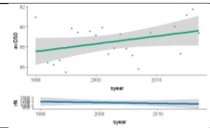
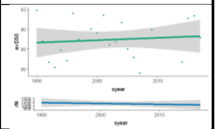
Although ΔGC scores remove some of the climate signal, Bastin et al and this study have shown there is still a residual climate signal in the scores. The slope in the ΔGC, or the ΔΔGC, between two observation times could be compared with the slope in the reference observations, at the same two observation times to indicate whether management impact on ground cover was improving (Figure 3.4.1). While Bastin et al had ungrazed enclosures as reference observations, this study used annual rainfall totals (RF4) as the reference. This was based on rainfall data availability and on the demonstrated strong correlation with GC and residual correlation with ΔGC scores (see heatmap plots in Appendix 4.1). ΔGC scores and annual rainfall scores were standardised to allow them to be compared (Willett, 1965).

Consideration was given to how the seasonal data should be filtered or grouped to analyse trends and to compare ground cover and rainfall data. From correlation analyses (see Appendix 4.1) data had been filtered to only include spring values as this provided the strongest Ground Cover Management Signal (GCMS). Similarly, 4-season rainfall for (current plus 3 preceding seasons) was identified as having the strongest association with seasonal ground cover.

Trend analyses were initially undertaken for seasonal ground cover scores and 4-season rainfall for a number of groupings based on the Pearson's r heat map (Appendix 4.1). Groupings were selected for z corrected GCMS for all data and for data where Pearsons r was above 0.7 (strong correlation) with ground cover and below 0.3 (weak correlation) for ground cover scores. Another set of groupings was selected where Pearson's r was above 0.5 (moderate) with ground cover and below 0.1 (no significant correlation) for ground cover scores.

Results of each of the four series of analyses are presented in Table 3.4.1.

Table 3.4.1: Trend data analyses for ground cover scores and z corrected scores

Groupings or filters for z corrected GCMS calculation Based on Pearson's r above 0.7 to below 0.3 (with the addition of all data as reference r 0.65/0.33)							
Slope reference	All data (for reference)	spring	spring, open grazing	spring, sparse timber	(Winter)	(Autumn)	(Summer)
GC scores							
zPlots		0 					
VGCpor	0.127	0.146	0.206	0.111	0.090	0.121	0.197
DeltaVGCpor	0.105	0.122	0.159	0.076	0.063	0.077	0.168
Groupings or filters for non z corrected GCMS calculation Based on Pearson's r above 0.5 to below 0.1							
	spring, forestry	spring, forestry, dry	spring, non-wet	spring, open grazing, non-wet	spring, sparse timber, non-wet		
GC scores							
VGCpor	0.085	0.025	0.121	0.114	0.036		
DeltaVGCpor	0.070	0.042	0.168	0.18	0.104		
Groupings or filters for non z corrected GCMS calculations for 2yr rainfa Based on Pearson's r above 0.5 to below 0.1							
	spring, forestry	spring, normal	spring, open grazing, normal	spring, sparse timber, normal	spring, timbered grazing, normal	spring, open grazing, non-wet	spring, sparse timbe non-wet
GC scores							
VGCpor	0.085	0.176	0.175	0.082	0.185	0.114	0.036
DeltaVGCpor	0.070	0.201	0.229	0.122	0.219	0.165	0.078

From Bastin et al. (2012) the strongest management signal from the DRCM was in dry years, spring. From this study, dry and normal years, spring data resulted in a more significant removal of climate signal with rf4/median ground cover r = 0.54 (moderate) and rf4/D50 ground cover score r = 0.10 (no significant correlation). For spring, all years the removal was significant (from r=0.72 to r=0.27). The residual weak correlation of r=0.27, however shows some climate signal in the spring, all year scores.

Trend for the spring, dry/normal years for the period of record was 0.121 (%/year) (Figure 3.4.2). Trend for spring, all years was 0.146 (Figure 3.4.3 (left)). When spring all years and rf4 data were standardized, the difference in slope (divergence) was calculated (Figure 3.4.3 (right)). This was then multiplied by the SD to give the Delta VGC standardized slope. This resulted in a slope of 0.122 which agreed with the slope of the spring dry/normal years with no standardization requirement. The Detla VGC

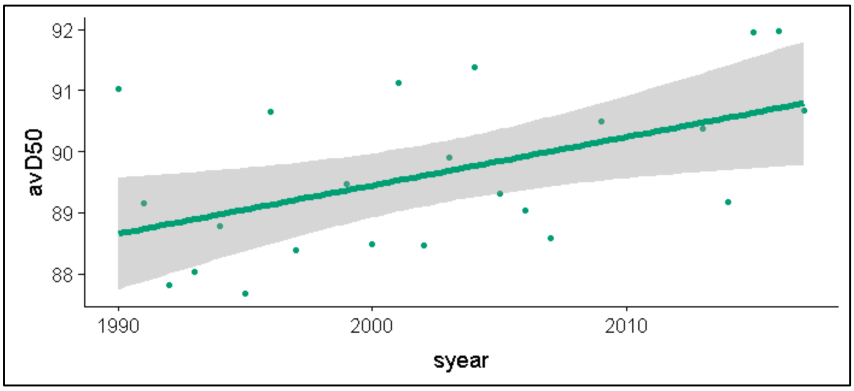


Figure 3.4.2: Trend in D50 ground cover scores for spring, dry/normal years
Slope = 0.121 %/year

standardized slope was adopted as the best measure of trend in ground cover management signal for all years – to be used for calculating adjustments to observed ground cover for synthesized model runs.

The trend analyses for modelling was to be done for two periods. The Landcare period was from 1990 to 2004 and the Regional NRM period from 2004 to 2017.

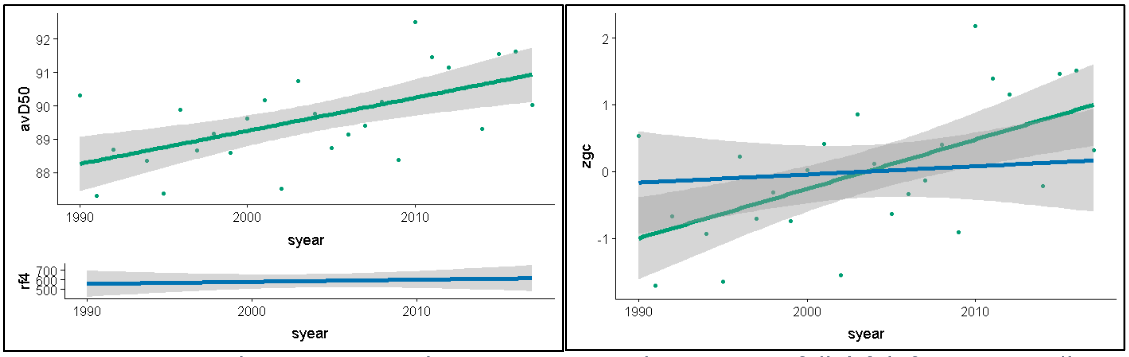


Figure 3.4.3: Trend in D50 ground cover scores and 1 year rainfall (rf4) for spring, all years (left) and z corrected (right).
D50 Slope = 0.146 %/year (left) and Delta zgc to zrf4 (right) SD D50 =0.122 %/*

Trends for 1990-2004 and 2004-2017 were calculated for both ΔGC and rf4. These represented trends in ΔGC (with some climate signal) and trends in climate. To allow these to be plotted together and compared, data were first tested to confirm data approximates normality with the Shapiro-Wilk test (Royston, 1995; R Core Team, 2018).

Shapiro-Wilk normality test for ΔGC

W = 0.97693, p-value = 0.7716

Shapiro-Wilk normality test rf4

W = 0.94624, p-value = 0.1592

(Royston, 1995, suggests p-value < 0.05 for rejection of the null hypothesis – so the null hypothesis of normality is adopted for standardisation of data)

Data was then standardised with:

$$(z)\ \Delta GC = (\Delta GC - \text{mean } \Delta GC) - SD\ \Delta GC \quad \text{Equation 1}$$

and

$$(z)\ rf4 = (rf4 - \text{mean } rf4) - SD\ rf4 \quad \text{Equation 2}$$

Trends in (z) ΔGC and (z) rf4 were determined with slopes representing the annual change in values averaged over each period (Figure 3.4.4). The difference in slopes ΔGCMS for each period represents ΔGC corrected for climate signal to reflect just the management signal. That is:

$$(z)\Delta GCMS\ slope = (z)\Delta GC\ slope - (z)\ rf4\ slope \quad \text{Equation 3}$$

To get the annual change in ΔGC Management Signal (GCMS) then we need to multiply the corrected values by the standard deviations.

*GCMS = Corrected (z)ΔGCMS slope * sd(ΔGC) Equation 4*

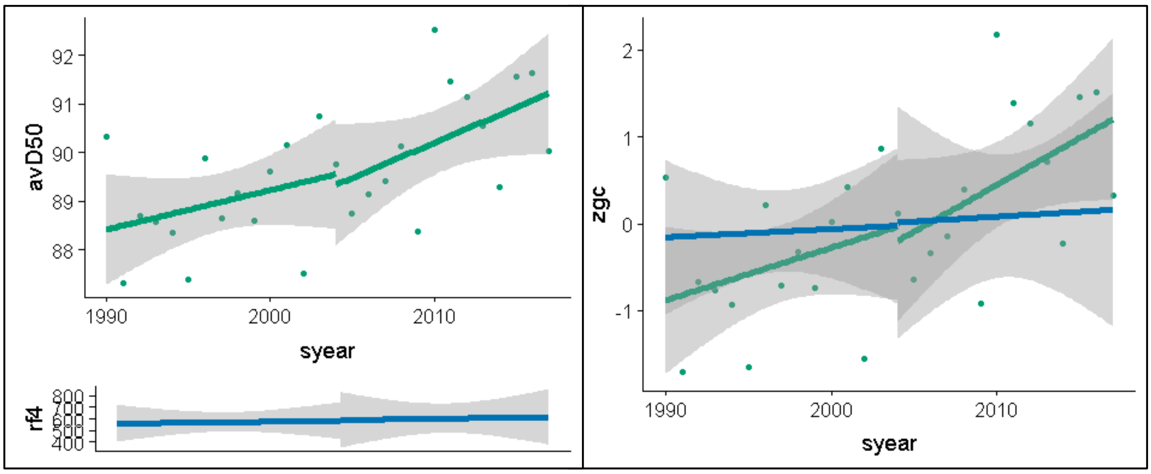


Figure 3.4.4: Trend in D50 ground cover scores and 1 year rainfall (rf4) for spring, all years (left) and z corrected (right).
Data split for Landcare (1990-2004) and Regional NRM (2004-2017)

The ground cover scores have a 1:1 linear relationship to Satellite Ground cover (from which they were derived) but a multiplier is applied to correct Visual Ground Cover data (Trevithick & Scarth, 2013). Trevethick and Scarth describe the variations between ground cover estimates from satellite data and from visual assessments. They also provide data that confirms that visual estimates tend to give lower values that remote sensed estimates and provide data for adjustment of remote sensing data for use in C-factor estimates for catchment modelling (Lu et al., 2001). The multiplier was derived from Trevethick and Scarth, 2013, data in the 20-80% range of the median GC for all sites (75-83%).

vgc multiplier = coef of the liner model
(Visual.Ground.Cover ~ Satelite.Ground Cover 75-83%)   Equation 5

And visual ground cover management signal (vGCMS) was then derived.

*vGCMS = VGC multiplier * GCMS   Equation 5*

The vGCMS was calculated separately for the Landcare Period (vGCMSlc) and for the NRM Investment period (vGCMSnrm).

Calculations were performed using the purpose written R script *060_Groundcover scores time series and trend analyses* (Appendix R).

Appendix 4.1 Groundcover scores results and dynamics

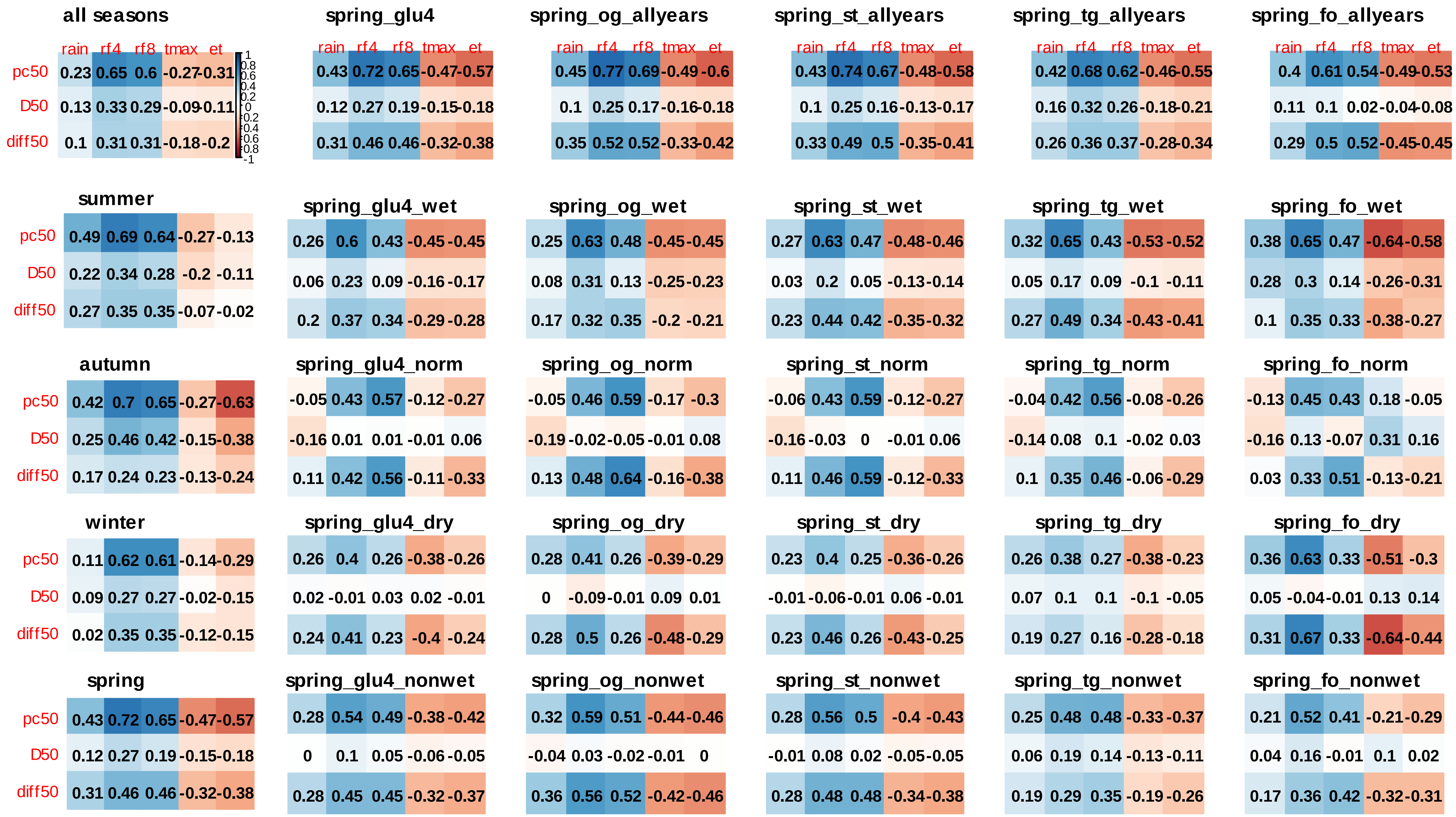


Figure 4.1.1: Excerpts from Correlation plots from groundcover data for 4 reference zones, control areas and over 50 properties in the Upper Maranoa study region. Climate data was lumped by climate zone – I.E. groundcover for each property or area within a climate zone was compared with seasonal climate summaries for the entire climate zone. Numbers in top two rows are the Pearson correlation (r). Pc50 = median ground cover; D50 = groundcover score derived from pc95(ref)-pc50; diff50 = pc50-D50 indicating the degree to which this "adapted Dynamic Reference Method" has removed climate signal. Climate indicators: rain=rf for current season; rf4=rf for current and preceding 3 seasons; rf8=rf for current and preceding 7 seasons; tmax=max temp for current season; et=evapotranspiration for current season. All p-values were <1.0%. Conclusions from these plots included:

- *aDRCM significantly reduces climate signal in all seasons, in all landscapes and in all years.*
- *aDRCM climate signal removal is most significant in spring*
- *aDRCM climate signal removal is least significant in wet years for all landscapes except timbered grazing where removal is most significant in wet years.*
- *Rf4 gives the strongest correlation and most significant removal and rain gives the least significant correlation but the aDRCM reduces the correlation cooefficient for all climate indicators.*

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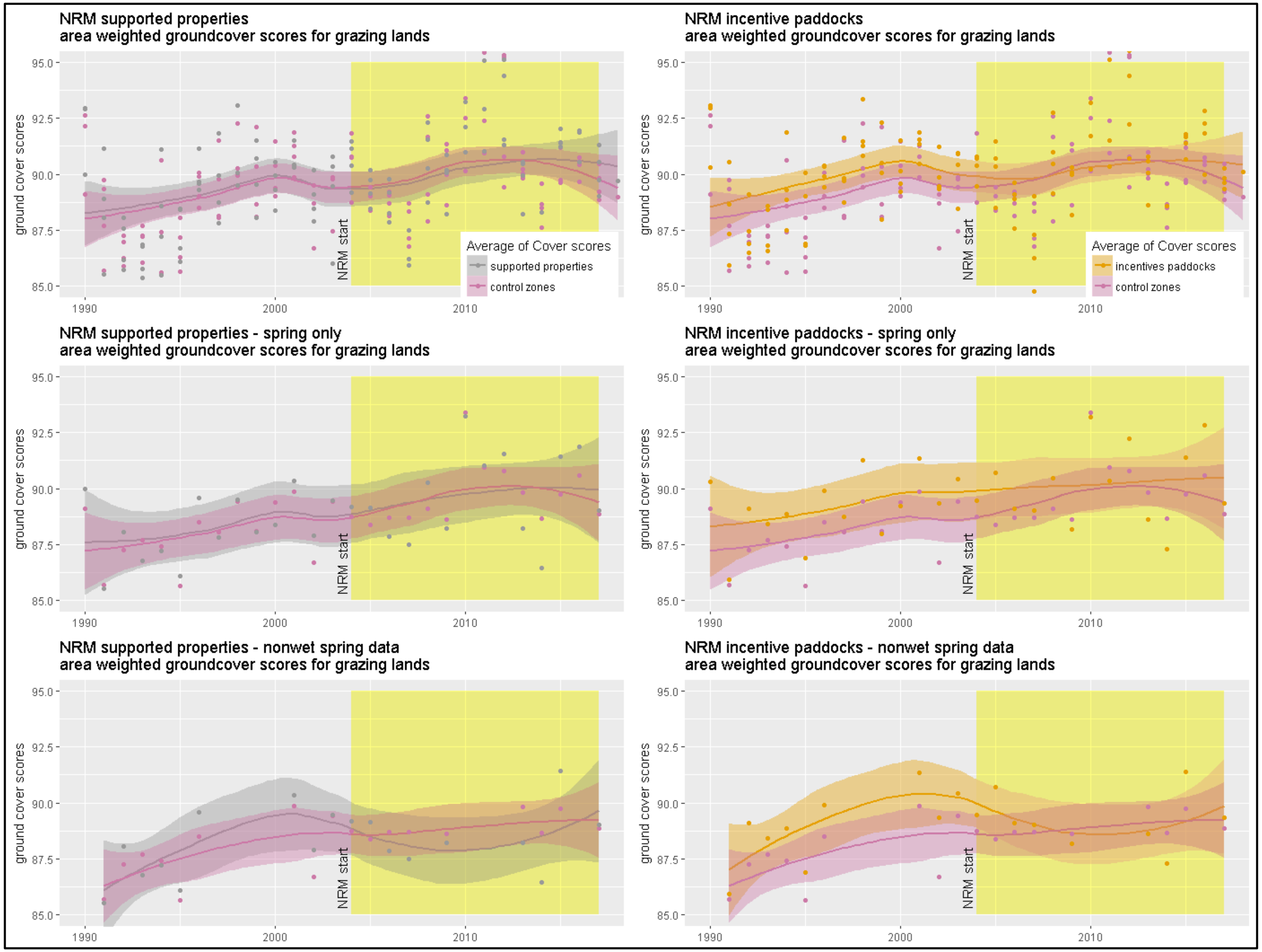


Figure 4.1.2: Moving average groundcover scores for properties and paddocks – with seasonal filters

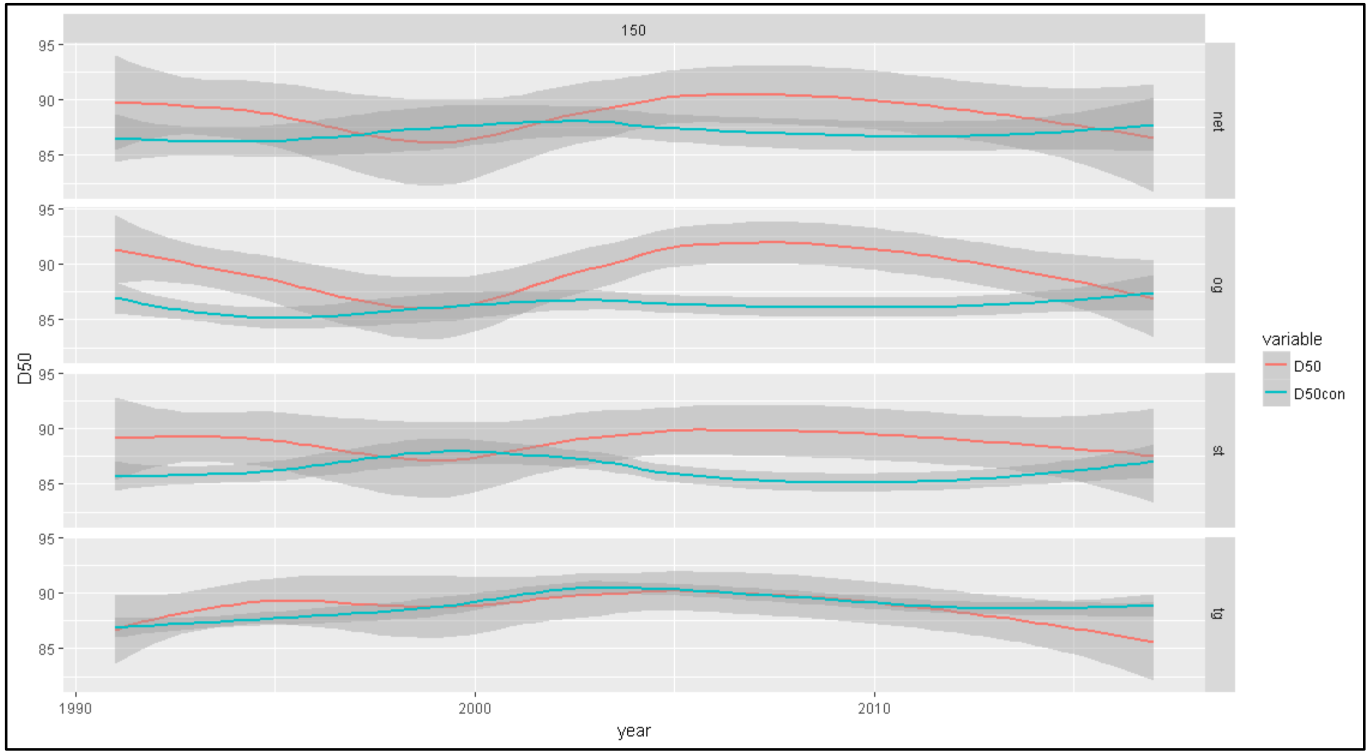
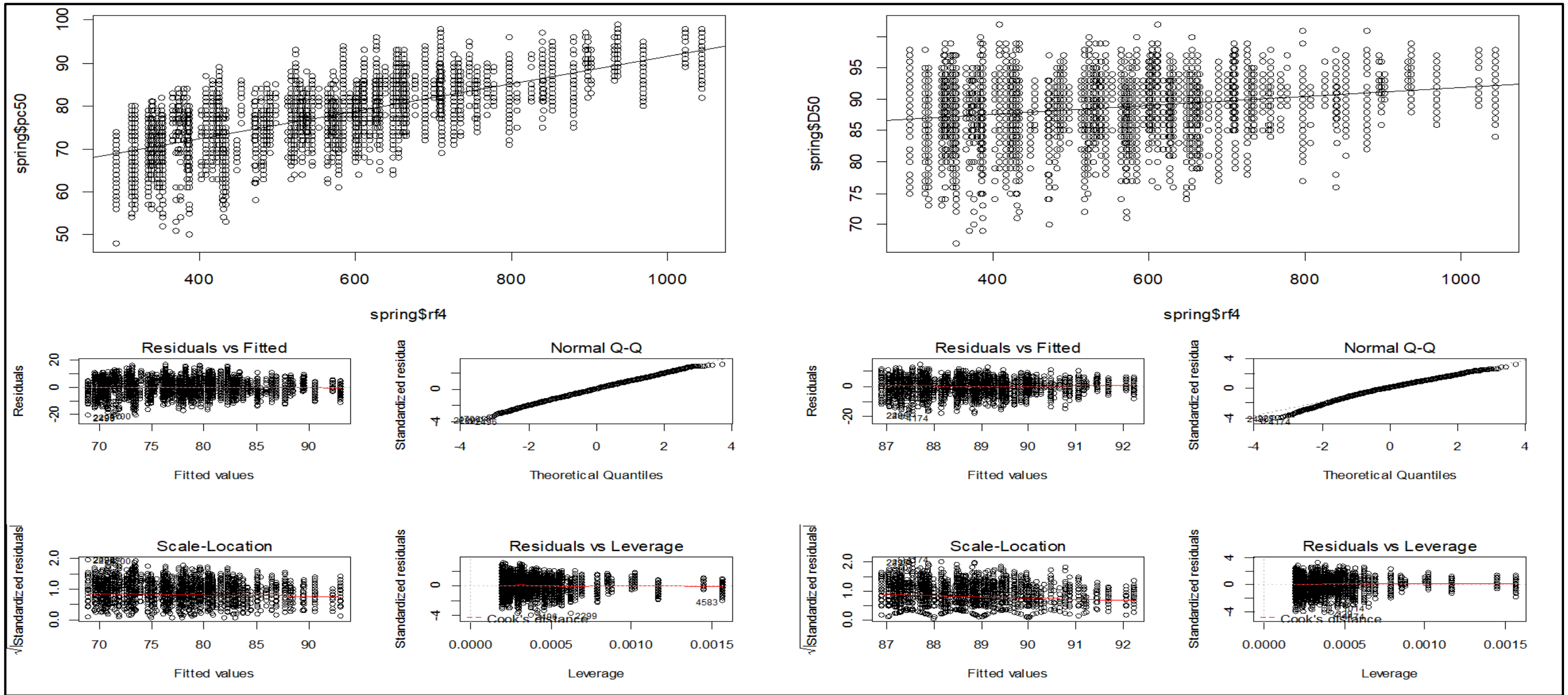


Figure 4.1.3: Sample plot of LOESS groundcover scores for supported property and for control (similar areas not receiving support).



Call: lm(formula = spring$pc50 ~ spring$rf4)
Residuals: Min 1Q Median 3Q Max
-21.9548 -3.7283 0.1878 3.8594 16.6692
Coefficients: Estimate Std. Error t value Pr(>|t|)
(Intercept) 5.951e+01 2.515e-01 236.57 <2e-16 ***
spring$rf4 3.213e-02 4.246e-04 75.67 <2e-16 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

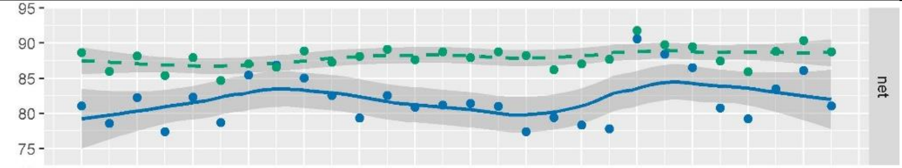
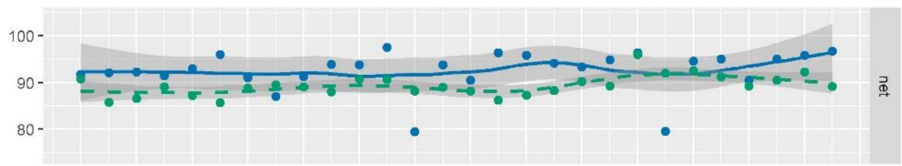
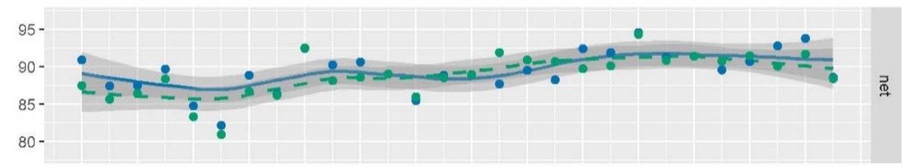
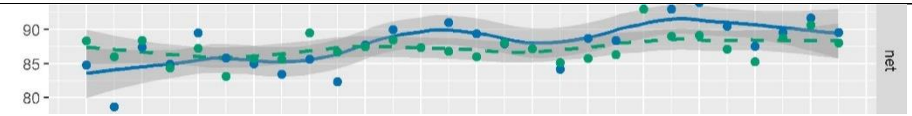
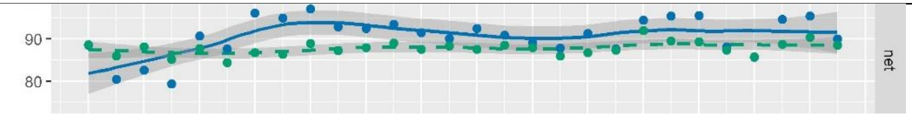
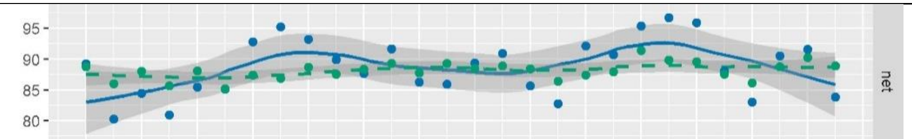
Residual standard error: 5.522 on 5023 degrees of freedom
(375 observations deleted due to missingness)
Multiple R-squared: 0.5327,Adjusted R-squared: 0.5326
F-statistic: 5726 on 1 and 5023 DF, p-value: < 2.2e-16

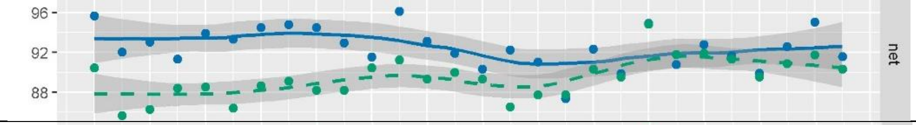
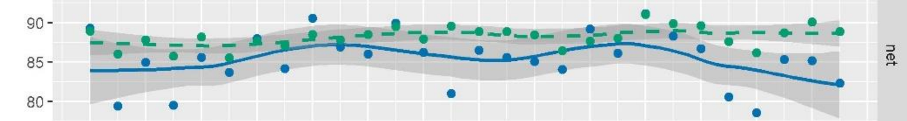
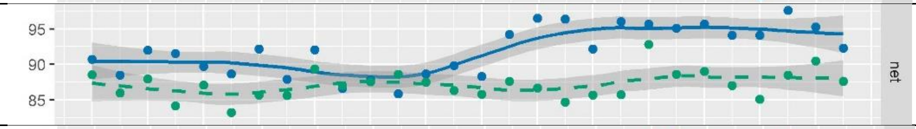
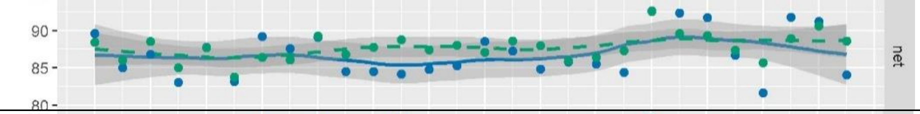
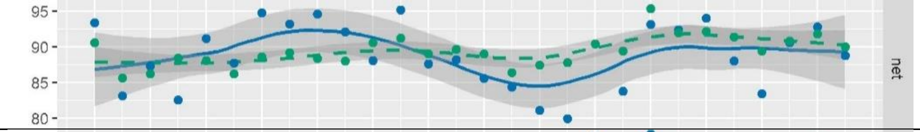
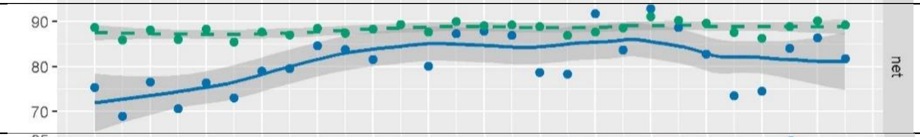
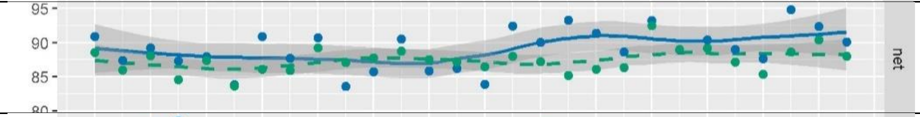
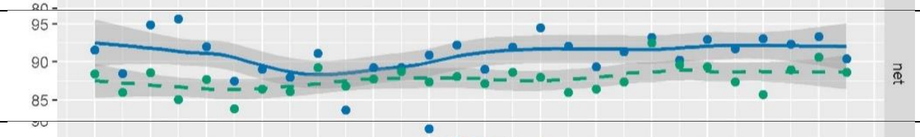
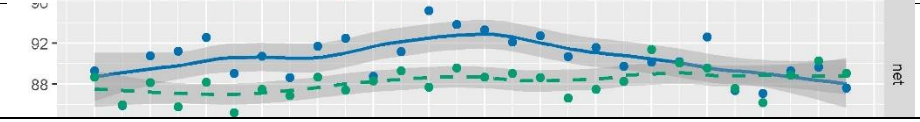
Call: lm(formula = spring$D50 ~ spring$rf4)
Residuals: Min 1Q Median 3Q Max
-20.3183 -2.7139 0.2878 3.0226 14.2861
Coefficients: Estimate Std. Error t value Pr(>|t|)
(Intercept) 8.480e+01 2.060e-01 411.6 <2e-16 ***
spring$rf4 7.128e-03 3.478e-04 20.5 <2e-16 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

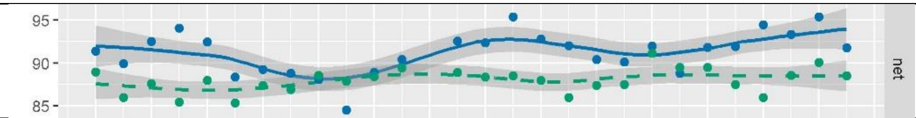
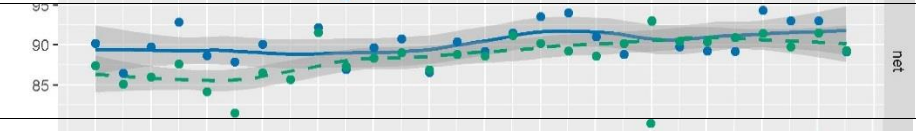
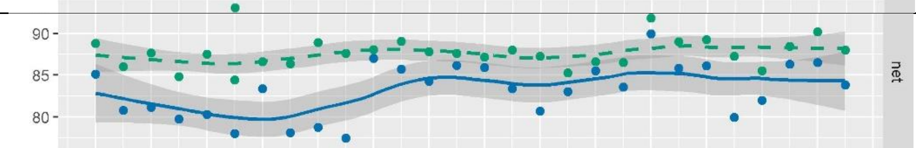
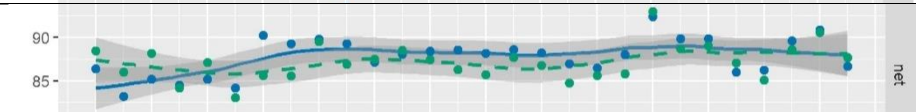
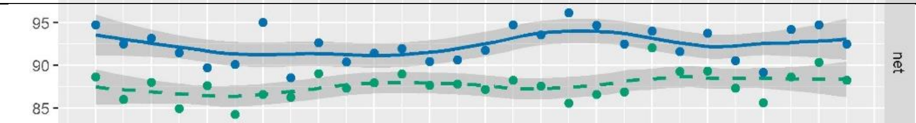
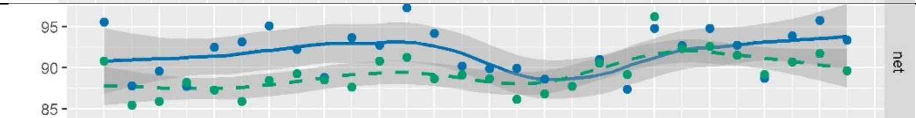
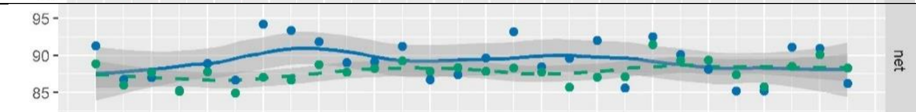
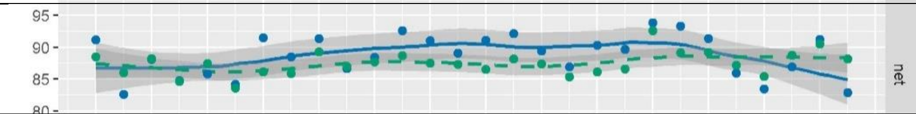
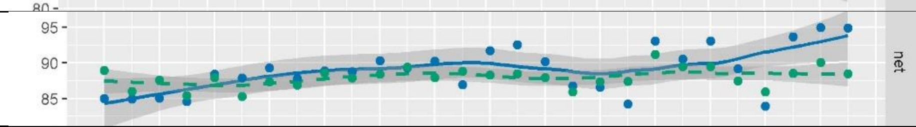
Residual standard error: 4.523 on 5023 degrees of freedom
(375 observations deleted due to missingness)
Multiple R-squared: 0.07717, Adjusted R-squared: 0.07699
F-statistic: 420 on 1 and 5023 DF, p-value: < 2.2e-16

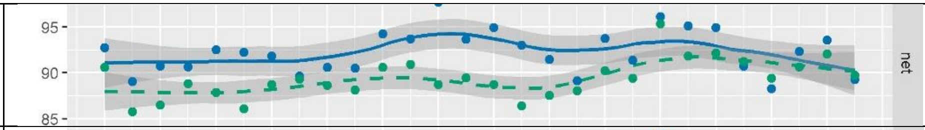
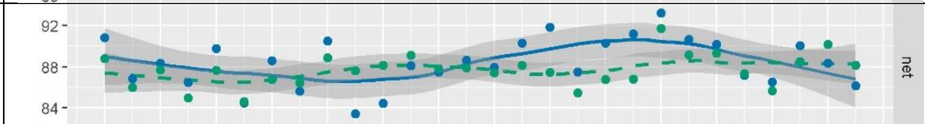
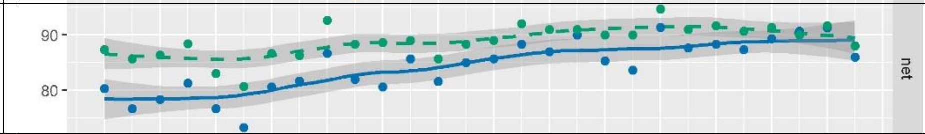
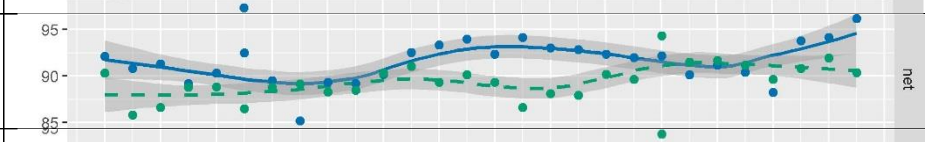
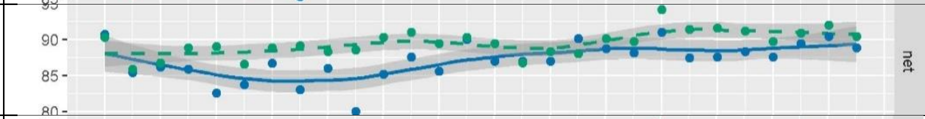
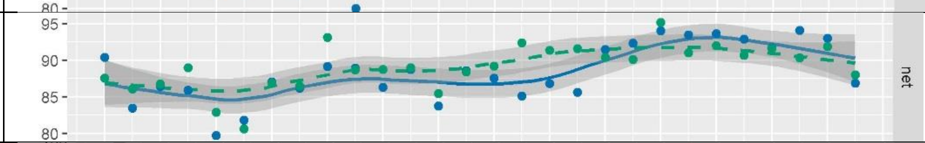
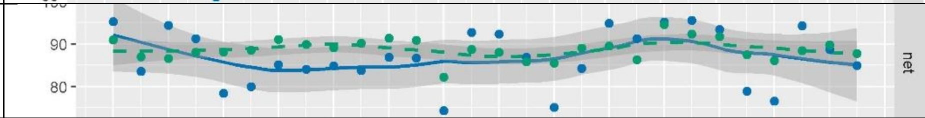
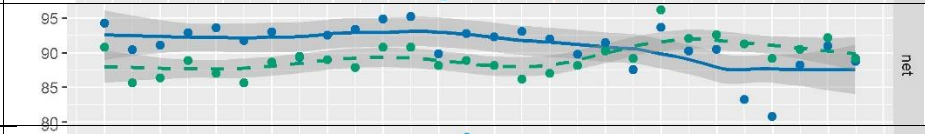
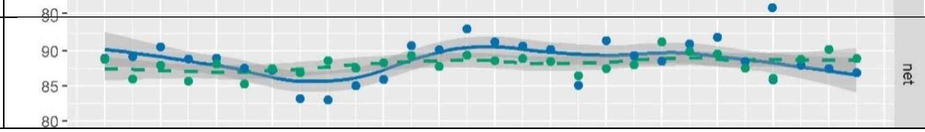
Figure 4.1.4: Tests of assumptions for Pearson's r for spring – median groundcover all sites no duplicates (pc50) & ground cover *scores (D50)*

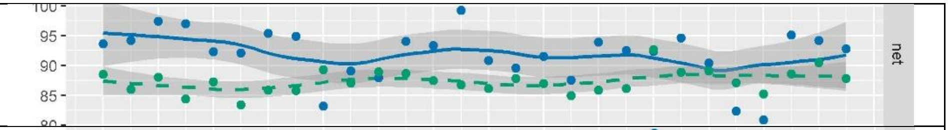
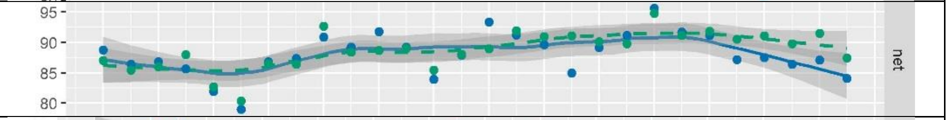
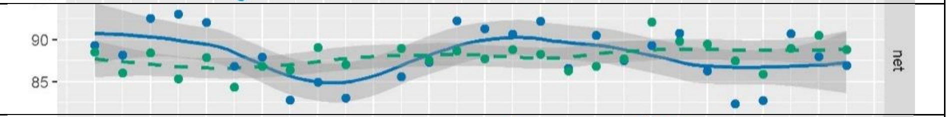
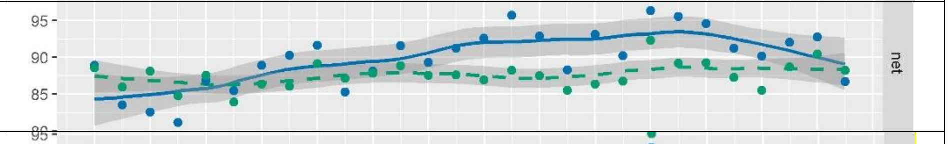
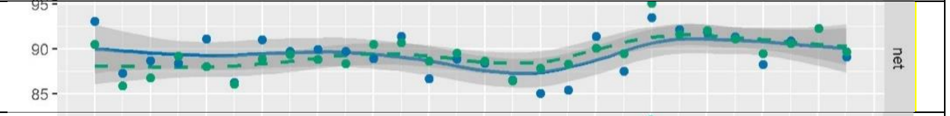
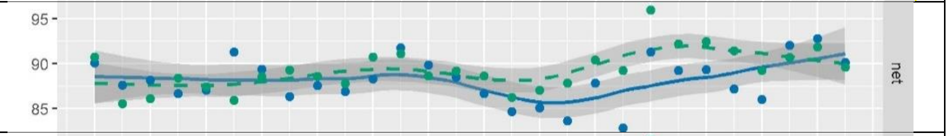
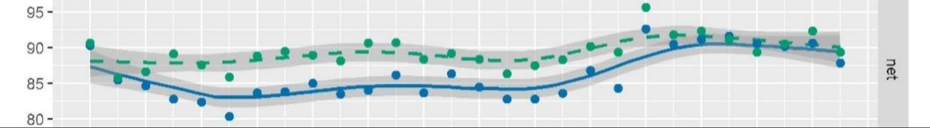
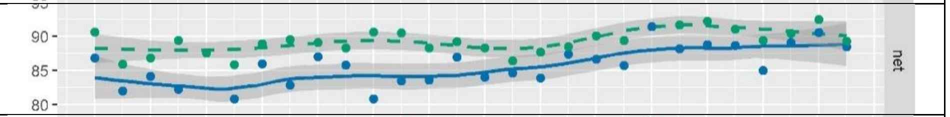
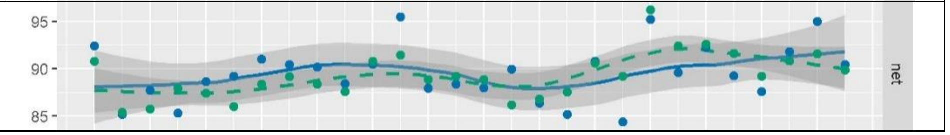
Appendix 4.2 Extension property results

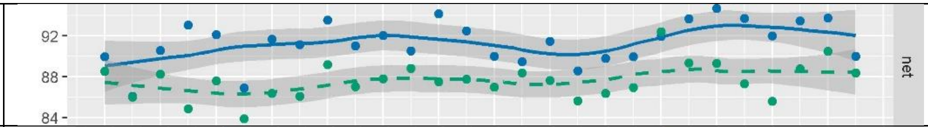
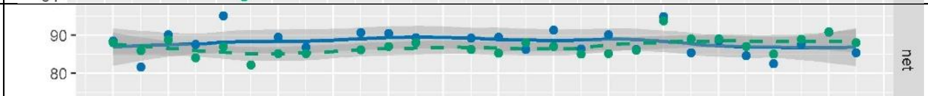
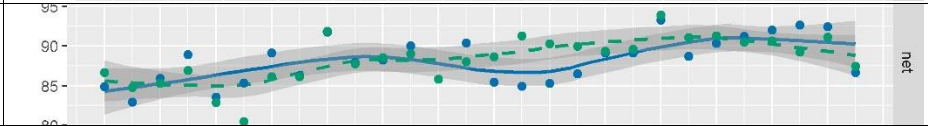
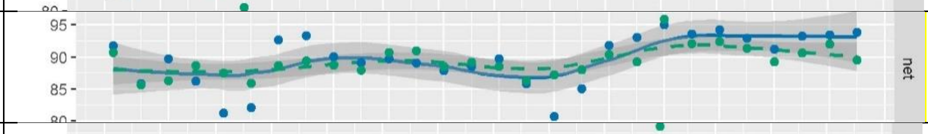
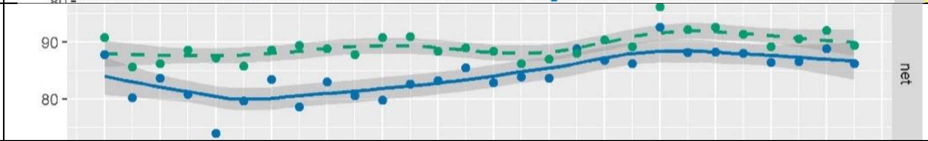
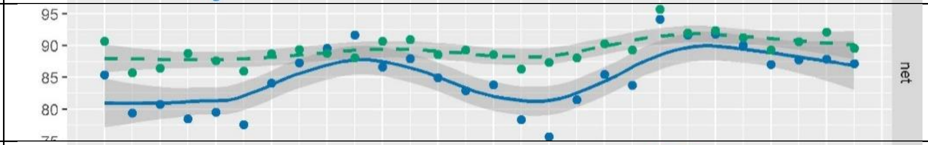
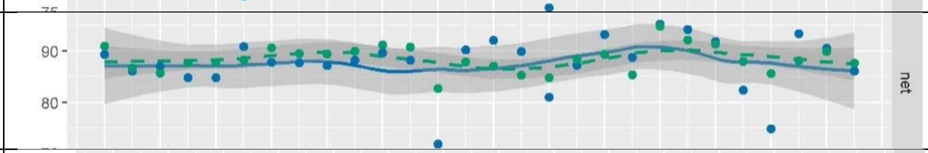
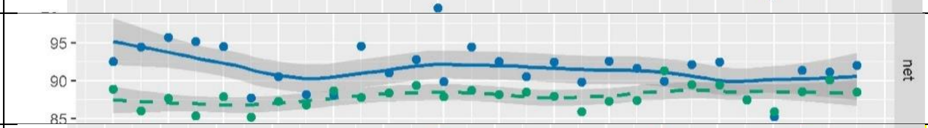
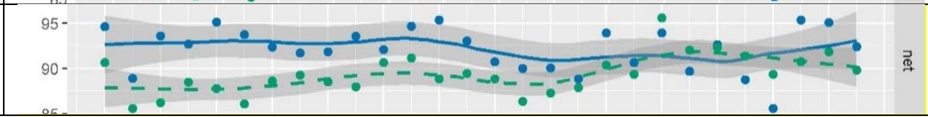
Property Code	Rating 1990	Rating 2004	Rating 2017	Δ LC	ΔReg NRM	Plot s 
010	1	1	1	0	0	
020	2	2	2	0	0	
030	2	3	3	-1	0	
040	4	2	3	2	-1	
050	4	2	2	2	0	
060	4	3	4	1	-1	

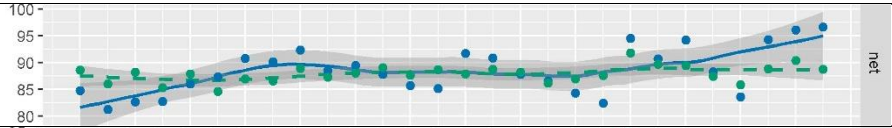
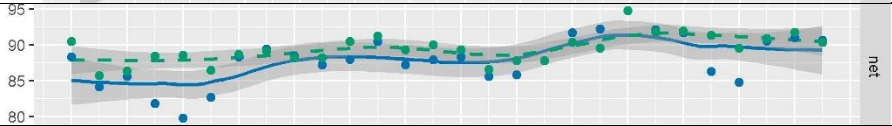
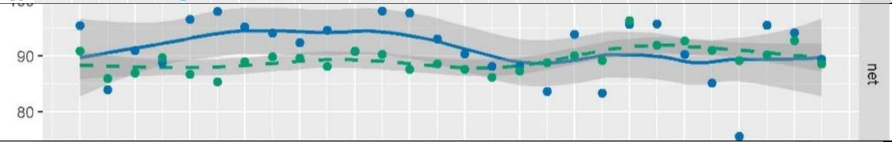
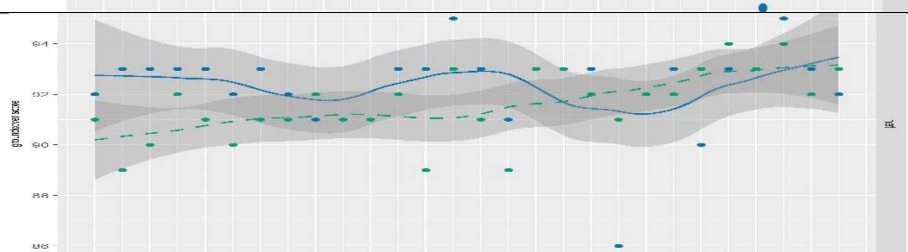
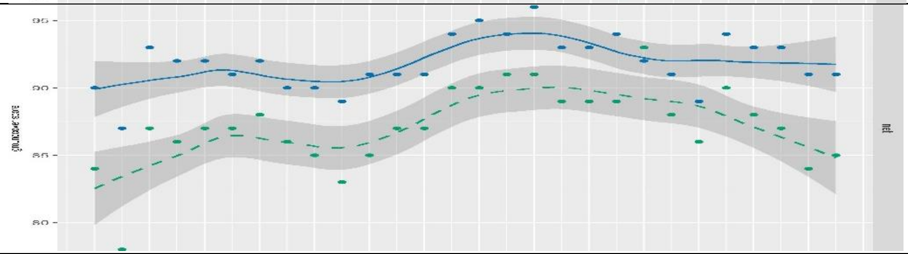
070	1	1	2	0	-1	
080	4	4	5	0	-1	
090	2	1	1	1	0	
100	3	4	3	-1	1	
110	3	4	3	-1	1	
120	5	4	4	1	0	
130	3	3	2	0	1	
140	2	1	2	1	-1	
150	3	1	3	2	-2	

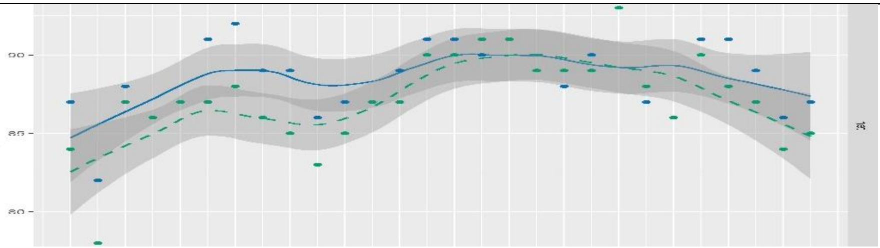
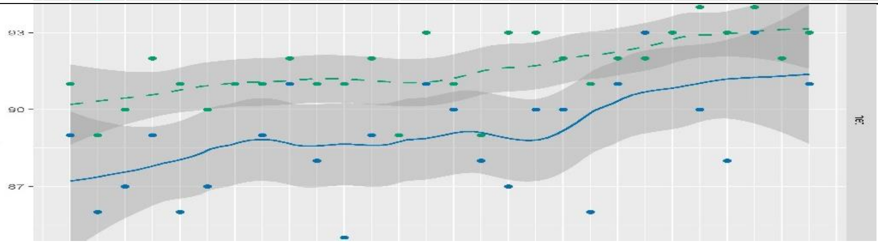
160	1	1	1	0	0	
170	2	3	3	-1	0	
180	4	4	4	0	0	
190	4	3	3	1	0	
200	1	1	1	0	0	
210	2	2	2	0	0	
220	3	2	3	1	-1	
230	3	2	4	1	-2	
240	4	2	1	2	1	

250	2	1	3	1	-2	
260	3	3	3	0	0	
270	1	2	3	-1	-1	
280	2	1	1	1	0	
290	3	3	3	0	0	
300	3	4	3	-1	1	
310	2	3	3	-1	0	
320	2	1	3	1	-2	
330	2	2	3	0	-1	

340	1	1	2	0	-1	
350	3	3	4	0	-1	
360	2	2	3	0	-1	
370	4	1	3	3	-2	
380	3	3	3	0	0	
390	3	3	3	0	0	
400	3	5	3	-2	2	
410	4	5	3	-1	2	
420	3	3	3	0	0	

430	3	1	2	2	-1	
440	3	3	3	0	0	
450	3	4	3	-1	1	
460	3	3	2	0	1	
470	4	4	3	0	1	
480	5	5	4	0	1	
490	3	3	3	0	0	
500	1	1	2	0	-1	
510	2	1	2	1	-1	

520	4	3	1	1	2	
530	4	3	3	1	0	
540	3	2	3	1	-1	
550	2	2	3	0	-1	
560	1	1	1	0	0	

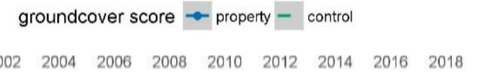
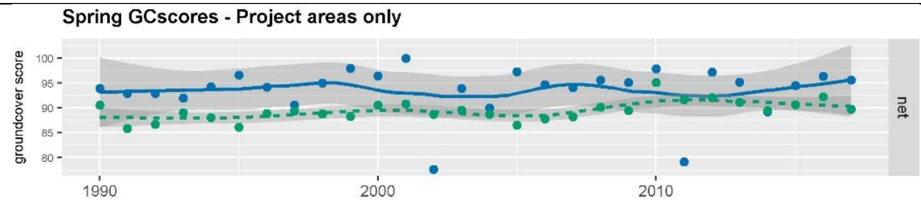
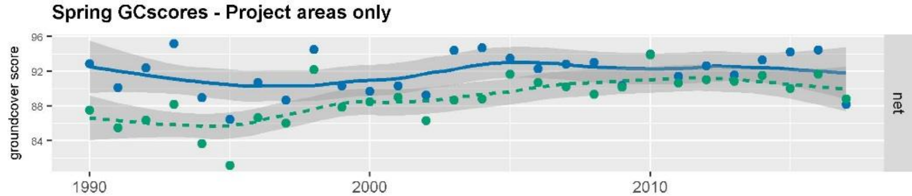
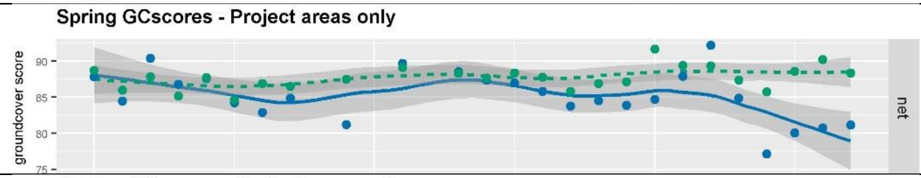
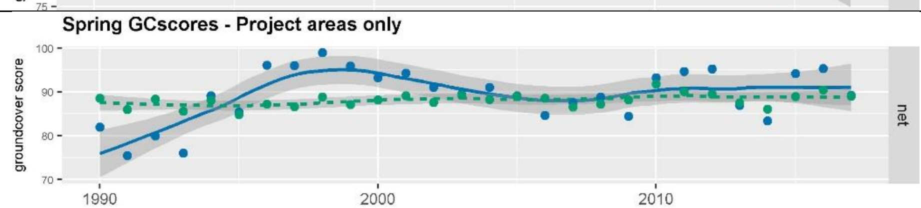
570	3	3	3	0	0	
580	4	4	4	0	0	

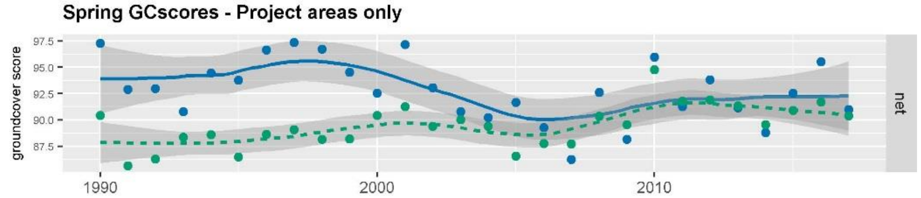
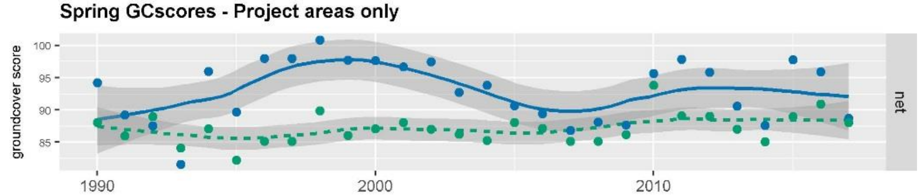
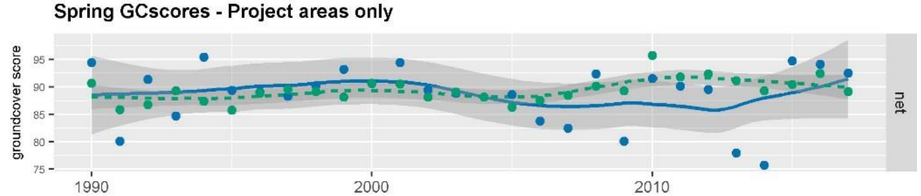
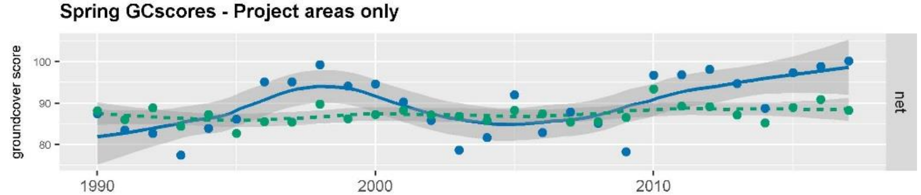
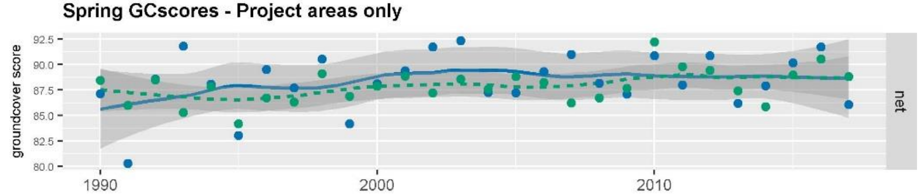
Rating based on visual assessment of “net” graph (area weighted mean of land use classes):

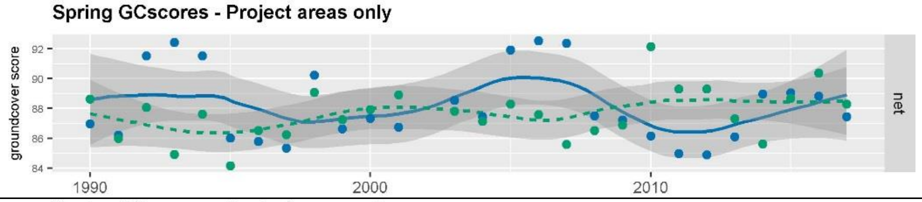
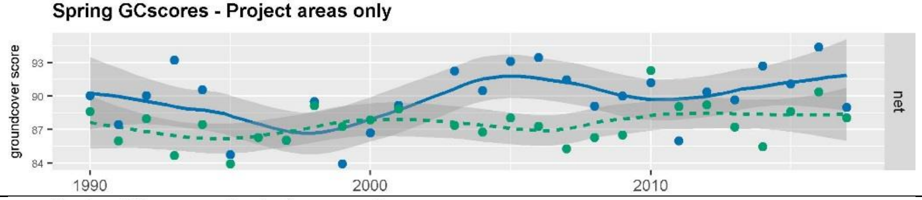
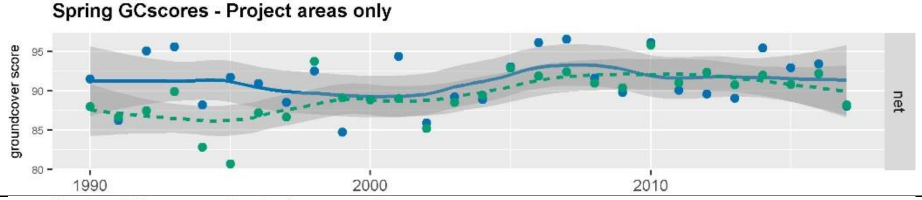
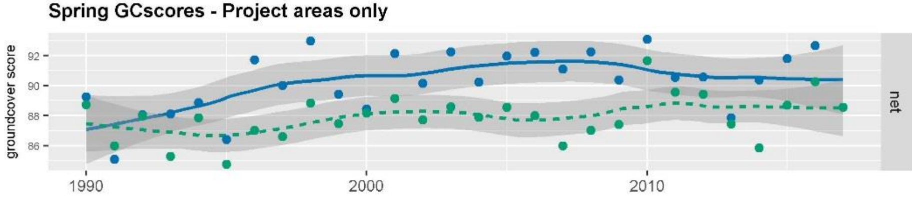
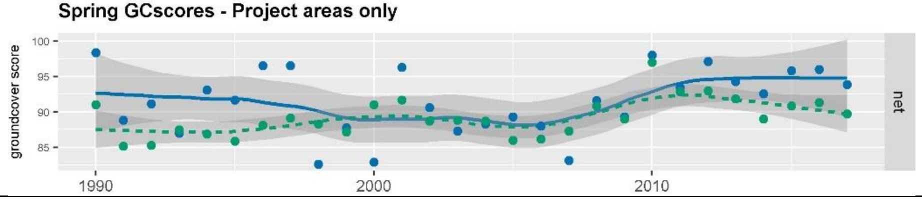
1. Property moving average line above control line and no overlap in confidence margins
2. Property moving average line above control line and overlap in confidence margins
3. Property moving average line is within the control confidence margins (in dark grey area)
4. Property moving average line below control line and overlap in confidence margins
5. Property moving average line below control line and no overlap in confidence margins

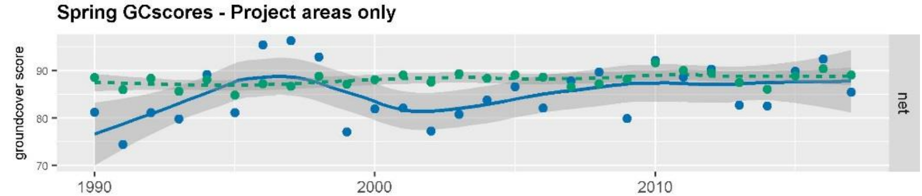
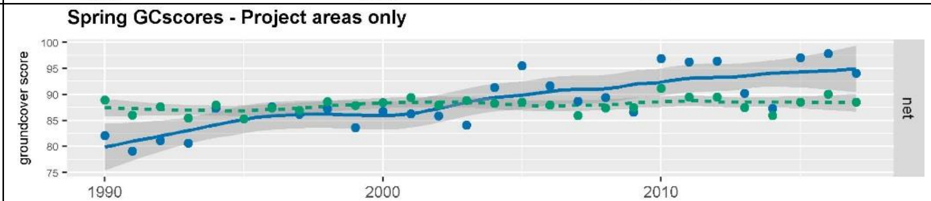
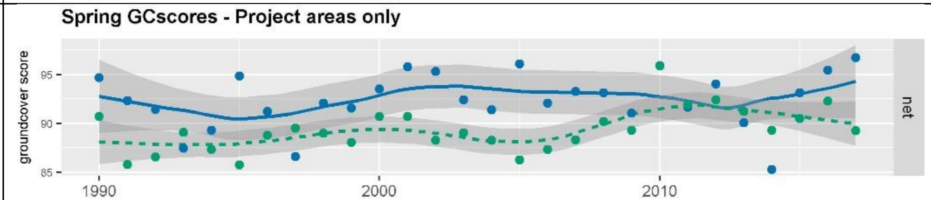
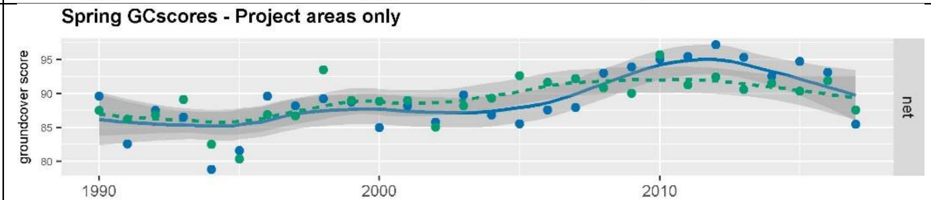
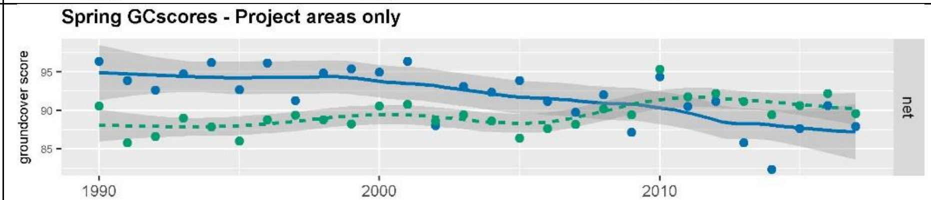
Summary	Landcare	Reg NRM
Improved	20	12
No Change	28	25
Declined	10	21

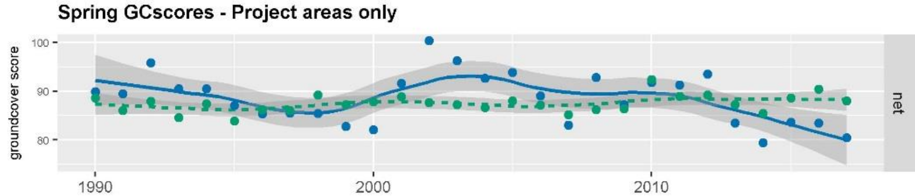
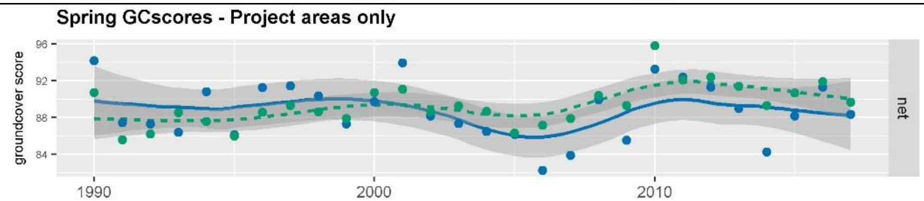
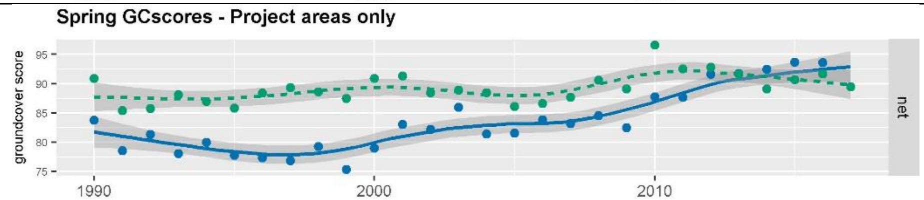
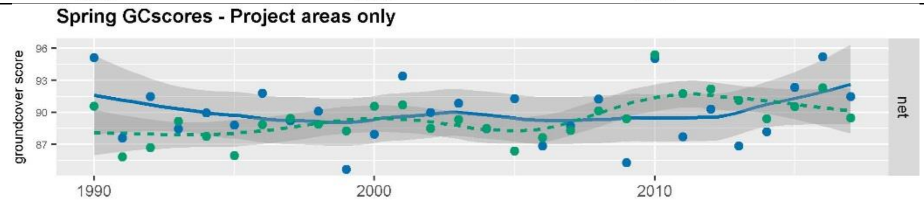
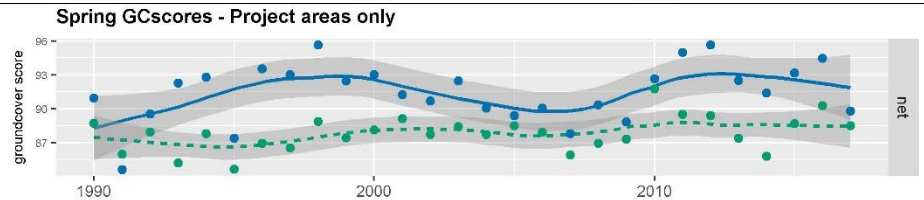
Appendix 4.3 Incentives paddock results

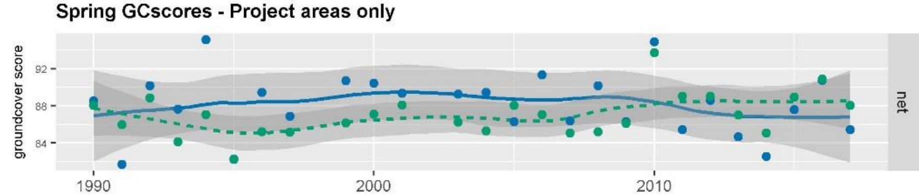
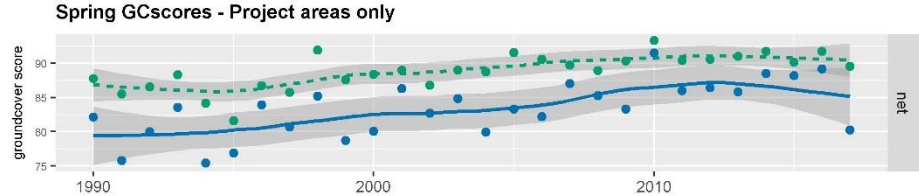
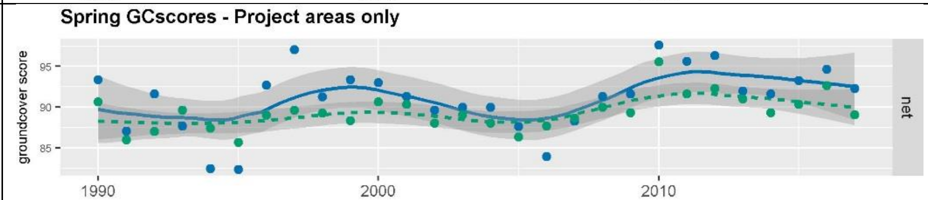
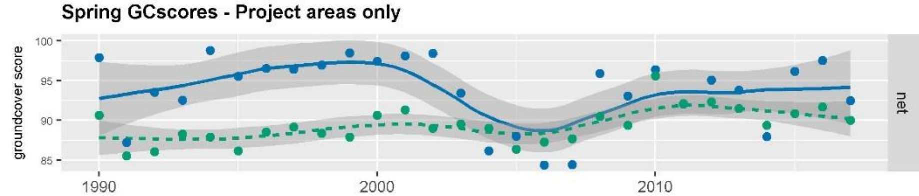
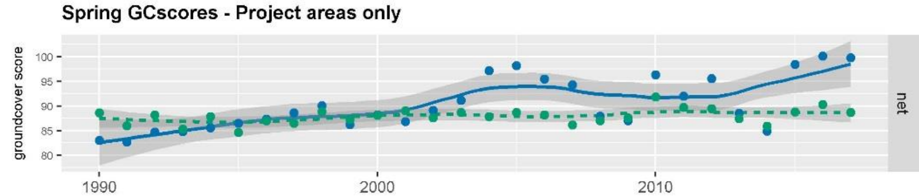
Property Code	Rating 1990	Rating 2004	Rating 2017	ΔLC	ΔReg NRM	Plot 
020	2	2	2	0	0	
030	1	1	3	0	-2	
040	3	3	5	0	-2	
050	5	3	2	2	1	

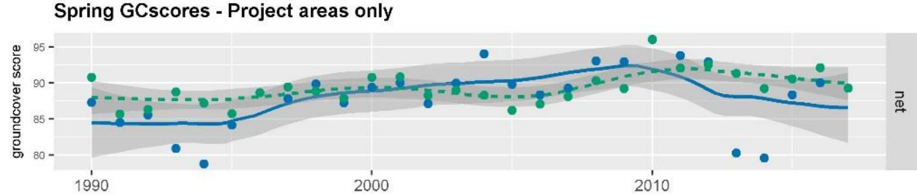
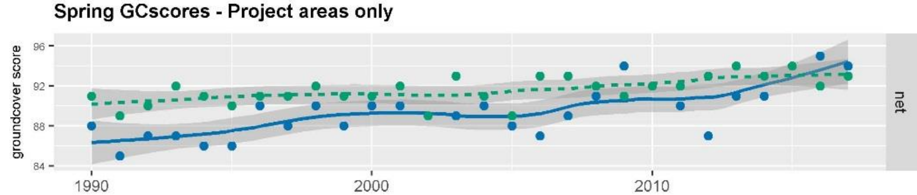
070	1	2	2	-1	0	
100	3	1	2	2	-1	
110	3	3	3	0	0	
130	4	3	1	1	2	
140	3	3	3	0	0	

150	3	3	3	0	0	
160	2	1	2	1	-1	
170	2	3	3	-1	0	
190	3	1	2	2	-1	
210	2	3	2	-1	1	

220	5	5	3	0	2	
240	5	3	1	2	2	
280	2	1	2	1	-1	
300	3	3	3	0	0	
320	1	1	4	0	-3	

330	2	1	5	1	-4	
380	3	4	3	-1	1	
400	5	5	3	0	2	
420	2	3	2	-1	1	
430	3	2	2	1	0	

440	3	2	3	1	-1	
450	1	1	2	0	-1	
460	3	3	2	0	1	
510	2	2	2	0	0	
520	4	1	1	3	0	

530	4	2	4	2	-2	
580	5	4	3	1	1	

Rating based on assessment of "net" ground cover score moving average plots (area weighted mean of ground cover scores in all land use classes within the study property or paddock):

1. Property moving average line above control line and no overlap in confidence margins
2. Property moving average line above control line and overlap in confidence margins
3. Property moving average line is within the control confidence margins (in dark grey area)
4. Property moving average line below control line and overlap in confidence margins
5. Property moving average line below control line and no overlap in confidence margins

Outcomes determined by change in rating at the start and finish of identified period.

Incentives paddock outcomes	**Landcare**	**Reg NRM**
Improved	13	10
No Change	13	10
Declined	5	11

Trend in ground cover scores across property – for properties mapped as having participated in extension programs

Outcome	1990-2004 all	2004-2017 all	2004-2017 properties WITH incentives	2004-2017 propertiesNO incentives
Improved	20	12	9	3
No Change	28	25	13	12
Declined	10	21	9	12

Appendix 4.4 Depersonalised Survey Data

Prop ID	landholder	Tenure	Outcome	land use	SCP	Year	Incentives	Other support	event info	event tech	incentives	incentive b	Other benefits	Climate eve	Market co	Changed m	Changed b	Other	GC data	mgGC scores	Recorded	Grand mana	No of ma	Ave decad > 5%	ratio yee cleared?
250	1	LL	Interview	Cattle	Yes	2005	No	No	4	3			3	2	3	1	3	3	Yes	NA	No	Same pers	2	50	No
260	2	LL	Survey	Cattle	Yes		Yes	Yes	3	3	4	3	3	4	4	1	1	3	Yes	Yes	No	Same perso	4	40	No
10	3	FH	Interview	Other	Yes		Yes	No	3	3	4	3	4	4	3	1	1	4	Yes	No	No	Same perso	2	50	No
270	4	LL	Interview	Cattle	Yes		No	No	3	3	1	1	NA	3	3	4	4	4	Yes	Yes	No	Same perso	3	50	Yes
20	5	FH	Interview	Cattle	Yes		Yes	Yes	4	3	4	3	3	3	3	1	1	3	Yes	Yes	Yes	Same perso	2	60	
280	5	LL	Survey	Cattle	Yes		Yes	Yes	4	3	4	3	3	3	3	1	1	3	Yes	Yes	Yes	Same pers	2	60	
30	6	FH																							
40	7	FH	Survey	Cattle	Yes	2005	No	No	3	3	NA	NA	3	1	1	1	1	1	NA	Yes	No	Same perso	1	50	No
470	8	LL	Survey	Cattle	Yes	2005	No	No	3	3	1	1	3	2	3	4	4	3	Yes	Yes	No	Same pers	3	50	No
300	9	LL																							
550	8	SF	Survey	Cattle	Yes	2005	No	No	3	3	1	1	3	2	3	4	4	3	Yes	Yes	No	Same perso	3	50	No
310	8	LL	Interview	Cattle	Yes	2005	No	No	3	3	1	1	3	2	3	4	4	3	Yes	Yes	No	Same perso	3	50	No
320	10	LL	Interview	Cattle	Yes	2005	Yes	Yes	3	3	4	4	3	4	3	3	3	3	Yes	NA	Yes	Same perso	2	30	No
560	11	SF	Survey	Cattle	Yes		Yes	Yes	3	3	4	3	3	4	4	1	1	3	Yes	Yes	No	Same pers	4	40	No
330	11	LL	Interview	Cattle	Yes		Yes	Yes	3	3	4	3	3	4	4	1	1	3	Yes	Yes	No	Same pers	4	40	No
340	11	LL	Survey	Cattle	Yes		Yes	Yes	3	3	4	3	3	4	4	1	1	3	Yes	Yes	No	Same perso	4	40	No
350	12	LL	Interview	Cattle	Yes	2005	No	No	3	3	1	1	2	3	3	1	4	4	Yes	No	No	Same perso	1	50	No
50	13	FH																							
360	14	LL																							
60	15	FH	Interview	Cattle	Yes		No	Yes	3	2	NA	NA	2	4	3	1	4	4	Yes	Yes	No	Same perso	2	40	No
370	15	LL	Survey	Cattle	Yes		No	Yes	3	2	NA	NA	2	4	3	1	4	4	Yes	Yes	No	Same pers	2	40	No
70	10	FH	Survey	Cattle	Yes	2005	Yes	Yes	3	3	4	4	3	4	3	3	3	3	Yes	NA	Yes	Same perso	2	30	No
380	16	LL	Interview	Cattle	Yes	2005	Yes	Yes	4	4	3	4	3	4	4	1	1	3	Yes	Yes	Yes	Same perso	2	60	Unknown
390	17	LL	Interview	Cattle	No		No	No	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Yes	Yes	No	Same perso	2	70	No
570	18	SF	Interview	Cattle	Yes		No	No	1	3	NA	NA	3	4	3	1	4	4	Yes	No		Same perso	1	60	No
80	18	FH	Survey	Cattle	Yes		No	No	1	3	NA	NA	3	4	3	1	4	4	Yes	No		Same pers	1	60	No
400	19	LL	Interview	Cattle	Yes	2005	Yes	No	3	3	4	4	4	4	4	1	3	3	Yes	Yes	No	Same pers	3	70	No
90	20	FH	Interview																						
410	4	LL	Survey	Cattle	Yes		No	No	3	3	1	1	NA	3	3	4	4	4	Yes	Yes	No	Same perso	3	50	No
100	21	FH	Interview - landholder held survey to finalise with reference to diary																						
110	22	FH	Interview - landholder held survey to finalise with reference to diary																						
420	22	LL	landholder held survey to finalise with reference to diary																						
120	0	FH																							
130	3	FH	Survey	Other	Yes		Yes	No	3	3	4	3	4	4	3	1	1	4	Yes	No	No	Same pers	2	50	No
140	23	FH	Interview	Cattle	Yes		Yes	Yes	4	3	4	4	1	1	1	2	1	3	Yes	NA	Yes	Close relat	2	40	No
430	23	LL	Survey	Cattle	Yes		Yes	Yes	4	3	4	4	1	1	1	2	1	3	Yes	NA	Yes	Close relati	2	40	No
150	24	FH	Interview - landholder held survey to finalise																						
440	24	LL	landholder held survey to finalise																						
160	24	FH	landholder held survey to finalise																						
170	25	FH	Interview	Cattle	Yes		Yes	Yes	3	2	4	3	NA	1	2	3	1	1	Yes	Yes	Yes	Same perso	2	30, 50	No
450	26	LL	Interview																						
180	27	FH	Interview																						
460	28	LL	Interview	Cattle	Yes	2005	Yes	Yes	4	2	4	3	4	2	2	1	4	NA	No	No	Yes	Same perso	2	70	
290	8	LL	Survey	Cattle	Yes	2005	No	No	3	3	1	1	3	2	3	4	4	3	Yes	Yes	No	Same pers	3	50	No
190	29	FH	Interview	Cattle	Yes	2004	Yes	Yes	4	3	4	4	2	3	3	1	1	1	Yes	Yes	No	Same pers	2	60, 60	No
480	30	LL	Interview																						
200	3	FH	Survey	Other	Yes		Yes	No	3	3	4	3	4	4	3	1	1	4	Yes	No	No	Same perso	2	50	No
490	31	LL	Interview	Cattle	Yes	2005	No	No	3	4	1	1	1	3	3	1	1	1	Yes	Yes	No	Same perso	2	70	No
500	17	LL	Survey	Cattle	No		No	No	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	Yes	Yes	No	Same pers	2	70	No
210	32	FH	Interview	Cattle	Yes	2005	Yes	Yes	4	4	4	3	3	4	4	4	4	3	Yes	NA	Yes	Same pers	2	40	No
510	32	LL	Survey	Cattle	Yes	2005	Yes	Yes	4	4	4	3	3	4	4	4	4	3	Yes	NA	Yes	Same perso	2	40	No
540	32	RE	Survey	Cattle	Yes	2005	Yes	Yes	4	4	4	3	3	4	4	4	4	3	Yes	NA	Yes	Same pers	2	40	No
220	33	FH	Interview	Sheep	Yes		No	No	1	1	NA	NA	1	4	1	1	1	4	Yes	Yes	No	Same pers	2	60	No
230	11	FH	Survey	Cattle	Yes		Yes	Yes	3	3	4	3	3	4	4	1	1	3	Yes	Yes	No	Same perso	4	40	No
240	34	FH	Interview	Cattle	Yes		Yes	Yes	4	2	4	4	3	4	4	1	2	2	Yes	Yes	No	Same perso	2	60	
520	34	LL	Survey	Cattle	Yes		Yes	Yes	4	2	4	4	3	4	4	1	2	2	Yes	Yes	No	Same pers	2	60	
530	35	SF	Survey	Cattle	Yes	2005	Yes	No	4	3	4	4	3	3	3	1	1	4	Yes	No	No	Same perso	2	50	No
580	35	LL	Interview	Cattle	Yes	2005	Yes	No	3	4	4	4	3	3	3	1	1	3	Yes	No	No	Same perso	2	50	Unknown

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Appendix 4.5 Landholder quotes and insights

Ref	Miscelleaneous quotes and insights from survey forms - edited or paraphrased as required to depersonalise as required by QMDC MOU and USQ Ethics
Member of public	Former Forestry area is to be harvested to the maximum extent under the Forestry Code - much higher clearing rate than was previously undertaken - not a sustainable rate of clearing
040	Bought the property in 2009 and have been concernced with the country's fragility since purchase.
320	2013/14 shouldn't be lower than 2002
320	[NRM activities] helps keep up to date with legislation
320	[NRM activities] shared challenges improves motivation
320	Transitional succession planning
380	[NRM activities] benefits included mapping and GPS recording of veg and infrastructure
380	[NRM activities] was good for flood recovery co-ordination and support
380	[inhibitors] Time away from home and after hours work for industry body
380	2014 managed burn shows up in "sparse timber" gc data
380	Some thinning (with permits) 2005 & 2016-17 5-6k Acres
319/500	On the books for SCP but not really active participants
319/500	Set stocking, same for many years
140/430	[Inhibitors] Instability of veg laws & mapping
140/430	[Inhibiitors] Controlling native grazing pressure
140/430	Significant regrowth clearing 2016 onwards NE paddock and SE paddocks
570/080	I also have NW corner across to [property] that is not mapped
570/080	[Inhibitors] 7 years early in NRM period - caring for partner with major health problems
570/081	2017 had lower feed body than 2014 plus some Pimelea
570/081	Can't understand why 2013/14 went so low.
010/130/200	Mixed sheep and cattle plus some forage/cash cropping
010/130/200	[NRM activities] was good for social benefits and capacity building/knowledge
010/130/200	[Inhibitors] Veg management/legislation
010/130/200	[Inhibitors] labour shortage - back packers require high level of supervision
010/130/200	Different properties in same climate zone have same management but different results - some cropping areas in best country likely confound results
250	[Inhibitors] Cashflow is limiting
250	[Inhibitors] Veg legislation and (lack of) stability of veg map is a problem. Should be "buy back" for changed veg status.
250	[Inhibitors] Should be "buy back" for changed veg status
250	[NRM activities] was good for social benefits and networking
250	noticed increased roos since cluster fencing around …
250	We also own other property [in catchment] and relatives next door [not mapped] did some Landare stuff with us
250	Natural springs were being impacted by stock. We fenced them off and use bore water for stock.
210/506	Cashflow
210/507	Uncertainty of veg legislation
210/508	Climate change/variability management options??

210/509	Increased accountability under changing legislation/regulations: EG biosecurity; veg management; animal welfare; tenure; many more with understanding and maintaining curent knowledge difficult and implications scary
210/510	Oil and Gas threat - tenure; access; groundwater security.
210/510	[Unmapped property] did some SCP too.
260/560/330 /340/230	[Inhibitors] Droughts main problem; floods lesser problem: cash flow balance. [Inhibitors] Markets - 2007-2010 & 2013/14 [Inhibitors] Weeds related to grazing pressure [Inhibitors] Banks - no relief from repayments in drought [Inhibitors] Box effect of cluster fencing (and dog fence) - some roo influxes and aggragations [Inhibitors] Regrowth control challenges compounded by changes in veg mapping and regulations. [Inhibitors] Sattelite GPS accuracy changes recently resulting in added problems managing regrowth. [NRM activities] Some people seemed to play the system better than others - preferential treatment - EG attending conferences and incentives availability/timings. Forage crop for ground cover and soil condition and rest other paddocks Pimilea last few years [Inhibitors] cash flow, climate, markets
280/020	[Inhibitors] cash flow, climate, markets
280/020	Mother of Millions - 4-5 head lost.
280/020	Ground cover show some of the impacts of climate and fires.
280/020	"sparse timber areas" not meaningful as they are on the edge of regrowth areas that sometimes get cleared and sometimes not.
280/020	4th generation on this property
280/020	GC reflects impact of climate periods and fire regime
280/020	After 3 wet years we had fire in open grazing areas followed by drought years (2013/14) the only pasture was in the timbered areas where fire had been followed
240/520	[NRM activities] was good for info exchange
240/521	[Inhibitors] Health problems
240/522	[Inhibitors] cash flow -Funding ratios - more $
220	Veg legislation - no scope for wholistic management of mapped veg
220	Veg legislation - stability and accuracy of mapping creates confusion
220	Project areas doughtful - no recollection of receiving incentives despite lots of
220	[Inhibitors] labour shortage - back packers require high level of supervision. Seem to know all their rights but not willing to accept any responsibilities.
370/060	Land that was previously a Forestry Lease has now been freeholded but state retains rights vested in timber for the property for some time
370/061	Some projects implemented - self funded
370/062	[NRM activities] Courses in town - monitoring and feed budgetting, Soil erosion
370/064	[Inhibitors] Stable veg laws seen as beneficial for production and environment - security of veg status would aviod panic clearing including for regrowth - ongoing changes in mapped areas and rules is scary and overwhelming in an industry where
370/065	[Inhibitors] Concerns about total exclusion fencing and native grazing pressure - unfenced "good country" is a magnet
400	Below average rain since 2012, Request RF data (SILO) - sent
400	[Inhibitors] Black striped Wallabies live in Brigalow and hammer pasture under
400	[Inhibitors] Veg clearing only in early years to beat pending veg legislation.
400	Stable veg laws seen as beneficial for production and environment.

400	Timber scores lower - possibly due to regrowth clearing and wallabies.
400	Some project areas not mapped.
350	[Inhibitors] Serious health problems resulting in constraints on time, finance and
350	Regrowth control 2015-17 especially 2017 with seems to be pulling the moving
350	High levels of Parhenium in recent years.
350	GC scores - last few years should be higher
350	[Inhibitors] timings and cash flow didn't line up.
350	[NRM activities] was good for networking
270/410	[Inhibitors] Cash flow limits timing for new water and fencing
270/411	[Inhibitors] unaware of incentives availability till too late.
270/412	[Inhibitor] - Parthenium and constraints on management due to Bluegrass and Echidna protection area rules.
270/413	Incorporating next generation into management - splitting herd across family with incremental learnings about breed characteristics.
490	Purchase and sale of another property with some cattle agisted offsite to help son
310/550/470/	Family succession plan over several years - maybe resulted in 470 getting
310/550/470/	Fire impacts condition and management.
460	GC and scores reflect management and fire impact. GCScores 2006/7 sitting low but destocked early so should be comparatively good. Consider checking with Forage 20% analyses - timber/open split not necessary - data up to 2000 looks right
460	Heat impact on people
460	Flooded market at normal selling time
460	Lost top labor source with son moving away
460	Management regime ongoing evolution especially since wholistic management course - triggered by change in family circumstances. Remote sensing water points
460	Former Forestry land freeholded, then Forestry harvested timber, then sent us a
460	Land type might be better split than timbered/open grazing
170	[Inhibitor] - Issue - risk or some concern about regrowth mapping change. Endorsed the idea of veg mapping stability & compensation for change.
170	Incentives helped start whole property management. Learnings from courses applied across whole property starting
170	Question 2017 GC and scores
580/530	Leasehold land (Forestry) has been freeholded
580/531	Project areas missed or not right on both properties
580/532	Check moving averags and scores (error subsequently found and updated plots sent
580/533	Coordinated monitoring plan fell through with changes in [NRM] staff and funding
580/534	2016/17 locally dry compared to neighbours
580/535	Some forestry areas may have been cleared
190	A lot of the tg areas in rocky hill country [may cause low cover] - some work being done now [fencing to land type]
190	2014-15 maybe some local variations in rainfall
190	Incentives areas - fenced stream plus more water points - better grazing spread

Appendix 4.6 Selected Journal Notes

Compiled from selected journal notes made by Paul Webb following interviews with landholders in the Upper Maranoa region from August to October, 2018

Most landholders expressed concerns about vegetation regulation with boundary changes for regulated vegetation not stable. Some indicated a tendency to clear regrowth more frequently and more aggresively than they would like - for fear that if they did not clear regrowth it would be reclassified as remnant.

Two landholders indicated they were having success in managing macropods by not shooting. They have found the alpha male seems to regulate mob populations and the numbers were acceptable for graziers. Both the landholders who have adopted this approach suggested that the harvesting requirement to shoot the larger animals first was counter productive as it is the larger alpha male that moderates populations.

One landholder indicated he was not shooting or baiting dogs. He was having success leaving the dogs and suggested the alpha male was moderating the populations. He was getting contractors in the "train" his cattle after calving. The training involved dogs harrassing the cattle untill they formed a close mob. The understanding is that the dogs will not attempt to take a calf that is in the mob but will only take seperated calves. In the absence of lone stock the dogs will settle for native species as their food source.

A number of couples are struggling with health issues. This has implications for property management and for finance with long travel time to specialist services in Roma, Toowoomba or Brisbane. There was talk of the children having some capacity to help out but this being limited by children's "town jobs" and family circumstances.

Every landholder family has stories that could fill a book. Local history, trials, tribulations, cleches and innovations were not captured in the survey process but were inspiring for the researcher. These people are individually and collectively an amazing group of people doing some amazing things every day - to put food on our plates.

Several landholders alluded to current option for some landholders to change Forestry leases over to freehold land. It was indicated that where this option was taken, the Queensland Government retains rights vested in timber on the property for some years. Landholders and an independant member of the public suggested that harvesting in these properties is currently occurring at accelerated rates. One person in particular with environmental qualifications and interests suggested freeholded former forestry land was being harvested at unsustainable rates. He hinted at a "pannick clearing" sentiment from the current "supposedly green" state government.

An amazing night was had around a camp fire at one property. The old ringer told story after story about his life experiences as a jackaroo, ringer and station hand over a period of about 60 years. Another book waiting to be written!

Property visits were much more engaging than meetings in town or (my experience of) workshops. Major advantage was that property visits engaged the wives in the husband and wife enterprises. Wives often not as involved in conversations about stock and pasture management but certainly on point when discussions linked to finance or reduced carrying capacity.

Significant stream bank and gully erosion observed on some properties and accros the catchment. Some of these would dwarf the soil loss numbers for adjoining landscapes. Erosion areas often showing exposed subsoils in duplex soil profiles with no veg and some tunnel erosion apparent in these subsoils (presumabley sodic).

Several mentions were made of corporate farms in the district with lack of local ownership and some diminished local business links. Corporate properties' capacity for gross changes (E.G. total exclusion fencing) was greater and they did not seem to be interested in working with other landholders in the vicinity. Some angst about this including about the impacts of foreigh owned companies with increased influence on landscapes and markets.

2014 and 2015 groundcover scores questioned by a few landholders. On review they were on properties with significant river flats or other low lying areas. Suspect there was an issue with Buffel pastures following the 2012 big flood.

Concerns about regrowth being "locked up" combined with changing GPS technology is leading to variations in boundaries of clearing. It was suggested by more than one lanholder that that makes the "sparse timber" areas dubiuos as they are mostly on the edges of cleared areas.

Appendix 4.7 Upper Maranoa field data review

Stocktake monitoring data (Aisthorpe et al., 2004) was available for 8 properties that had received some support from NRM projects. Landholders from these properties agreed to make data available to validate or refine results of remote sensing groundcover analyse. When data was reviewed, some challenges arose in efforts to compare monitoring data with remote sensing data. Difficulties arose in both spatial and temporal dimensions.

Spatially, Stocktake sample results were attributed to a site with a latitude and longitude. This single point attribute did not adequately describe the dimensions of the sample area for comparison with remote sensing data pixels. Similarly, remote sensing data pixels are 30m by 30m and do not align directly with sample areas covered in stocktake groundcover and pasture biomass assessments. To achieve a provisional assessment, a selection of Stocktake results were compared with groundcover data that was within an area which:

- included the site latitude and longitude and,
- included similar visual appearance to the site latitude and longitude from apparent soil colour and tree density.

Temporally, satellite derived groundcover data was accessed from VegMachine seasonal groundcover values (Scarth et al., 2016). Data for each pixel is summarised by season using a “medoid” (Flood, 2013). Seasonal data is then summarised for selected pixels with a variety of onscreen or downloadable tables and plots. This seasonal data may, or may not be representative of groundcover observed at a point in time during that season by the Stocktake method. To achieve a provisional assessment, a selection of Stocktake results were compared with seasonal groundcover for the (three month) season during which the Stocktake assessment was undertaken.

From the available Stocktake sample results, available data for one property was used to investigate the similarities between remote sensing groundcover assessments and visual groundcover observations. The property selected had the most comprehensive monitoring records of all 8 participating properties including 63 records from 2012 to 2017. Many samples require further investigation to confirm locations and circumstances at the time of sampling. 27 samples were suitable for immediate use.

From selected samples, landholder data does show some correlation with satellite derived data but there is a lot of noise in the data (See Figure 4.7.1). Verbal feedback

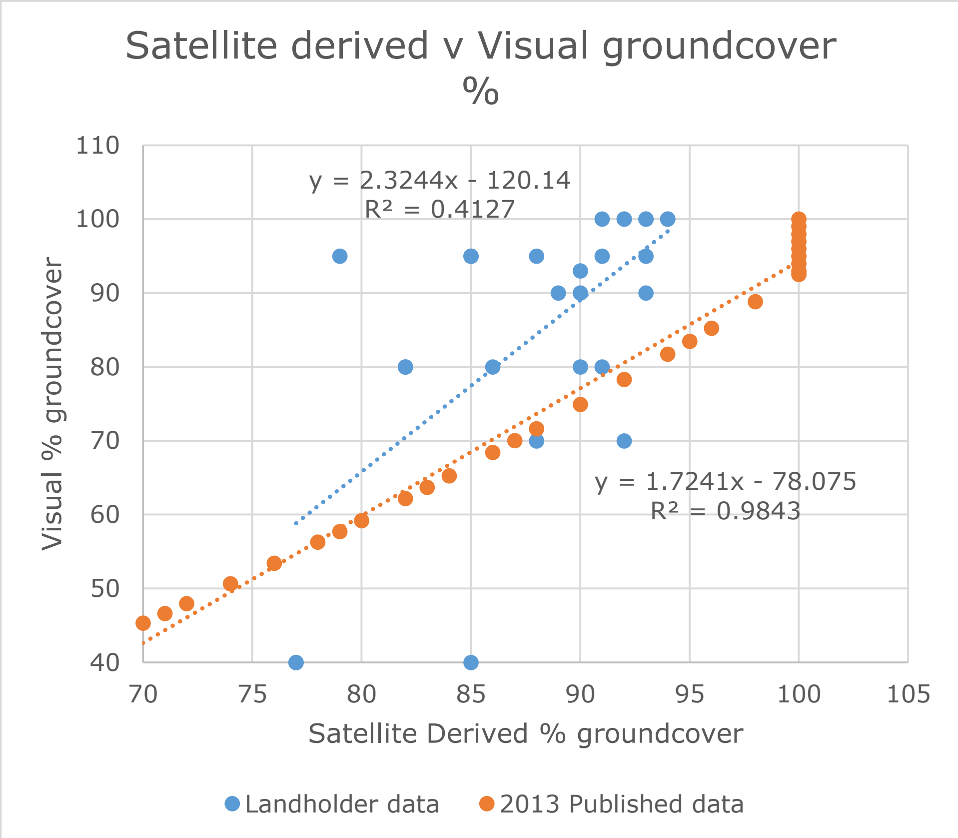

FIGURE 4.7.1: CORRELATIONS BETWEEN LANDHOLDER SUPPLIED STOCKTAKE GROUNDCOVER ESTIMATES AND VEGMACHINE SEASONAL GROUNDCOVER DATA, AND, PUBLISHED VISUAL VERSES SATELLITE DERIVED GROUNDCOVER CORRELATIONSHIP (TREVITHICK & SCARTH, 2013).

from landholder interviews was arguably a stronger indication of the reliability of remote sensed data. The verbal feedback was consistent that the remote sensing groundcover dynamics reflected seasonal conditions and, to some degree, management decisions.

Verbal feedback generally indicated remote sensing groundcover values were higher than visual estimates. This agrees with published data but not with the results of selected Stocktake values compared with VegMachine seasonal groundcover summaries.

More thorough investigation is required and recommended to use this available Stocktake data to inform ongoing remote sensing and visual monitoring data interaction. The value of this combined landholder dataset includes the benefits of:

- Consistent industry standard monitoring methods,

- Data through wet and dry periods,
- Data across a number of different land types, and,
- Inclusion in the data of vegetation characteristics in a variety of vegetation types and densities.

Detailed investigation requires considered input from the consultant who has collected most of the Landholder data. Input would include time with the consultant viewing satellite imagery to determine the most suitable remote sensing data pixels to be compared with individual monitoring sites. A suggested approach would be to select the pixel in which the site location point sits together with enough surrounding pixels (1 or 2 pixel buffer all round) to include the full extent of any monitoring transects.

Detailed investigation would also require liaison with Queensland Government Remote Sensing staff to access monthly or possibly single sample groundcover estimates for specific groups of pixels related to monitoring sites. Such investigation would be subject to landholder consent and maintenance of privacy through anonymity of specific locations in any published results. Other finer resolution data held in the Queensland Government archive could also be considered for a more detailed investigation. This may include MODIS, SPOT 4 and 5, LiDAR and Quickbird images (Kumar & Mutanga, 2017).

The exchange of monitoring data with Queensland Government staff required for further investigation is outside the scope of this study. Such data exchange would in fact compromise the Ethics Approval and related data use MOUs associated with this study.

Appendix 5.1 Review of anomalies in groundcover scores

Several Landholders questioned the low cover and the low cover scores for 2013 and 2014. Properties that highlighted this issue had common characteristics of open grazing dominating the low scores and of significant low-lying areas that may have been inundated in the 2012 floods. One Landholder manages a property with river frontage that showed these low 2013/14 scores and manages another property in higher country that did not show the low 2013/14 scores. Management was consistent across both properties from approximately 2010. These properties were selected for further investigation utilising a number of Forage products. Both properties ("river" and "ridge") are in the same climate landscape so the spring ground cover scores were expected to be similar.

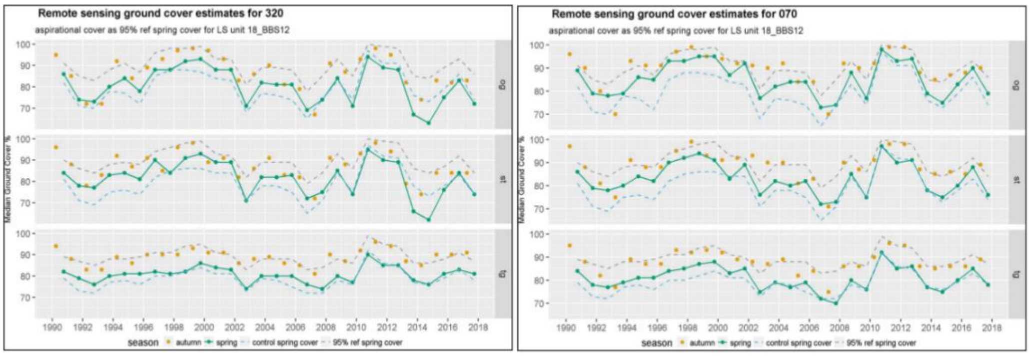

FIGURE 5.1.1: SPRING GROUND COVER MEDIAN VALUES (GREEN TRACE) FOR RIVER PROPERTY (LEFT) AND RIDGE PROPERTY (RIGHT) IN THE SAME CLIMATE LANDSCAPE AND SIMILAR MANAGEMENT. PEAKS AND TROUGHS ARE MOSTLY SIMILAR BUT THE RIVER PROPERTY SHOWS A GREATER DECLINE IN OPEN GRAZING AND SPARSELY TIMBERED GRAZING LANDS IN 2013/14.

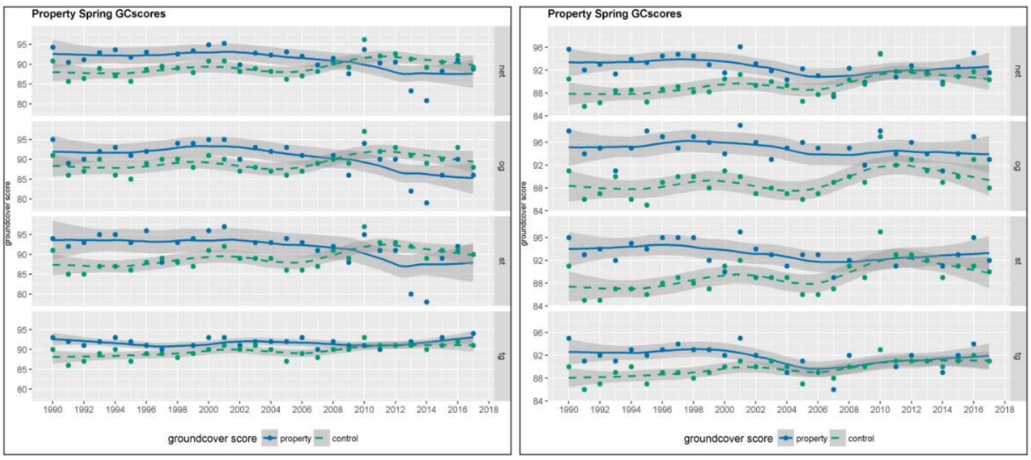

FIGURE 5.1.2: SPRING GROUND COVER SCORES (BLUE DOTS WITH BLUE LINE AS MOVING AVERAGE) FOR RIVER PROPERTY (LEFT) AND RIDGE PROPERTY (RIGHT) SHOWING POORER PERFORMANCE IN THE RIVER PROPERTY AFTER 2010, AND ESPECIALLY IN 2013/14.

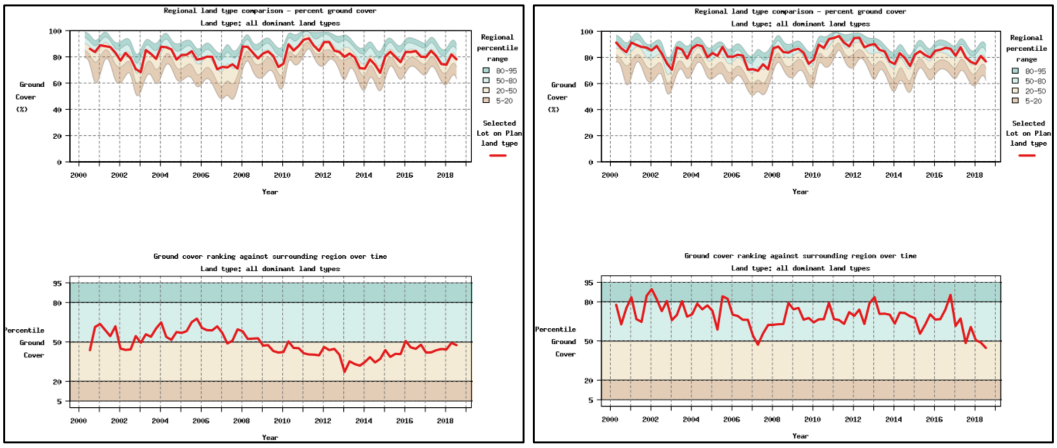

Figure 5.1.3: Forage ground cover regional comparison extracts for river property (left) and ridge property (right) showing similar results to those from Figures 5.1.1-2. Median ground cover traces (top) show similar peaks and troughs except for 2013/14 where troughs in river property are more extreme. Ground cover rankings (bottom) confirm this with 2013/14 being the lowest on record.

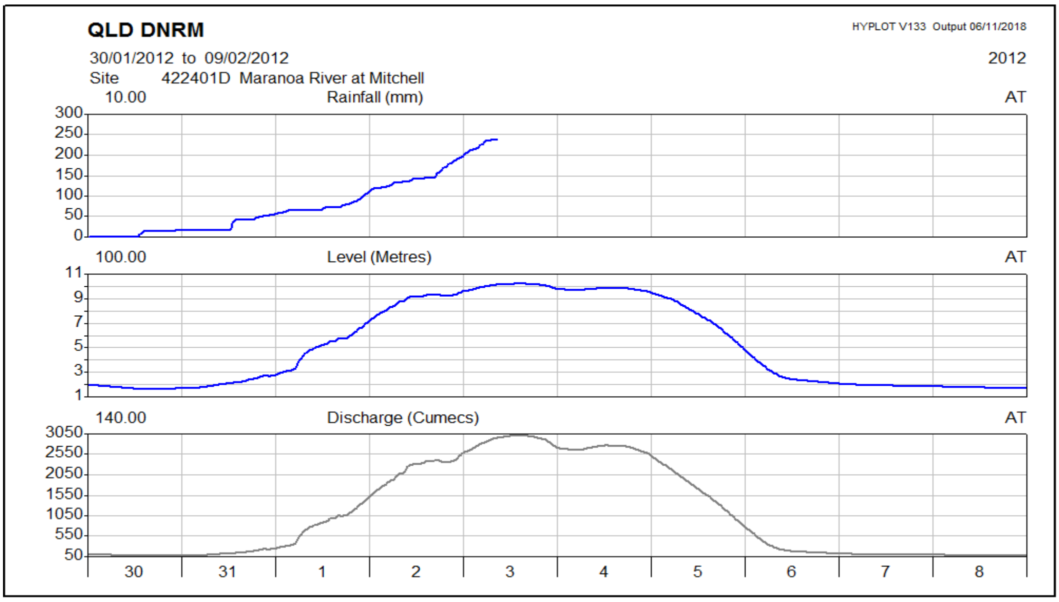

Figure 5.1.4: Stream Gauging station data showing overbank flows in Maranoa River likely to have extended over 3 or 4 days.

Streamflow data from the stream gauging station on the Maranoa River at Mitchell indicates that if over bank flow occurs anywhere from 6-9m then pastures could have been inundated for up to 4 days (Figure 5.1.4: Stream Gauging station data showing overbank flows in Maranoa River likely to have extended over 3 or 4 days.

Anderson, 1974 indicates that Buffel grasses are not flood tolerant but he indicates a 6 day threshold for plant death (Anderson, 1974, p. 38). Anderson's work, however also flags reduced resilience to flood impact of Buffel in hotter conditions. Maximum temperatures in the 2012 flood period were higher than in Andersons experiment periods (Anderson, 1974, p. 38; Bureau of Meteorology, 2018, Mitchell PO data). Case studies from central Queensland also indicate 2-3 day inundation threshold (Queensland Department of Agriculture and Fisheries, 2013). It is likely, therefore, that Buffel in low-lying areas, particularly near the Maranoa River suffered considerable mortality after the 2012 flood and took some time to re-establish resulting in areas of low ground cover in 2013 and 2014. This does not fully explain significant areas of bare ground in 2013 and 2014, however, as some areas away from the river

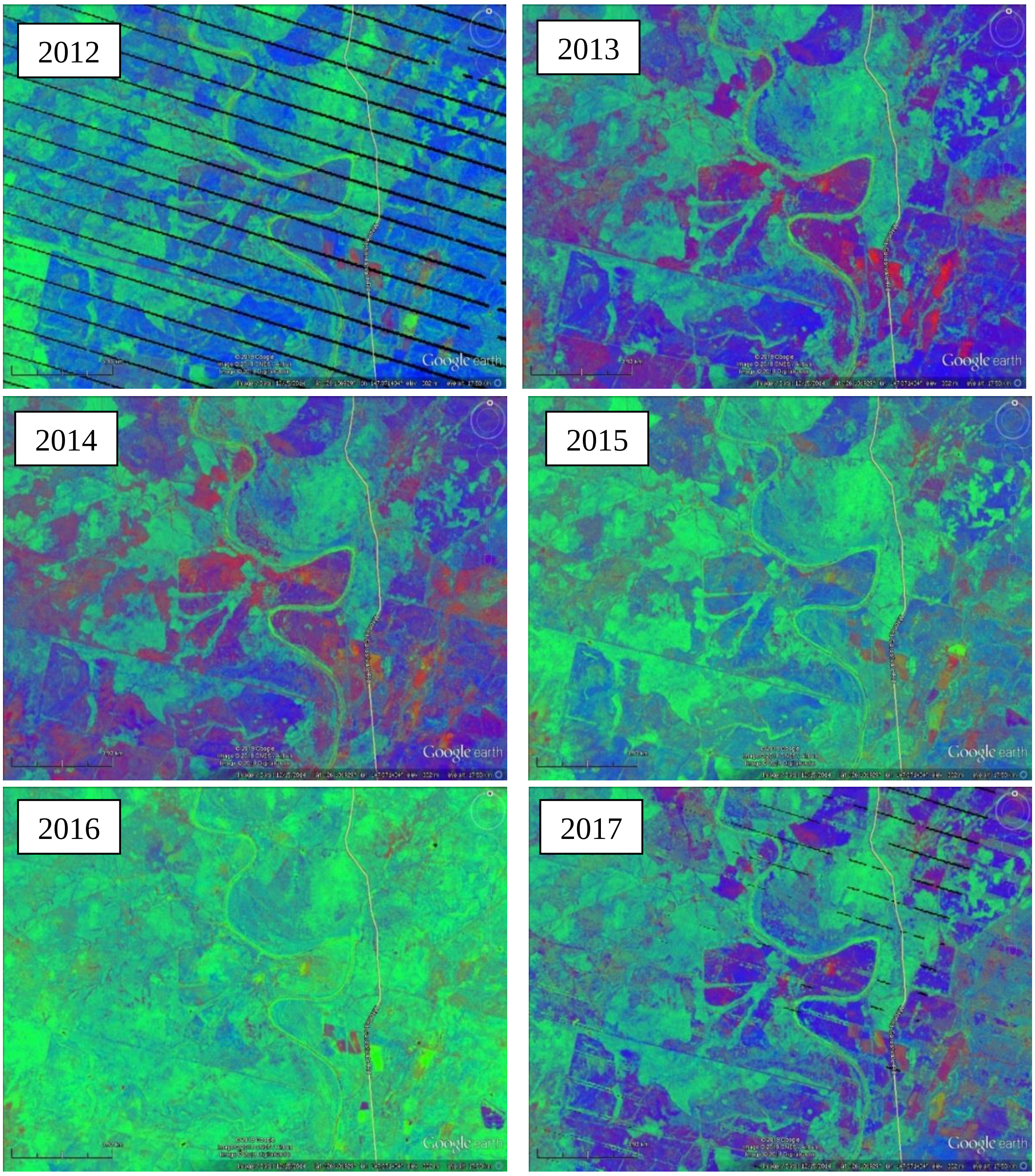

FIGURE 5.1.5: FRACTIONAL GROUND COVER FOR SPRING 2012-2017 NEAR THE MARANOA RIVER NORTH OF MITCHEL SHOWING VERY POOR COVER IN 2013/14 FOLLOWING 2012 FLOOD. 2017 SHOWS A MORE NORMAL DRY YEAR WITH MORE ISOLATED bare AREAS LIKELY TO BE AROUND INFRASTRUCTURE AND WATER POINTS (JOINT REMOTE SENSING RESEARCH PROGRAM, 2018). 30M PIXELS HAVE GRADUATED COLOUR SCALE WITH GREEN FOR GREEN ORGANIC MATTER, BLUE FOR NON-GREEN ORGANIC MATTER AND RED FOR BARE GROUND.

also show areas of low cover. It is suggested that some flat areas were waterlogged due to river levels and run-on from ridges (cf Johns, 1981, p. 49). Buffel recovery from inundation and waterlogging has been shown to take 12-24 months (Queensland Department of Agriculture and Fisheries, 2013; Lowe & Bowdler, 1977, p. 234).

Conclusion

Many paddock areas in the Upper Maranoa catchment showed poor ground cover in 2013 and 2014. These were mostly in open grazing areas and in low-lying areas. It is likely that the low ground cover was due to inundation and waterlogging of Buffel dominant pastures in the 2012 flood. The pastures appeared to recover after the two bad years. The poor performance of these areas could be associated with a combined climate and geographic anomaly. The dilemma was not universal across the catchment despite similarities in conditions. It would appear, therefore, that in some instances grazing management was able to mitigate the flood impact on pastures and pasture recovery.

In future flood events, graziers and other stakeholders could consider the possible impact on pastures and adopt management options suggested in QDAF, 2013 such as:

- [In non flood conditions] maintain a good body of feed when the buffel is healthy to ensure good ground cover and a good seed bank,
- When a flood damages the buffel, use plenty of spelling and graze judiciously to re-establish the buffel,
- Short duration high density grazing helps to germinate seed,
- Also consider reseeding,
- Actively manage weeds during recovery.

References

Anderson, E. (1974). The Reaction of Seven Cenchrus Ciliaris L. Cultivars to Flooding. *Tropical Grasslands*, *8*(1), 33-40.

Bureau of Meteorology. (2018). *Climate Data Online*. Retrieved from http://www.bom.gov.au/climate/data/

Johns, G. (1981). Hydrological processes and herbage production in shrub invaded Poplar Box (Eucalyptus populnea) woodlands. *The Rangeland Journal*, *3*(1), 45-55. doi: https://doi.org/10.1071/RJ9810045

Joint Remote Sensing Research Program. (2018). *Fractional ground cover for Australia derived from USGS Landsat images*: Made available by Queensland Department of Evnironment and Science under Creative Commons Licence (https://creativecommons.org/licenses/by/4.0/legalcode)

Lowe, K. F., & Bowdler, T. M. (1977). Tropical grass and legume yield on a Soloth soil in sub-coastal South-Eastern Queensland. *Tropical Grasslands*, *11*, 223-230.

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Appendix R Scripts used for data processing and plotting

Explanatory notes

Temporal and spatial data were mostly analysed using R. “R is a free software environment for statistical computing and graphics” (R Core Team, 2018). Scripts were developed and run on the RStudio platform for project purposes. For the purpose of documenting the scripts for this Appendix, scripts were converted to R Markdown documents and then “Knitted” to Word documents. In this way both the coding and the outputs of “chunks” of script are available for review and for reuse in future work.

The knitted word documents that follow are from either final runs of scripts used in the study. Many iterations of the scripts were run to explore and explain data in the context of the Upper Maranoa landscape. Where deemed appropriate for future use, variations were left in the scripts as remarks.

References for R, for RStudio and for packages used in each script are included in the References section of each of the following Knitted script files. Each script file document is included as a separate section of this Appendix R document. The format and layout of knitted scripts is:

000_Script Identification number and name

Explanatory text for the script.

Sub heading for a chunk of code

```
# remark or explanatory note within chunk of code

R functions (R objects created or called by functions,

             Input or output parameters )
* text outputs of code (plot outputs may also show but with no leading *)
```

010_SILO climate data preparation

Developed and run by Paul Webb, 2019.

Inputs: SILO daily climate data text files (FAO56 format) with file names reflecting subcatchment IDs Daily data includes 37 lines of metadata, headers on line 38, units on line 39 and data from line 40

Input data columns: Day Date2 T.Max Smx T.Min Smn Rain Srn Evap Sev Radn Ssl VP Svp RHmaxT RHminT FAO56

Desired outputs are seasonal summaries for each input variable with Seasons being: Summer (Dec-Feb); Autumn (Mar-May); Winter (Jun-Aug); Spring (Sep-Nov) Desired outputs Site_ID(from import file name) Year(from Date) Season(from Date) plus selected variables from the available variables of: Tmax(Max) Tmin(Min) Rain(Total) Evap(Total) Radn(mean) VP(mean) RHmaxT(max) RHminT(min) FAO56(total)

Output data files for each selected climate variable are ready for cluster analysis

Preliminaries

```
# make library call for required R packages (assumes packages already inst
alled)
library(lubridate)
library(tools)
library(data.table)
library(reshape2)
library(rstudioapi)

* Warning: package 'rstudioapi' was built under R version 3.5.3

library(knitr)

# Set  datadir (Inputs) directory
datadir <- paste0(getwd(),"/Inputs")

# A colorblind-friendly palette with grey from
# http://www.cookbook-r.com/Graphs/Colors_(ggplot2)/#a-colorblind-friendly
-palette
cbp <- c("#999999", "#E69F00", "#56B4E9",
         "#009E73", "#F0E442", "#0072B2", "#D55E00", "#CC79A7")
# cbp clues (from plotrix::color.id)
#       (grey60, orange2, steelblue2,
#               darkcyan, goldenrod1, dodgerblue3, darkorange, pink3)

print(paste("Work Directory:",getwd()))
print(paste("Data Input directory:",datadir))
print("Memory limit set to:")
memory.limit(size=32584)

* [1] "Work Directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCresearchP
roject/PostConfirmationDocs/Thesis/RScripts/010_ClimateDataPrep"
* [1] "Data Input directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCres
earchProject/PostConfirmationDocs/Thesis/RScripts/010_ClimateDataPrep/Inpu
ts"
* [1] "Memory limit set to:"
* [1] 32584
```

Import climate data from SILO FAO56 files

Warning: Run time 4 hours

```
# Create import file function
importfile <- function(filename){
  #identify source data file - sdf <- file.name
  sdf <- file.name
  #Read data into temp data file - format: tdf <- read.table(txtfile,)
  tdf <- read.table(file=sdf,header=FALSE,skip=39)
  colnames(tdf) <- c("Date","Day","Date2","T.Max","Smx","T.Min","Smn","Rai
n","Srn",
                     "Evap","Sev","Radn","Ssl","VP","Svp","RHmaxT","RHminT
","FAO56")
  #delete quality code columns
  tdf2 <- tdf[-c(1,2,5,7,9,11,13)]

  #add Month and Year columns
  tdf2$Month <- month(format.Date(tdf2$Date2))
  tdf2$Year <- year(dmy(tdf2$Date2))
  #Make Syear column with December incremented by one for summer Season
  tdf2$Syear <- ifelse(tdf2$Month==12,tdf2$Year+1,tdf2$Year)
  #Create Season Column and populate from Month with
  # Summer=12-2;Autumn=3-5;Winter=6-8;Spring=9-11
  tdf2$Season <- ifelse(tdf2$Month %in% c(12,1,2),"Summer",
                        ifelse(tdf2$Month %in% c(3,4,5),"Autumn",
                               ifelse(tdf2$Month %in% c(6,7,8),"Winter",
                                      "Spring")))
  #add column for Site_ID (from input filename without ".txt")
  tdf2$SC_ID <- file_path_sans_ext(basename(sdf))
  #Convert tdf2 to data table
  tdf2 <- data.table(tdf2)

  #aggregate data to seasonal summary data
  #Note include relevant variables from full list (Rain=sum(Rain),
  # Tmax=max(T.Max),Tmin=min(T.Min),Evap=sum(Evap),Radn=mean(Radn),
  # VP=mean(VP),RHmaxT=max(RHmaxT),RHminT=min(RHminT),FAO56=sum(FAO56))
  # for Dates, Rain, Tmax, Tmin and FAO56 only use:
  ssd<- as.data.frame(tdf2[,j=list(Rain=sum(Rain),
                     Tmax=max(T.Max),Tmin=min(T.Min),FAO56=sum(FAO56)),
                     by = list(SC_ID,Syear,Season)])
  #Delete first and last row (incomplete seasons)
  #assumes data sorted chronologically
  ssd <- ssd[-c(1,nrow(ssd)),]

  #write aggregated data to a seasonal climate archive
  write.table(ssd, file="sclarchive.txt",append = TRUE, sep = " ",
              eol = "\n",row.names=FALSE,col.names=FALSE)
  #compile list of processed site files
  write.table(basename(sdf), file="sitelist.txt",append = TRUE, sep = " ",
              eol = "\n",row.names=FALSE,col.names=FALSE)
  }
#end of importfile function definition

#Start loop for to call importfile function for all *.txt files in data di
rectory
file.names <- dir(datadir,pattern=".txt",full.names=TRUE)
#check destination files blank
#unlink("sclarchive.txt")
```

```
#unlink("sitelist.txt")
#for(file.name in file.names){importfile(file.name)}
# end loop

# File in Work Directory "sclarchive.txt" is a space delimeted seasonal cl
imate data for all processes sites
# File in Work Directory "sitelist.txt" contains a list of sites processed
.
# Check number of files imported and data format
sitelist <- read.table(file="sitelist.txt",header=FALSE)
print(paste("No of SILO data files imported into seasonal climate archive
=",nrow(sitelist)),quote = FALSE)
sclarchive <- read.table(file="sclarchive.txt")
colnames(sclarchive) <- c("SC_ID","Syear","Season","Rain","Tmax","Tmin","F
AO56")
head(sclarchive)

* [1] No of SILO data files imported into seasonal climate archive = 6941
*           SC_ID Syear Season  Rain Tmax Tmin FAO56
* 1 141.50_24.00  1889 Autumn  73.1 40.0  9.0 458.8
* 2 141.50_24.00  1889 Winter  48.6 27.5  4.5 298.7
* 3 141.50_24.00  1889 Spring  29.8 39.5  5.0 598.6
* 4 141.50_24.00  1890 Summer 232.6 42.5 20.5 632.0
* 5 141.50_24.00  1890 Autumn 129.2 38.0  8.0 429.6
* 6 141.50_24.00  1890 Winter  86.2 27.5  2.5 299.1
```

Import seasonal climate archive data into RStudio sca

Includes addition of headers and lat/lon columns

```
sca <- read.table(file="sclarchive.txt")

#Use headers to match those assigned to ssd file in importfile function
# for summary variables plus Dates, Rain, Tmax, Tmin and FAO56 only use:
colnames(sca) <- c("SC_ID","Syear","Season","Rain","Tmax","Tmin","FAO56")
#add SeasonNo column,"Yr_Sn", to maintain chronology
#Summer=1,Autumn=2,Winter=3,Spring=4
sca$Sn_No <- ifelse(sca$Season=="Summer",1,
                    ifelse(sca$Season=="Autumn",2,
                           ifelse(sca$Season=="Winter",3,4)))
#Insert lat and long columns into sca dataset
sca$lon <- substr(sca$SC_ID,1,6)
#include "-" to ensure correct hemisphere!
sca$lat <- paste0("-",substr(sca$SC_ID,8,12))

write.table(sca, file = "sca.txt",append = FALSE, sep = " ",
            eol = "\n",row.names=FALSE,col.names=TRUE)

head(sca)

*           SC_ID Syear Season  Rain Tmax Tmin FAO56 Sn_No    lon    lat
* 1 141.50_24.00  1889 Autumn  73.1 40.0  9.0 458.8     2 141.50 -24.00
* 2 141.50_24.00  1889 Winter  48.6 27.5  4.5 298.7     3 141.50 -24.00
* 3 141.50_24.00  1889 Spring  29.8 39.5  5.0 598.6     4 141.50 -24.00
* 4 141.50_24.00  1890 Summer 232.6 42.5 20.5 632.0     1 141.50 -24.00
* 5 141.50_24.00  1890 Autumn 129.2 38.0  8.0 429.6     2 141.50 -24.00
* 6 141.50_24.00  1890 Winter  86.2 27.5  2.5 299.1     3 141.50 -24.00
```

Seperation of variables into seperate datafiles for HiClimR multivariate analyses

```
#Reshape rain data and create lat and lon files
HCR_Rain <- dcast(sca,SC_ID+lon+lat~Syear+Sn_No,value.var="Rain")
lon <- as.vector(HCR_Rain$lon)
write.table(lon, file = "lon.txt",append = FALSE, sep = " ",
            eol = "\n",row.names=FALSE,col.names=TRUE)
lat <- as.vector(HCR_Rain$lat)
write.table(lat, file = "lat.txt",append = FALSE, sep = " ",
            eol = "\n",row.names=FALSE,col.names=TRUE)

#remove lon and lat columns from Rain data file
HCR_Rain <- subset(HCR_Rain,select=-c(lon,lat))
#write Rain table to text file for recreating in new RStudio session
write.table(HCR_Rain, file = "HCR_Rain.txt",append = FALSE, sep = " ",
            eol = "\n",row.names=FALSE,col.names=TRUE)

#Resphape data for other variables - no lon or lat required:
HCR_Tmax <- dcast(sca,SC_ID~Syear+Sn_No,value.var="Tmax")
write.table(HCR_Tmax, file = "HCR_Tmax.txt",append = FALSE, sep = " ",
            eol = "\n",row.names=FALSE,col.names=TRUE)
HCR_Tmin <- dcast(sca,SC_ID~Syear+Sn_No,value.var="Tmin")
write.table(HCR_Tmin, file = "HCR_Tmin.txt",append = FALSE, sep = " ",
            eol = "\n",row.names=FALSE,col.names=TRUE)
HCR_FAO56 <- dcast(sca,SC_ID~Syear+Sn_No,value.var="FAO56")
write.table(HCR_FAO56, file = "HCR_FAO56.txt",append = FALSE, sep = " ",
            eol = "\n",row.names=FALSE,col.names=TRUE)
print("Sample of variable output file - Seasonal RF totals from HCR_Rain")
head(HCR_Rain[,c(1:8)])
print("...")
head(HCR_Rain[,c((ncol(HCR_Rain)-6):ncol(HCR_Rain))])

* [1] "Sample of variable output file - Seasonal RF totals from HCR_Rain"
*           SC_ID 1889_2 1889_3 1889_4 1890_1 1890_2 1890_3 1890_4
* 1 141.50_24.00   73.1   48.6   29.8  232.6  129.2   86.2   53.5
* 2 141.50_24.10   75.8   47.8   31.0  238.6  130.6   86.4   52.3
* 3 141.50_24.20   81.7   50.3   34.1  249.9  136.8   89.8   54.5
* 4 141.50_24.30   85.8   50.7   35.9  258.3  140.2   90.1   54.7
* 5 141.50_24.40   89.3   50.4   37.3  265.7  142.7   88.9   54.3
* 6 141.50_24.50   91.4   48.8   37.9  271.9  143.6   85.8   52.8
* [1] "..."
*   2016_2 2016_3 2016_4 2017_1 2017_2 2017_3 2017_4
* 1  144.2  101.1  113.3  109.2    4.4    4.1   55.2
* 2  135.8   96.1  112.0  105.7    4.8    3.7   54.4
* 3  131.2   99.0  115.1  105.7    5.3    3.8   56.3
* 4  125.7   97.8  114.4  103.6    5.5    3.4   54.9
* 5  119.7   95.6  114.4   99.6    5.2    3.0   54.2
* 6  113.9   90.8  112.9   97.8    5.4    2.4   52.5
```

Output files and Script files

```
print(paste("Output files in ",getwd()),quote=F)
print(list.files(getwd()))

* [1] Output files in  C:/Users/q9823679/ownCloud/Shared/USQ_QMDCresearchP
roject/PostConfirmationDocs/Thesis/RScripts/010_ClimateDataPrep
*  [1] "010_ClimateDataPrep.docx"      "010_ClimateDataPrep.R"
*  [3] "010_ClimateDataPrep.rmd"       "010_ClimateDataPrep_bak.docx"
*  [5] "HCR_FAO56.txt"                 "HCR_Rain.txt"
*  [7] "HCR_Tmax.txt"                  "HCR_Tmin.txt"
*  [9] "Inputs"                        "lat.txt"
```

```
* [11] "lon.txt"                       "sca.txt"
* [13] "sclarchive.txt"                "sitelist.txt"
* [15] "word-styles-reference-01.docx"
```

Compile Reference List

```
citations <- function(includeURL = T, includeRStudio = F) {
    if(includeRStudio == TRUE) {
        ref.rstudio <- RStudio.Version()$citation
        #ref.rstudio <- rstudioapi::versionInfo()$citation
        if(includeURL == FALSE) {
            ref.rstudio$url = NULL;
        }
        print(ref.rstudio, style = 'text')
        cat('\n')
    }

    cit.list <- c('base', names(sessionInfo()$otherPkgs))
    for(i in 1:length(cit.list)) {
        ref <- citation(cit.list[i])
        if(includeURL == FALSE) {
            ref$url = NULL;
        }
        print(ref, style = 'text')
        cat('\n')
    }
}

#call function and tidy up code
prn <- capture.output(citations())
#tidy up output
prn1 <- sub("_", "",prn)
Rprint <- sub("_.", ".",prn1)
# add citation for function used to create citations and for RStudio
cit_func <- paste0("RStudio Team (2018). RStudio: Integrated Development E
nvironment for R. RStudio, Inc., Boston,
MA.\n","\n","Reference list produced from adaptation of MS Berends' citati
ons() function accessed from stackoverflow at: https://stackoverflow.com/q
uestions/15688758/r-stats-citation-for-a-scientific-paper")

# to print references without showing script call in knitted Word file use
:
# ```{r message=FALSE, warnings=FALSE, echo=FALSE comment=NA, results='hol
d'}
# cat(Rprint,sep="\n")
# cat(cit_func,sep="\n")
# ```
```

References

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Grolemund G, Wickham H (2011). "Dates and Times Made Easy with lubridate." Journal of Statistical Software. *40*(3), 1-25. <URL: http://www.jstatsoft.org/v40/i03/>.

RStudio Team (2018). RStudio: Integrated Development Environment for R. RStudio, Inc., Boston, MA.

Reference list produced from adaptation of MS Berends' citations() function accessed from stackoverflow at: https://stackoverflow.com/questions/15688758/r-stats-citation-for-a-scientific-paper

End of Script

020_Cluster analysis and landscape mapping

Developed and run by Paul Webb, 2019.

Inputs - Climate data files from 010 script in Inputs dir under wd: “hcr_rain.txt”,“lon.txt”,“lat.txt”,“hcr_tmax.txt”,“hcr_tmin.txt”,“hcr_et.txt” Outputs - Climate class spatial and csv data files in wd:

Library calls and Operating environment settings

```
# make library call for required R packages (assumes packages already inst
alled)
library(HiClimR) # core function of script

* Warning: package 'HiClimR' was built under R version 3.5.3

library(rgdal) # for readOGR functions
library(sp) # Classes and Methods for Spatial Data
library(randomcoloR) # to create color palette for plotting
library(rmapshaper) # for 'Geospatial' Operations
library(ggplot2) #  for 'declaratively' creating graphics
library(data.table) # Extension of `data.frame`
library(stringr) # for Common String Operations
library(raster) # for gridded spatial Data Analysis and Modeling
library(rgeos) # Interface to Geometry Engine
library(NbClust) # for determining the best number of clusters
library(utils)
#library(rstudioapi) # for R Studio session info tools
#rstudioapi package creates errors with knitr

#Sart date/time:
startt <- Sys.time()
dt <- format(startt, format = "_%b_%d_%Y")

# Set  wd and datadir (Inputs) directory
# assumes wd is script root directory - need to set in rstudio
# rem out for rmd process as root directory is default
#setwd(dirname(rstudioapi::getActiveDocumentContext()$path))
datadir <- paste0(getwd(),"/Inputs")

#Set plot output device
#options(device="RStudioGD")

# Create color pallette (randomcoloR)
n <- 50
palette <- distinctColorPalette(n)
n <- NULL

print(paste("Work Directory:",getwd()))
print(paste("Data Input directory:",datadir))
print("Memory limit set to:")
memory.limit(size=32584)

* [1] "Work Directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCresearchP
roject/PostConfirmationDocs/Thesis/RScripts/020_Cluster analysis and lands
cape mapping"
* [1] "Data Input directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCres
earchProject/PostConfirmationDocs/Thesis/RScripts/020_Cluster analysis and
landscape mapping/Inputs"
```

```
* [1] "Memory limit set to:"
* [1] 32584
```

Load climate and lat/long data as data tables

from txt files HCR_[Var], lon, lat created in 00_climate… script From datadir

```
#set wd to datadir for imports
setwd(datadir)
cat(paste("data files accessed from:\n",getwd()))

#for Rain only include lon and lat
hcr_rain <- read.table(file="hcr_rain.txt",header=TRUE,sep = " ")
lon <- read.table(file="lon.txt",header=TRUE,sep = " ")
lat <- read.table(file="lat.txt",header=TRUE,sep = " ")

#for other Variables
hcr_tmax <- read.table(file="hcr_tmax.txt",header=TRUE,sep = " ")
hcr_tmin <- read.table(file="hcr_tmin.txt",header=TRUE,sep = " ")
hcr_et <- read.table(file="hcr_fao56.txt",header=TRUE,sep = " ")
#create rf matrix from full HCR_Rain
arf <- data.matrix(hcr_rain,rownames.force = F)
#remove "clim_id" column but keep clim_id as row names
arf <- arf[,-1]
rownames(arf) <- hcr_rain[ ,1]

# reset wd to script root directory
#setwd(dirname(rstudioapi::getActiveDocumentContext()$path))
#getwd()

#Create other variable matrices and establish clim_id as row names
tmax <- data.matrix(hcr_tmax)
tmax <- tmax[ ,-1]
rownames(tmax) <- hcr_tmax[ ,1]
tmin <- data.matrix(hcr_tmin)
tmin <- tmin[ ,-1]
rownames(tmin) <- hcr_tmin[ ,1]
et <- data.matrix(hcr_et)
et <- et[ ,-1]
rownames(et) <- hcr_et[ ,1]

#setwd("../")
#cat(paste("wd reset to root at: \n",getwd()))

* data files accessed from:
*  C:/Users/q9823679/ownCloud/Shared/USQ_QMDCresearchProject/PostConfirmat
ionDocs/Thesis/RScripts/020_Cluster analysis and landscape mapping/Inputs
```

Remove columns for climate years to be excluded

See original script for options

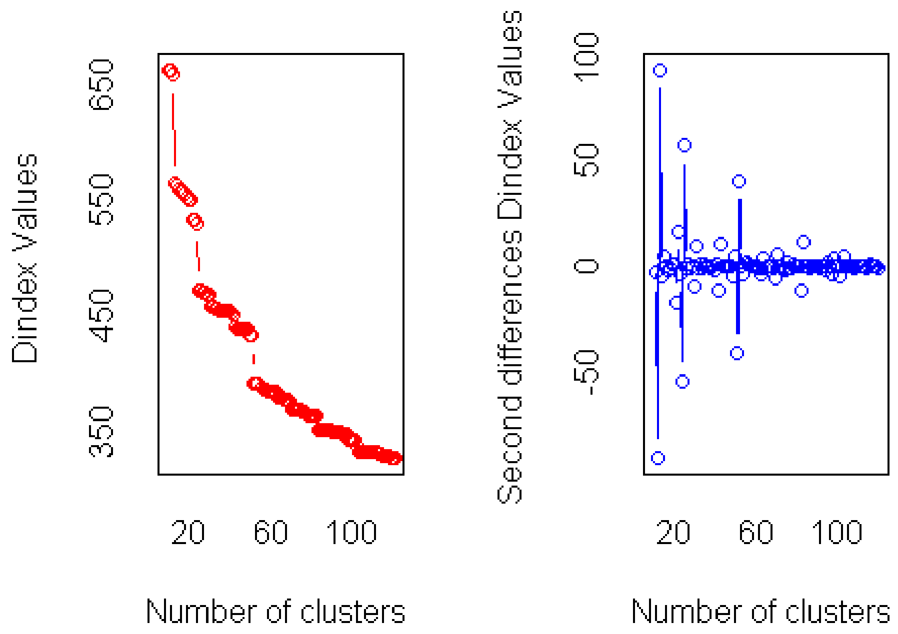
```
#This file using (r) for available groundcover period Autumn 1990 to sprin
g 2017 #(inclusive) select columns 405:515
rs <- which(colnames(arf)=="X1990_2") #r start
re <- which (colnames(arf) == "X2017_4") # r end

arf_r <- subset(arf,select=c(rs:re))
et_r <- subset(et,select=c(rs:re))
```

```
tmax_r <- subset(tmax,select=c(rs:re))
tmin_r <- subset(tmin,select=c(rs:re))

# calculate tmean using average of tmax and tmin - I.E by season.
tmean_r <- matrix(data=(tmax_r+tmin_r)/2,nrow=nrow(tmax_r),ncol=ncol(tmin_r),
                dimnames=list(rownames(tmax_r),colnames(tmax_r)))

# remove superfluous datasets to manage PC memory
rm(et, tmax, tmin)
```

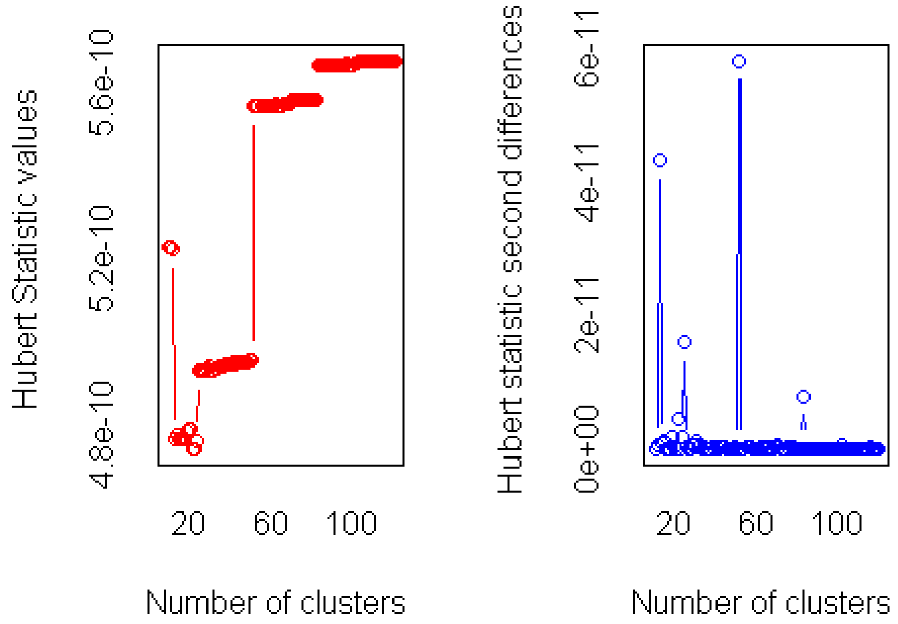
Identify nominal number of clusters

noting especially hubert and dindex graphical indexes Note: long run time - over 1 hr per index run

```
dindex_clust <- NbClust(arf_r,min.nc = 10, max.nc = 120,
       method = "mcquitty", index= "dindex", alphaBeale = 0.05)
```




```
hubert_clust <- NbClust(arf_r,min.nc = 10, max.nc = 120,
       method = "mcquitty", index= "hubert", alphaBeale = 0.05)
```




```
# all_clust <- NbClust(arf_r,min.nc = 10, max.nc = 120,
#         method = "mcquitty", index= "all", alphaBeale = 0.05)

* *** : The D index is a graphical method of determining the number of clu
sters.
*                 In the plot of D index, we seek a significant knee (the
significant peak in Dindex
*                 second differences plot) that corresponds to a significa
nt increase of the value of
*                 the measure.
*
* *** : The Hubert index is a graphical method of determining the number o
f clusters.
*                 In the plot of Hubert index, we seek a significant knee
that corresponds to a
*                 significant increase of the value of the measure i.e the
significant peak in Hubert
*                 index second differences plot.
*
```

Call hiclimr for rainfall variable for period of record

```
w <- HiClimR(arf, lon=lon,lat=lat, geogMask = F,
             country="aus", method = "mcquitty",
             k=52,plot = T,
             dendrogram=F,labels=rownames(rf),cex=3)
dend <- as.dendrogram (w)
plot(dend,leaflab="none")

*
* PROCESSING STARTED
*
* Checking Multivariate Clustering (MVC)...
* ---> x is a matrix
* ---> single-variate clustering: 1 variable
```

```
* Checking data...
* ---> Checking dimensions...
* ---> Checking row names...
* ---> Checking column names...
* Data filtering...
* ---> Computing mean for each row...
* ---> Computing variance for each row...
* ---> Checking rows with near-zero-variance...
* ---> 0 rows found, variance =  0
* Data preprocessing...
* ---> Applying mask...
* ---> Checking columns with missing values...
* Agglomerative Hierarchical Clustering...
* ---> Computing correlation/dissimilarity matrix...
* ---> Starting clustering process...
* ---> Constructing dendrogram tree...
* Calling cluster validation...
* ---> Computing cluster means...
* ---> Computing inter-cluster correlations...
* ---> Computing intra-cluster correlations...
* ---> Computing summary statistics...
* Generating region map...
*
* PROCESSING COMPLETED
*
* Running Time:
*    user  system elapsed
*   18.88    1.52   20.56
* Time difference of 20.54988 secs
```

HiClimR multi-variate cluster analyses

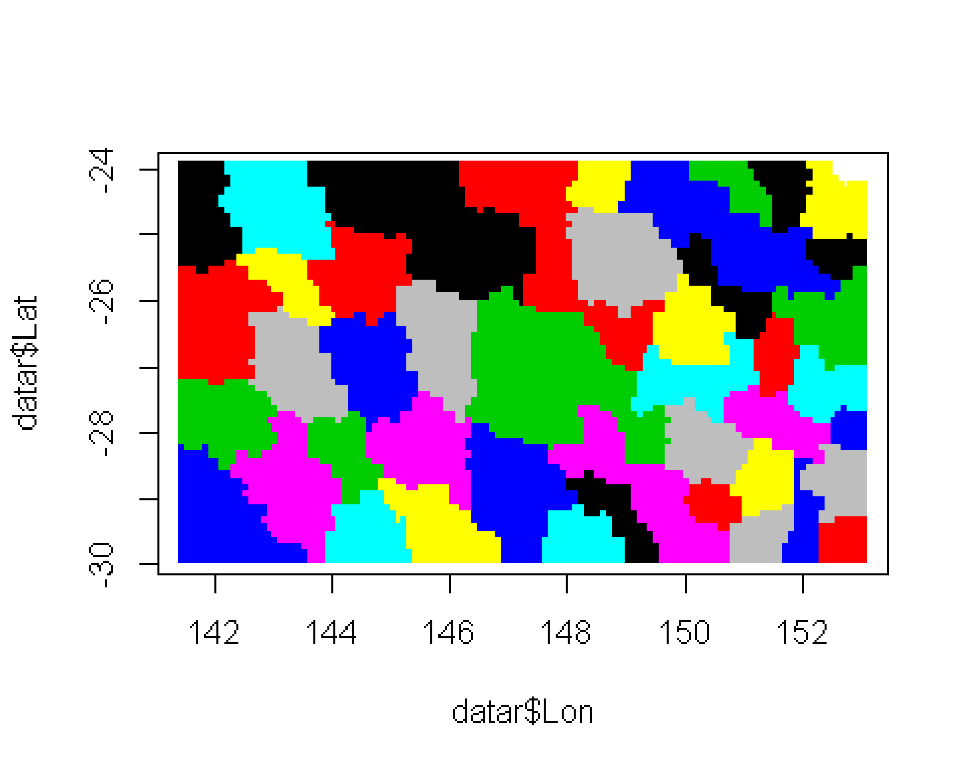
```
#set HiClimR input variables
idt <- list(FALSE,FALSE,FALSE,FALSE) # detrend data before analysis?
is <- list(TRUE,TRUE,TRUE,TRUE) #standardise data?
iwv <- list(1,0.5,0.25,0.25) #variable weights (rf,et,tmax,tmin)
ipc <-NULL
im <- "mcquitty" #cluster analysis method
# options: "regional","ward","single","complete","average","mcquitty","med
ian","centroid"
ik <- 52  #no of clusters
al <- 0.05

# HiClimR call
# see original r Script for extra options' code

#options(device="RStudioGD") #requires RStudio plot window to be large eno
ugh

r <- HiClimR(x=list(arf_r,tmean_r,tmax_r,tmin_r), lon=lon,lat=lat, geogMas
k = FALSE,country="AUS",
             detrend=idt,standardize = is,weightMVC=iwv,method=im,nPC=ipc,
             k=ik,alpha = 0.05,
             plot=T,
             dendrogram=F,labels=rownames(arf_r),cex=3)
dend <- as.dendrogram (r)
plot(dend,leaflab="none")

# rv <- validClimR(r,k=55,alpha=0.05,plot=F)
```

```
*
* PROCESSING STARTED
*
* Checking Multivariate Clustering (MVC)...
* ---> x is a list
* ---> multivariate clustering: 4 variables
* Checking variable weights...
* ---> weight for variable #1: 1
* ---> weight for variable #2: 0.5
* ---> weight for variable #3: 0.25
* ---> weight for variable #4: 0.25
* Checking data...
* ---> Checking dimensions...
* ---> Checking row names...
* ---> Checking column names...
* Data filtering...
* ---> VARIABLE #1:
* ---> Computing mean for each row...
* ---> Computing variance for each row...
* ---> Checking rows with near-zero-variance...
* ---> 0 rows found, variance =  0
* ---> VARIABLE #2:
* ---> Computing mean for each row...
* ---> Computing variance for each row...
* ---> Checking rows with near-zero-variance...
* ---> 0 rows found, variance =  0
* ---> VARIABLE #3:
* ---> Computing mean for each row...
* ---> Computing variance for each row...
* ---> Checking rows with near-zero-variance...
* ---> 0 rows found, variance =  0
* ---> VARIABLE #4:
* ---> Computing mean for each row...
* ---> Computing variance for each row...
* ---> Checking rows with near-zero-variance...
* ---> 0 rows found, variance =  0
* Data preprocessing...
* ---> VARIABLE #1:
* ---> Applying mask...
* ---> Checking columns with missing values...
* ---> Standardizing data...
* ---> VARIABLE #2:
* ---> Applying mask...
* ---> Checking columns with missing values...
* ---> Standardizing data...
* ---> VARIABLE #3:
* ---> Applying mask...
* ---> Checking columns with missing values...
* ---> Standardizing data...
* ---> VARIABLE #4:
* ---> Applying mask...
* ---> Checking columns with missing values...
* ---> Standardizing data...
* ---> Updating variance for multivariate clustering...
* Agglomerative Hierarchical Clustering...
* ---> Computing correlation/dissimilarity matrix...
* ---> Starting clustering process...
* ---> Constructing dendrogram tree...
* Calling cluster validation...
```

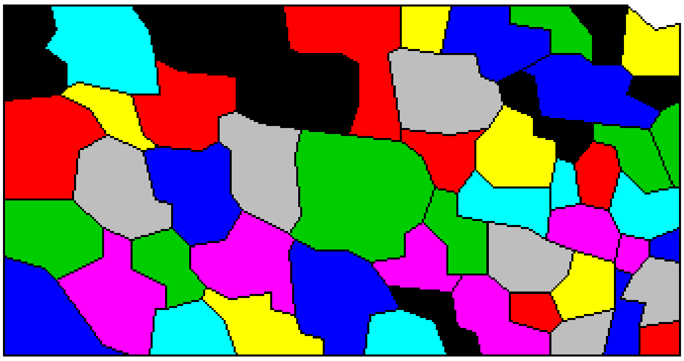
```
* ---> Computing cluster means...
* ---> Computing inter-cluster correlations...
* ---> Computing intra-cluster correlations...
* ---> Computing summary statistics...
* Generating region map...
*
* PROCESSING COMPLETED
*
* Running Time:
*    user  system elapsed
*   17.47    1.31   18.80
* Time difference of 18.81286 secs
```

Prepare Cluster data for spatial data merging

```
# Convert output to data frame and label/tidy columns
datar <- as.data.frame(list(r$labels,lon,lat,r$region))

# tidy up columns
colnames(datar) <- list("clim_id","Lon","Lat","CClass")
rownames(datar) <- NULL
# check outputs confirm (n=climate site count) genuine values for 4 variab
les in each data? dataframe

# convert HiClimR output to polygons and simplify
rasterr <- rasterFromXYZ(datar[ ,c(2,3,4)],digits=5)
qmdbb_sc__ <- ms_simplify(rasterToPolygons(rasterr, na.rm=TRUE, digits=5,
dissolve=T))
crs(qmdbb_sc__) <- "+init=EPSG:3577 +proj=aea +lat_1=-18 +lat_2=-36 +lat_0
=0
+lon_0=132+x_0=0 +y_0=0 +ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +units=m +no_d
efs"

# plot raster and simplified polygon Climate Clusters
plot(datar$Lon,datar$Lat,col=datar$CClass,pch=15)
```



```r
plot(qmdbb_sc__,col=qmdbb_sc__$CClass)
```



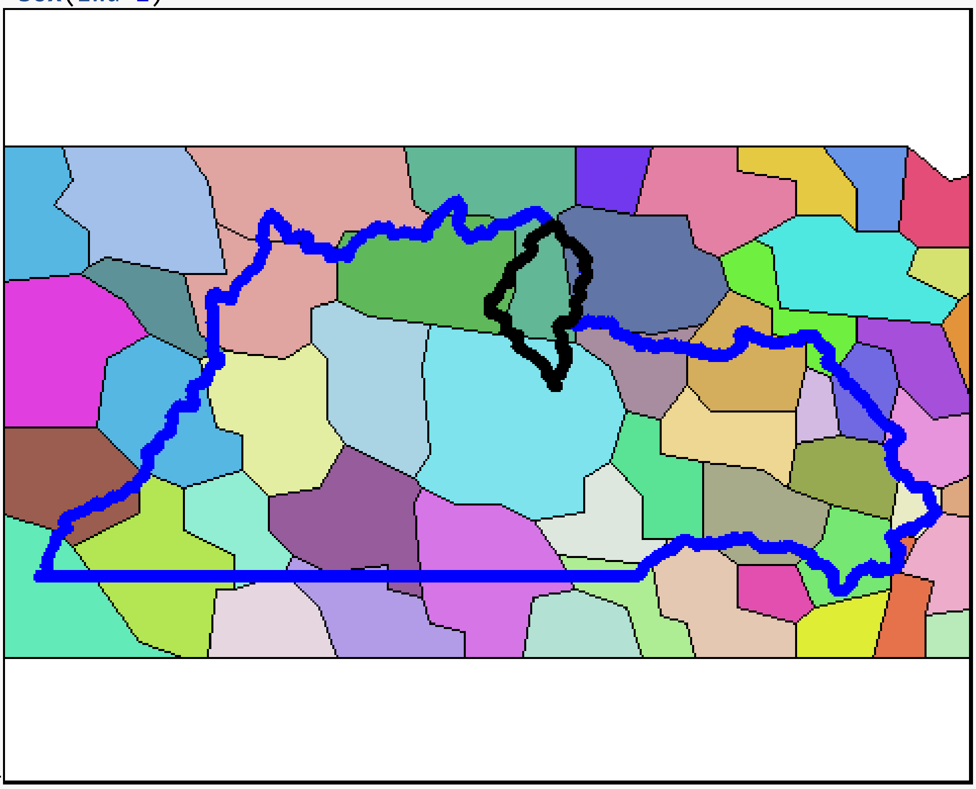
```r
# Read in other spatial data files - assumes all in GDA94 datum
# QMDBB
qmdbb <- readOGR(datadir,"qmdb_gda94")
crs(qmdbb) <- "+init=EPSG:3577 +proj=aea +lat_1=-18 +lat_2=-36 +lat_0=0
+lon_0=132+x_0=0 +y_0=0 +ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +units=m +no_d
efs"

# subIBRA regions
qmdbb_s_i_ <- readOGR(datadir,"subIBRA")
crs(qmdbb_s_i_) <- "+init=EPSG:3577 +proj=aea +lat_1=-18 +lat_2=-36 +lat_0
=0
+lon_0=132+x_0=0 +y_0=0 +ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +units=m +no_d
efs"

# Climate zones (52_400) developed in ArcGIS from climate clusters and sub
IBRAS
#  simplified and dissolved areas under 400 sq km
qmdbb_sci_ <-  readOGR(datadir,"subIBRA_ccl52_400")

* Warning in readOGR(datadir, "subIBRA_ccl52_400"): Z-dimension discarded

crs(qmdbb_sci_) <- "+init=EPSG:3577 +proj=aea +lat_1=-18 +lat_2=-36 +lat_0
=0
+lon_0=132+x_0=0 +y_0=0 +ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +units=m +no_d
efs"

# Add grazing land use - NOTE large file so long process - used ArcGIS
#qbum_s__l <-  readGDAL(paste0(datadir,"/qbum_s__l.txt"))
#crs(qbum_s__l) <- "+init=EPSG:3577 +proj=aea +lat_1=-18 +lat_2=-36 +lat_0
=0
#+lon_0=132+x_0=0 +y_0=0 +ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +units=m +no_
defs"
```

```
# combined sci and s__l  in ArcGIS for scil Climate Landscapes
#  - NOTE large file so long process - used ArcGIS
#qbum_scil <-  readGDAL(paste0(datadir,"/qbum_scil.txt"))
#crs(qbum_scil) <- "+init=EPSG:3577 +proj=aea +lat_1=-18 +lat_2=-36 +lat_0
=0
#+lon_0=132+x_0=0 +y_0=0 +ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +units=m +no_
defs"

# Upper Maranoa wq zone (study area)
qbum <- readOGR(datadir,"um_gda94")
crs(qbum) <- "+init=EPSG:3577 +proj=aea +lat_1=-18 +lat_2=-36 +lat_0=0
+lon_0=132+x_0=0 +y_0=0 +ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +units=m +no_d
efs"

# Koeppen Climate Classes
kpz.rg <- readOGR(datadir,"kpz")
crs(kpz.rg) <- "+init=EPSG:3577 +proj=aea +lat_1=-18 +lat_2=-36 +lat_0=0
+lon_0=132+x_0=0 +y_0=0 +ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +units=m +no_d
efs"

* OGR data source with driver: ESRI Shapefile
* Source: "C:\Users\q9823679\ownCloud\Shared\USQ_QMDCresearchProject\PostC
onfirmationDocs\Thesis\RScripts\020_Cluster analysis and landscape mapping
\Inputs", layer: "qmdb_gda94"
* with 1 features
* It has 1 fields
* OGR data source with driver: ESRI Shapefile
* Source: "C:\Users\q9823679\ownCloud\Shared\USQ_QMDCresearchProject\PostC
onfirmationDocs\Thesis\RScripts\020_Cluster analysis and landscape mapping
\Inputs", layer: "subIBRA"
* with 90 features
* It has 2 fields
* OGR data source with driver: ESRI Shapefile
* Source: "C:\Users\q9823679\ownCloud\Shared\USQ_QMDCresearchProject\PostC
onfirmationDocs\Thesis\RScripts\020_Cluster analysis and landscape mapping
\Inputs", layer: "subIBRA_ccl52_400"
* with 166 features
* It has 14 fields
* Integer64 fields read as strings:  FID_subIBR InPoly_FID FID_mcquit rmps
hpr
* OGR data source with driver: ESRI Shapefile
* Source: "C:\Users\q9823679\ownCloud\Shared\USQ_QMDCresearchProject\PostC
onfirmationDocs\Thesis\RScripts\020_Cluster analysis and landscape mapping
\Inputs", layer: "um_gda94"
* with 1 features
* It has 1 fields
* OGR data source with driver: ESRI Shapefile
* Source: "C:\Users\q9823679\ownCloud\Shared\USQ_QMDCresearchProject\PostC
onfirmationDocs\Thesis\RScripts\020_Cluster analysis and landscape mapping
\Inputs", layer: "kpz"
* with 10 features
* It has 7 fields
* Integer64 fields read as strings:  OBJECTID GRIDCODE
```

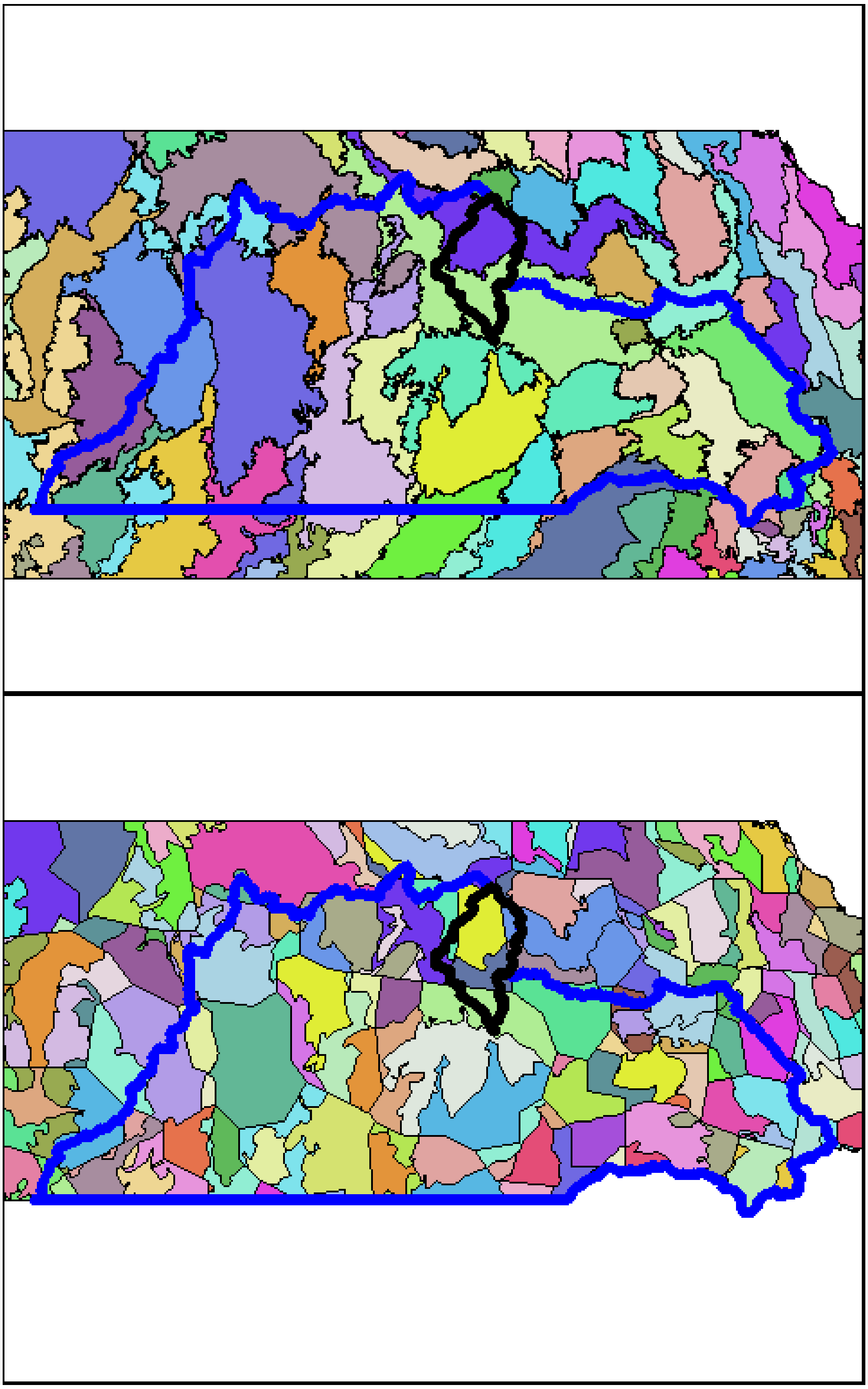
Basin plots showing data merging

```
# set plot parameters to view data
#options(device="RStudioGD") #requires RStudio plot window to be large eno
ugh
```

```r
par(mfrow=c(1, 1))
par(mgp=c(0,0,0),mar=c(0,0,0,0),oma=c(0,0,0,0))
#par(xaxs="i",yaxs="i")
#par(pin=c(5.8,3))

for (pdata in c(qmdbb_sc__,qmdbb_s_i_,qmdbb_sci_)) {
  plot(qmdbb,border="black")
  #plot(qbum_sci, asp=1, col=palette,legend=F, lwd=0.001) # (needs plenty
of plot screen space)
  #raster::plot(rasterr, add=T, asp=1, col=palette,legend=F)
  plot(pdata, add=T,col=palette)
  plot(qmdbb,add=T,border="blue",lwd=6)
  plot(qbum, add=T, border="black",lwd=6)
  box(lwd=2)
```



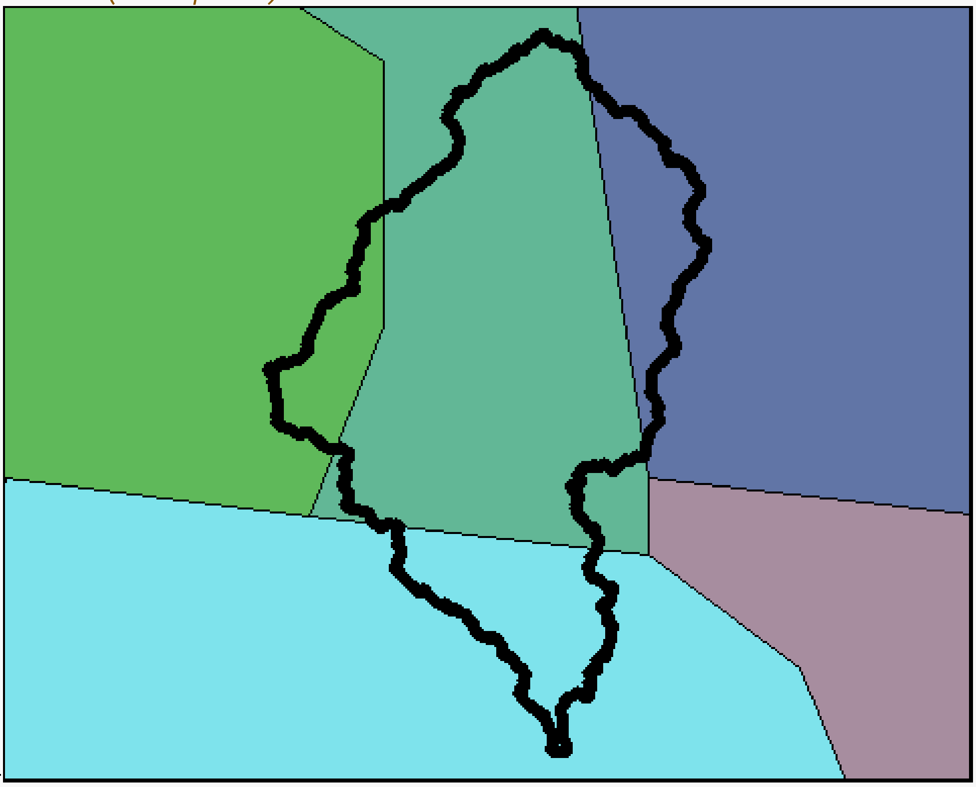
```r
}
```



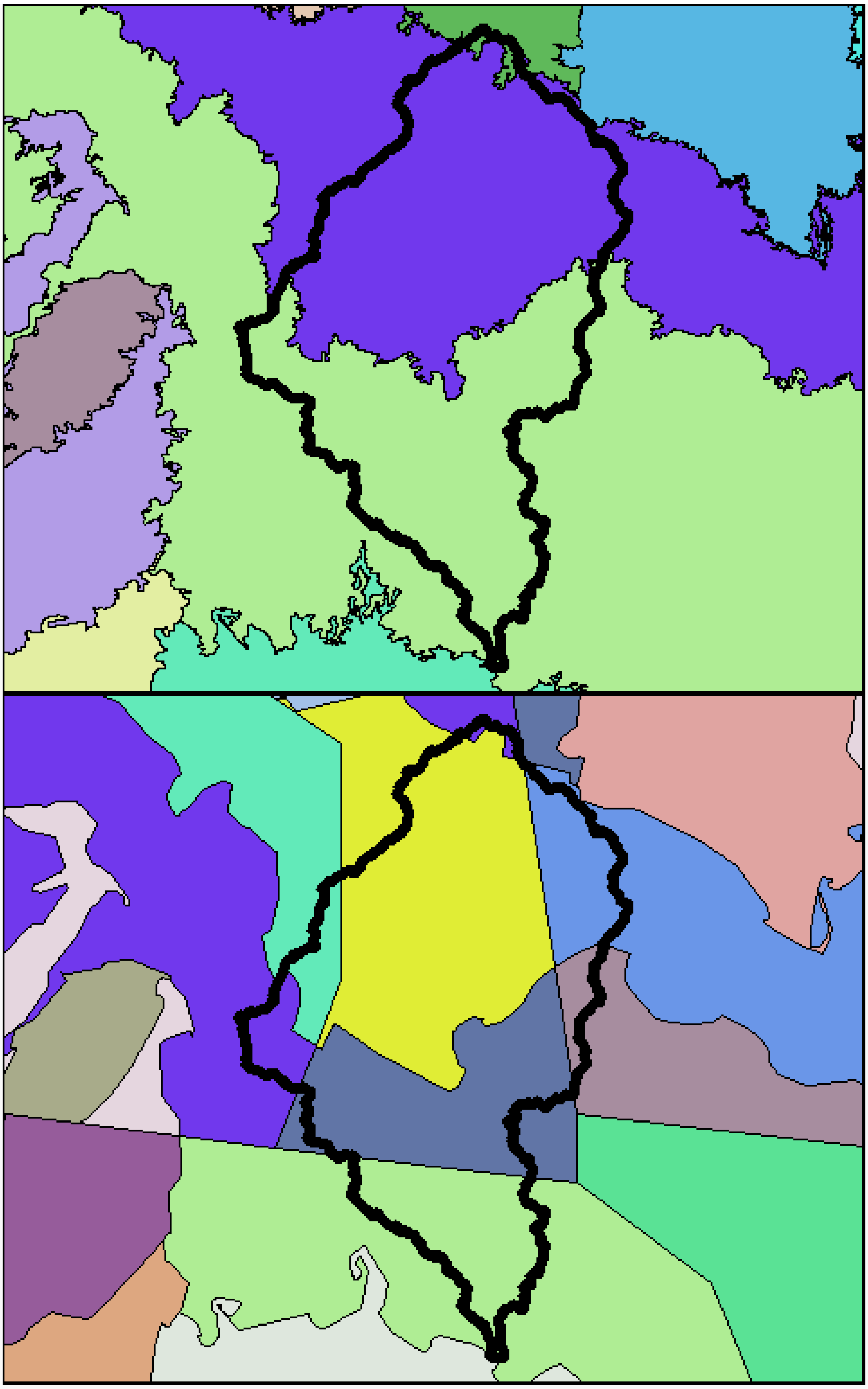
Upper Maranoa Plots showing data merging implications for study catchment

```
# set plot parameters to view data
par(mfrow=c(1, 1))
par(mgp=c(0,0,0),mar=c(0,0,0,0),oma=c(0,0,0,0))
#par(xaxs="i",yaxs="i")
#par(pin=c(3,4))

# for testing pdata <- qbum_s__l
```

```
for (pdata in c(qmdbb_sc__,qmdbb_s_i_,qmdbb_sci_)) { #,qbum_s__l)) { #,qbu
m_scil)) {
  plot(qbum,border="black", lwd=6)
  #plot(qbum_sci, asp=1, col=palette,legend=F, lwd=0.001)
  # (needs plenty of plot screen space)
  #raster::plot(rasterr, add=T, asp=1, col=NA,legend=F)
  plot(pdata, add=T,col=palette)
  plot(qbum, add=T, border="black",lwd=6)
  box(lwd=2)
  #title(main=pdata)
```



```
}
```



```
# for larger raster files ArcGIS was used for maps
# this applied to um_s__l and um_scil
# R could not handle these large rasters with UM catchment
# overlay
```

Export HiClimR outputs for groundcover analyses

```
# define output filename that reflects method and number of clusters
ofn <- paste(im,ik,dt,sep="" )
```

```
# define short filename for poly output
sfn <- paste(im,ik,dt,sep="" )
# define csv filename for csv output
cfn <- paste(im,ik,dt,".csv",sep="" )
# Climate Clusters as raster file - GIFF format
writeRaster(rasterr,ofn, format = "GTiff",overwrite=T )
# Climate Clusters as shapefile
writeOGR(qmdbb_sc__,dsn=getwd(), overwrite=T,
        layer =sfn,driver="ESRI Shapefile" )
# csv file with clim_id, Lon, Lat, CClass
write.csv(datar,cfn, row.names=F )
```

#' record run time (assumes whole script run in one go)

```
runtime <- difftime(Sys.time(),startt,units = "secs" )
print(paste("runtime in H:M:S",format(.POSIXct(runtime,tz="GMT"), "%H:%M:%
S" )))

* [1] "runtime in H:M:S 03:04:47"
```

Output files and Script files

```
print(paste("Output files in ",getwd()),quote=F)
print(list.files(getwd()))

* [1] Output files in  C:/Users/q9823679/ownCloud/Shared/USQ_QMDCresearchP
roject/PostConfirmationDocs/Thesis/RScripts/020_Cluster analysis and lands
cape mapping
*  [1] "_020_Cluster_analysis_and_landscape_mapping.rmd"
*  [2] "~$rd-styles-reference-01.docx"
*  [3] "020_Cluster analysis and landscape mapping.docx"
*  [4] "020_Cluster analysis and landscape mapping.R"
*  [5] "020_Cluster analysis and landscape mapping.rmd"
*  [6] "020_Cluster_analysis_and_landscape_mapping.rmd"
*  [7] "020_Cluster_analysis_and_landscape_mapping_files"
*  [8] "Inputs"
*  [9] "mcquitty52_May_13_2019.csv"
* [10] "mcquitty52_May_13_2019.dbf"
* [11] "mcquitty52_May_13_2019.prj"
* [12] "mcquitty52_May_13_2019.shp"
* [13] "mcquitty52_May_13_2019.shx"
* [14] "mcquitty52_May_13_2019.tif"
* [15] "word-styles-reference-01.docx"
```

Compile Reference List

```
citations <- function(includeURL = T, includeRStudio = F) {
    if(includeRStudio == TRUE) {
        ref.rstudio <- RStudio.Version()$citation
        if(includeURL == FALSE) {
            ref.rstudio$url = NULL;
        }
        print(ref.rstudio, style = 'text')
        cat('\n')
    }
    cit.list <- c('base', names(sessionInfo()$otherPkgs))
    for(i in 1:length(cit.list)) {
        ref <- citation(cit.list[i])
        if(includeURL == FALSE) {
            ref$url = NULL;
        }
```

```
        print(ref, style = 'text')
        cat('\n')
    }
}
#call function and tidy up code
prn <- capture.output(citations())
#tidy up output
prn1 <- sub("_", "",prn)
Rprint <- sub("_.", ".",prn1)
# add citation for function used to create citations and for RStudio
cit_func <- paste0("RStudio Team (2018). RStudio: Integrated Development E
nvironment for R. RStudio, Inc., Boston, MA.\n","\n","Reference list produ
ced from adaptation of MS Berends' citations() function accessed from stac
koverflow at: https://stackoverflow.com/questions/15688758/r-stats-citatio
n-for-a-scientific-paper")
# to print references without showing script call in knitted Word file use
:
# ```{r message=FALSE, warnings=FALSE, echo=FALSE comment=NA, results='hol
d'}
# cat(Rprint,sep="\n")
# cat(cit_func,sep="\n")
# ```
```

References

R Core Team (2018). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. <URL: https://www.R-project.org/>.

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Reference list produced from adaptation of MS Berends' citations() function accessed from stackoverflow at: https://stackoverflow.com/questions/15688758/r-stats-citation-for-a-scientific-paper

End of Script

030_Climate and groundcover data collation

Developed and run by Paul Webb, 2019.

Script to merge FAO56 derived climate data with summary groundcover data

Inputs (datadir): From 010_ClimateDataPrep Seasonal Climate Archive “sca.txt” From 020_ClimateDataClusterAnalysis mcquitty52_MMM_DD_YYYY.csv data file with clim_id, Lon, Lat, CClass fields From ArcMAP combination of climate class 52 and subIBRA v7 codes with small (<400 sq km) polygons eliminated qb_sci____52_400 shape file (8 files) in Inputs directory /DSITI_gc_data directory with GC summary data from DSITI file for each scilapp unit (333) assumes reference, treated and control datasets derived from ArcGIS and used to query QG Remote Sensing to get GC data summaries with files named s_c_i_l_a_p_p_results(csv) s - two character Study code (bd=Bulloo Downs) c - two digit Climate class zone (from HiClimR CMA mcquitty 52 outputs) i - three character and two digit IBRA subregion v7 code l - two character glu4 landuse code - og, st, tg, fo a - three character Activity code - ref, con, ??? (reference, control, ripped/scp/other) p - three digit Property id (000 for reference (whole landscape zone) p - three digit Project id (000 for whole property)

Outputs: txt files in wd sca_clr_tmp.txt sca_all.txt sc_ci.txt gc_sc.txt GroundCover collated with Seasonal Climate

Library calls and Operating environment settings

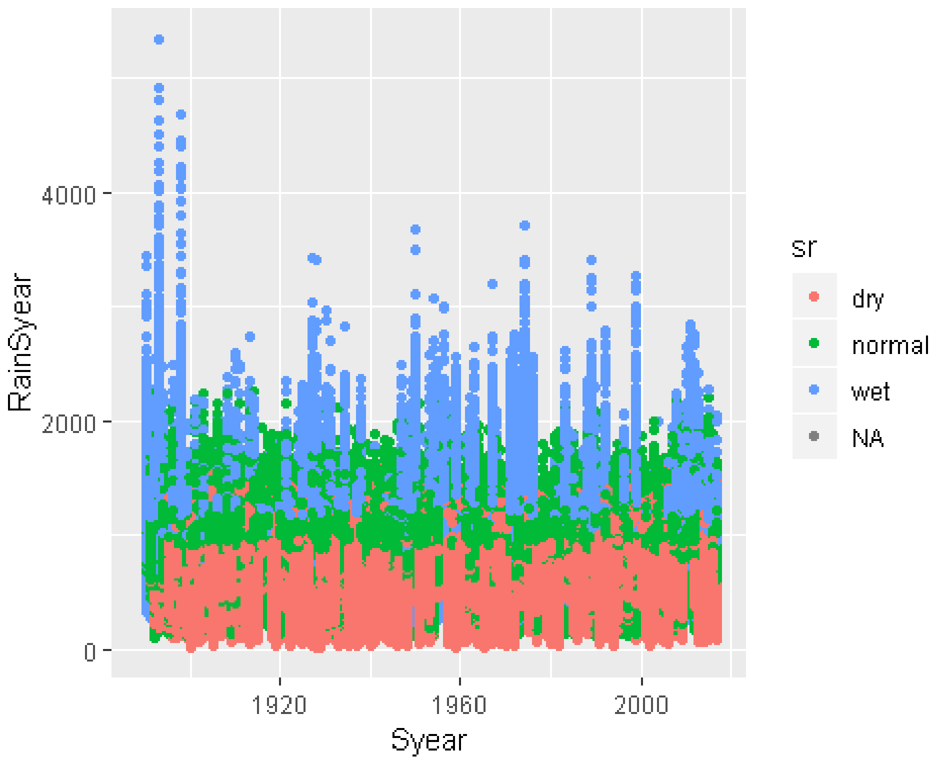
```
#make library calls for required R packages (assumes packages already inst
alled)
library(rgdal)
library(sp)
library(randomcoloR)
library(tools)
library(ggplot2)
library(grid)
library(reshape2)
library(raster)
library(data.table)
library(stringr)
library(dplyr)
library(qdapTools)

* Warning: package 'qdapTools' was built under R version 3.5.3

library(knitr) # to ensure knitr citations included in References
# library(rstudioapi) # package creates errors with knitr

#Sart date/time:
startt <- Sys.time()
dt <- format(startt, format = "_%b_%d_%Y")

# Set  wd and datadir (Inputs) directory
# assumes wd is script root directory - need to set in rstudio
# rem out for rmd process as root directory is default
# setwd(dirname(rstudioapi::getActiveDocumentContext()$path))
datadir <- paste0(getwd(),"/Inputs")

print(paste("Work Directory:",getwd()))
print(paste("Data Input directory:",datadir))
print("Memory limit set to:")
memory.limit(size=32584)
```

```
* [1] "Work Directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCresearchP
roject/PostConfirmationDocs/Thesis/RScripts/030_Climate and groundcover da
ta collation"
* [1] "Data Input directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCres
earchProject/PostConfirmationDocs/Thesis/RScripts/030_Climate and groundco
ver data collation/Inputs"
* [1] "Memory limit set to:"
* [1] 32584
```

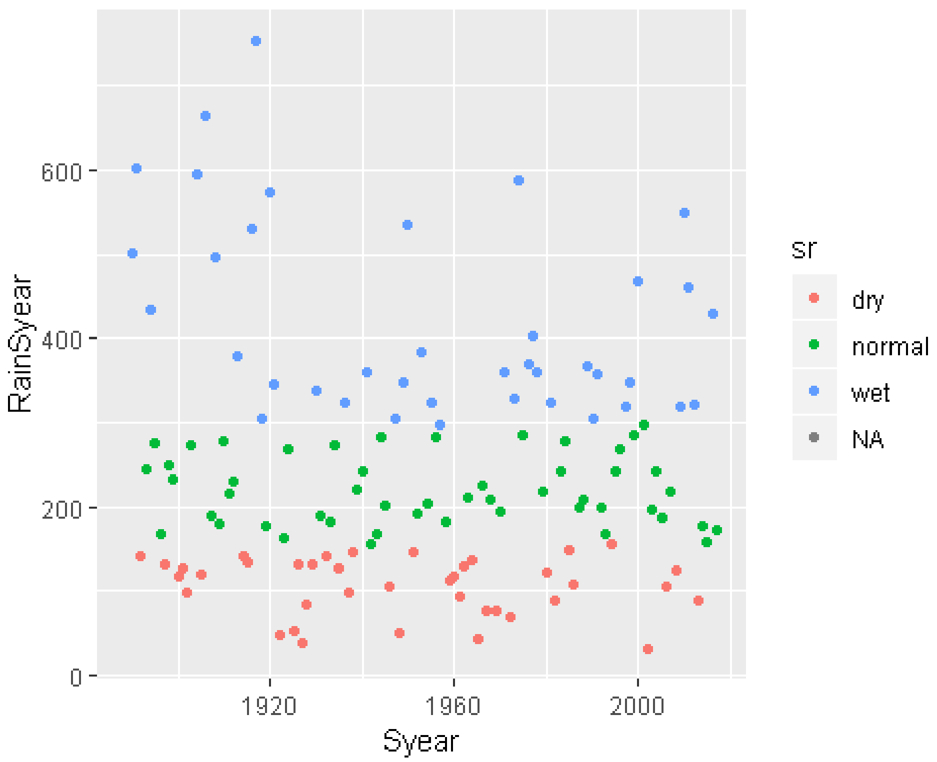
Import and manipulate climate data

```
#Import seasonal climate archive data into RStudio sca and assign Climate
Class

sca <- read.table(file=paste0(datadir,"/sca.txt"),header=T)

#add Yr_Season column and Tmean column
sca$Yr_Season <- paste0(sca$Syear,"_",sca$Sn_No)
sca$Tmean <- (sca$Tmax+sca$Tmin)/2
#reorder columns
sca <- sca[c(1:3,8,11,4:7,12,9:10)]

#'Assign landscape unit id (climate class_subIBRA)
#'from SC_ID in climate datafile
#'with reference to ArcMAP generated
#'clim_id_with_sci_52_400.txt file in Mapfiles directory

# Assign ci from SC_ID from ARCMap output
sc_ll <- read.delim(paste0(datadir,"/clim_id_with_sci_52_400.txt"),
                    sep=",")
sc_ll <- sc_ll[ ,-1]
sc_ll$ci <- substr(sc_ll$qb_sci____,4,11)

sca$ci <- sc_ll$ci[match(sca$SC_ID,sc_ll$clim_id)]
colnames(sca)[colnames(sca)=="FAO56"] <- "et"
head(sca)

*           SC_ID Syear Season Sn_No Yr_Season  Rain Tmax Tmin    et Tmean
* 1 141.50_24.00  1889 Autumn     2    1889_2  73.1 40.0  9.0 458.8 24.50
* 2 141.50_24.00  1889 Winter     3    1889_3  48.6 27.5  4.5 298.7 16.00
* 3 141.50_24.00  1889 Spring     4    1889_4  29.8 39.5  5.0 598.6 22.25
* 4 141.50_24.00  1890 Summer     1    1890_1 232.6 42.5 20.5 632.0 31.50
* 5 141.50_24.00  1890 Autumn     2    1890_2 129.2 38.0  8.0 429.6 23.00
* 6 141.50_24.00  1890 Winter     3    1890_3  86.2 27.5  2.5 299.1 15.00
*      lon lat        ci
* 1 141.5 -24 01_CHC03
* 2 141.5 -24 01_CHC03
* 3 141.5 -24 01_CHC03
* 4 141.5 -24 01_CHC03
* 5 141.5 -24 01_CHC03
* 6 141.5 -24 01_CHC03

#Assign season ratings (sr) from climate (Rain) "terciles"
#' from Syears (IE year(x) from December(x-1) to November(x))
#' Trim sca rows to gc data climate period -with 2 year lead in
#  (I.E. gc available from Autumn 1990 so trim climate to include data fro
m Autumn 1988)
sca_all <- sca #make copy of all data for reference in determining "tercil
es"
# export sca_all for future use in infilling aspirational gc for pre 1990
```

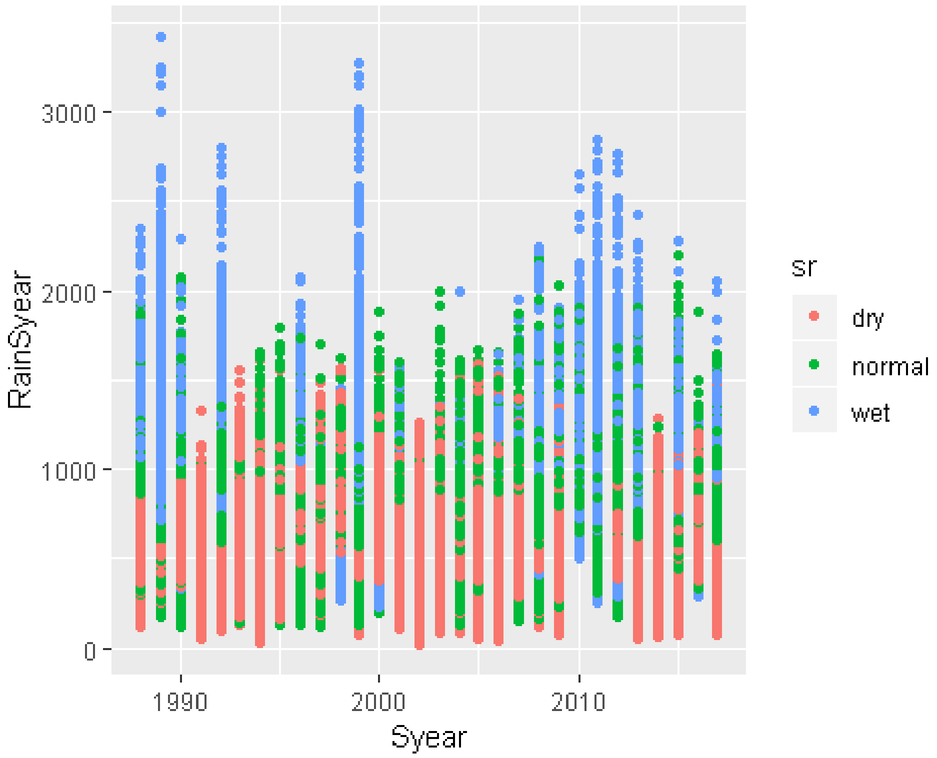
```
write.table(sca_all, file = "sca_allyears.txt",append = FALSE, sep = " ",
            eol = "\n",row.names=FALSE,col.names=TRUE)

sca <- subset(sca,sca$Yr_Season>"1988_1")

sca_clrwk <- melt(sca_all,id.vars=list("SC_ID","Syear","Season"),measure.v
ars=list("Rain","Tmean","Tmax","Tmin","et"))
sca_clr <- dcast(sca_clrwk,SC_ID+Syear~variable,sum) #annual summaries - t
otals
# note that only rf totals sensible as annual totals
write.table(sca_clr, file = "sca_clr_tmp.txt",append = FALSE, sep = " ",
            eol = "\n",row.names=FALSE,col.names=TRUE) #for use in excel t
o validate tercile splits

# create data frame and create dry/normal/wet "sr" ratings for each SC_ID
by Syear RF totals
# and S2year RF totals and dry/normal/wet "sr2" ratings
DT<-as.data.table(sca_clr)
DT$Rain[DT$Syear<1890] <- NA #1890 first complete Syear Rain value
DT$Rain[DT$Syear==2018] <- NA #2018 data incomplete
colnames(DT)[colnames(DT)=="Rain"] <- "RainSyear" # to avoid confusion wit
h seasonal Rain values
DT$Rain2yr <- DT$RainSyear+data.table::shift(DT$RainSyear,n=1,NA,"lag") #
Create column with 2year RF totals
DF <- as.data.frame(DT[,list(Syear,RainSyear,Rain2yr,(findInterval(RainSye
ar,quantile(RainSyear,c(0,0.3,.70,1.0),na.rm=T))),
                             (findInterval(Rain2yr,quantile(Rain2yr,c(0,0.
3,.70,1.0),na.rm=T)))),
                        by=SC_ID])
DF$sr <- ifelse(DF$V4==1,"dry",
                ifelse(DF$V4==2,"normal","wet"))
DF$sr2yr <- ifelse(DF$V5==1,"dry",
                ifelse(DF$V5==2,"normal","wet"))
DF <- DF[ ,-c(5:6)] # delete temp variable columns
# DF ready for merging with climate summaries
head(DF)

#check sr ratings are sensible
ggplot(data=DF,aes(x=Syear,y=RainSyear,color=sr,fill=sr)) +
  geom_point(data=DF,aes(x=Syear,y=RainSyear,color=sr,fill=sr))

* Warning: Removed 6941 rows containing missing values (geom_point).
```




```
#check for single site
ggplot(data=DF[which(DF$SC_ID=="141.50_24.00"),],aes(x=Syear,y=RainSyear,color=sr,fill=sr)) +
  geom_point(data=DF[which(DF$SC_ID=="141.50_24.00"),],aes(x=Syear,y=RainSyear,color=sr,fill=sr))

* Warning: Removed 1 rows containing missing values (geom_point).
```

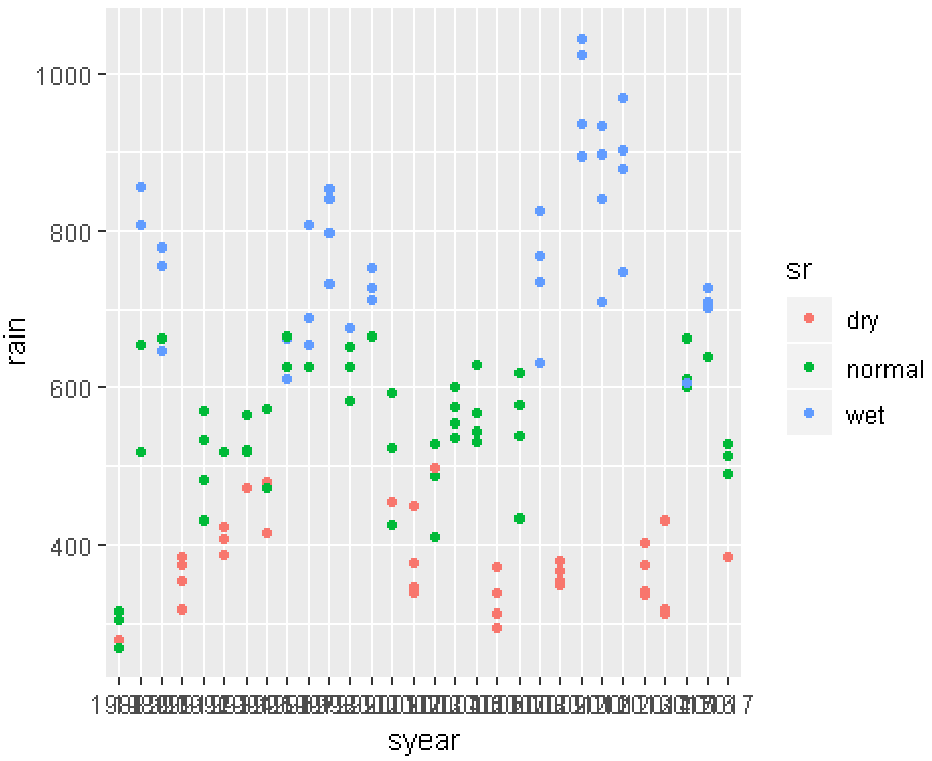


```
#' bring sr accross to seasonal climate archive (sca)
#' and summarise on ci & Yr_Season

# bring sr (and sr2yr) accross to sca
sca2 <- merge(sca,DF,by=c("SC_ID","Syear"))
sca <- sca2 #[ ,-(2:3)]

#check sr ratings are sensible
ggplot(data=sca,aes(x=Syear,y=RainSyear,color=sr,fill=sr)) +
  geom_point(data=sca,aes(x=Syear,y=RainSyear,color=sr,fill=sr))
```




```
# convert all column names to lower case for consistency
names(sca) <- tolower(names(sca))
# ensure factor status of appropriate columns:
# ("sc_id", "yr_season","syear", "season", "sn_no",  "ci", "sr", "sr2yr")
factors <- c("sc_id", "yr_season","syear", "season", "sn_no",  "ci", "sr",
"sr2yr")
sca[factors] <- lapply(sca[factors],factor)
head(sca)

*           SC_ID Syear RainSyear Rain2yr     sr  sr2yr
* 1 141.50_24.00  1889        NA      NA   <NA>   <NA>
* 2 141.50_24.00  1890     501.5      NA    wet   <NA>
* 3 141.50_24.00  1891     602.8  1104.3    wet    wet
* 4 141.50_24.00  1892     141.4   744.2    dry    wet
* 5 141.50_24.00  1893     244.9   386.3 normal normal
* 6 141.50_24.00  1894     433.3   678.2    wet    wet
*           sc_id syear season sn_no yr_season  rain tmax tmin    et tmean
* 1 141.50_24.00  1988 Autumn     2    1988_2 114.6 40.0  8.5 441.4 24.25
* 2 141.50_24.00  1988 Winter     3    1988_3  52.5 31.0  3.5 321.9 17.25
* 3 141.50_24.00  1988 Spring     4    1988_4   2.0 41.5  8.0 636.2 24.75
* 4 141.50_24.00  1989 Summer     1    1989_1  41.6 43.5 19.5 692.0 31.50
* 5 141.50_24.00  1989 Autumn     2    1989_2 162.2 38.5 12.5 398.6 25.50
* 6 141.50_24.00  1989 Winter     3    1989_3   3.2 33.5  1.5 284.0 17.50
```

```
*      lon lat       ci rainsyear rain2yr     sr  sr2yr
* 1 141.5 -24 01_CHC03     208.1   408.3 normal normal
* 2 141.5 -24 01_CHC03     208.1   408.3 normal normal
* 3 141.5 -24 01_CHC03     208.1   408.3 normal normal
* 4 141.5 -24 01_CHC03     367.1   575.2    wet normal
* 5 141.5 -24 01_CHC03     367.1   575.2    wet normal
* 6 141.5 -24 01_CHC03     367.1   575.2    wet normal

#summarise sca on ci & Yr_Season
# variables: season, sn_No, rain, tmax, tmin, tmean, et, sr, sr2yr
# summ method: Mode, Mode, median, median, median, median, median, Mode, M
ode

sca_dt <- data.table(sca)
# Mode funcion from Jay's solution on https://stackoverflow.com/questions/
32684931
# /how-to-aggregate-data-in-r-with-mode-most-common-value-for-each-row
Mode <- function(x) {
  ux <- unique(x)
  ux[which.max(tabulate(match(x, ux)))]
}

sca_dt_summ <- sca_dt[ ,
                        .(syear=Mode(syear),season=Mode(season), sn_no=Mod
e(sn_no),
                          rain=median(rain), tmax=median(tmax), tmin=media
n(tmin),
                          tmean=median(tmean), et=median(et),
                          sr=Mode(sr), sr2yr=Mode(sr2yr),
                          rainmax=max(rain),rainmin=min(rain)),
                       by = .(ci,yr_season)
]
# consolidate as seasonal climate by climate class dataframe and .txt expo
rt
sc_ci <- as.data.frame(sca_dt_summ)
write.csv(sc_ci,"sc_ci.txt")
write.csv(sca_all, "sca_all.txt") # seasonal climate archive - climate dat
a identical for all SC_ID within ci s.
# remove temp/work files
rm(DF,DT,sc_ll,sca,sca_all,sca2,sca_clr,sca_clrwk,sca_dt,sca_dt_summ,facto
rs)
head(sc_ci)

#summarise by syear and plot to confirm sr rating is sensible
sc_ci_yr_rain <- aggregate(rain~ci+syear, data=sc_ci, FUN=sum)
sc_ci_yr_sr <- aggregate(sr~ci+syear, data=sc_ci, FUN=first)
sc_ci_yr <- merge(x=sc_ci_yr_rain,y=sc_ci_yr_sr,by=c("ci","syear"))
sc_ci_yr_um <-  sc_ci_yr[sc_ci_yr$ci %in% c("18_BBS10","18_BBS12","19_BBS1
2","24_BBS12"),]

ggplot(data=sc_ci_yr_um, aes(x=syear, y=rain, color=sr,fill=sr)) +
  #geom_boxplot(data=data, aes(x=syear, y=rf4)) +
  geom_point(data=sc_ci_yr_um, aes(x=syear, y=rain))
```




```
*          ci yr_season syear season sn_no   rain tmax tmin tmean     et
* 1 01_CHC03    1988_2  1988 Autumn     2  92.70 40.5  7.5 24.00 433.55
* 2 01_CHC03    1988_3  1988 Winter     3  51.40 30.5  3.0 16.75 312.25
* 3 01_CHC03    1988_4  1988 Spring     4   8.70 42.0  7.0 24.50 628.90
* 4 01_CHC03    1989_1  1989 Summer     1  56.15 43.0 19.0 31.00 692.80
* 5 01_CHC03    1989_2  1989 Autumn     2 150.00 38.5 12.5 25.50 386.70
* 6 01_CHC03    1989_3  1989 Winter     3   7.80 32.5  1.0 16.75 268.70
*       sr  sr2yr rainmax rainmin
* 1 normal normal   123.7    47.1
* 2 normal normal    77.6    31.3
* 3 normal normal    21.2     1.7
* 4    wet    wet    90.8    39.3
* 5    wet    wet   234.1    97.9
* 6    wet    wet    14.3     2.3
```

Import and manipulate groundcover data

```
#' create GC data file with site ID, Yr_Season, GC% columns
#' use all groundcover files in datadir/DSITI_gc_data
# Files named as s_c_i_l_a_p_p.txt with:
#   s - two character project ID
#   c - two digit climate class from McQuitty 52 outputs
#   i - IBRA subregion (v7) code
#   l - two character grazing land use code (forestry, open gr, sparse tim
ber, timbered gr)
#   a - action (ref erence, con trol, scp, rip ped...)
#   p - property ID for area defined by lot on plan combined with tenure.
#   p - paddock ID for incentivised works grouped on each property
#       on nominated sediment benefit and contract year
# File contents: year,season,count (RF), and (gc) percentiles (5,20,50,80,
95)

#' add Null gc values for 2 yr leadin period
# Create leadin rows for gc files
```

```
fill=NULL
fill <- data.frame(a=c("1988,autumn,,,,,,",
                       "1988,winter,,,,,,",
                       "1988,spring,,,,,,",
                       "1988,summer,,,,,,",
                       "1989,autumn,,,,,,",
                       "1989,winter,,,,,,",
                       "1989,spring,,,,,,",
                       "1989,summer,,,,,,"
                       )
)

fill <- data.frame(str_split_fixed(fill$a,",",8),stringsAsFactors=TRUE)
colnames(fill) <- colnames(read.csv(
  "C:/Program Files/RStudio/qb_Upper_Maranoa/Inputs/DSITI_gc_data/um_18_BB
S10_fo_con_000_000_results")
)
fill[fill==""] <- NA
fill[ ,c(3:8)] <- lapply(fill[ ,c(3:8)],as.double)

#' Import gc data files from GC source directory
# create file list
#setwd(outputs)
filenames <- list.files(path=paste0(datadir,"/DSITI_gc_data"),
                        pattern = "*.",full.names=TRUE)

gc <- NULL #to ensure no existing data in dataframe to be populated

#set up dataset headers
dataset <- data.frame(read.table(
  "C:/Program Files/RStudio/qb_Upper_Maranoa/Inputs/DSITI_gc_data/um_18_BB
S10_fo_con_000_000_results",
  header=TRUE, sep=","))[0,] #header from first datafile

for (file in filenames) {
    temp_dataset <-read.table(file, header=TRUE, sep=",")
    temp_dataset$year <- as.factor(temp_dataset$year)
    temp_dataset <- rbind(fill,temp_dataset)
    temp_dataset$site <- as.factor(basename(file))
    dataset<-rbind(dataset, temp_dataset)
    rm(temp_dataset)
}

gc <- dataset
rm(dataset,fill)
gc <- gc[ ,c(9,1,2,4:8)]
gc[,1] <-as.factor(gsub("_results.csv","",gc[,1], fixed=TRUE) )
for(i in 4:8) {
  gc[,i] <- as.numeric(gc[,i])
}

* Warning: NAs introduced by coercion

* Warning: NAs introduced by coercion

* Warning: NAs introduced by coercion

* Warning: NAs introduced by coercion
```

```
* Warning: NAs introduced by coercion

head(gc)

*                                  site year season percentile_5
* 1 um_18_BBS10_fo_con_000_000_results 1988 autumn           NA
* 2 um_18_BBS10_fo_con_000_000_results 1988 winter           NA
* 3 um_18_BBS10_fo_con_000_000_results 1988 spring           NA
* 4 um_18_BBS10_fo_con_000_000_results 1988 summer           NA
* 5 um_18_BBS10_fo_con_000_000_results 1989 autumn           NA
* 6 um_18_BBS10_fo_con_000_000_results 1989 winter           NA
*   percentile_20 percentile_50 percentile_80 percentile_95
* 1            NA            NA            NA            NA
* 2            NA            NA            NA            NA
* 3            NA            NA            NA            NA
* 4            NA            NA            NA            NA
* 5            NA            NA            NA            NA
* 6            NA            NA            NA            NA

# manipulate ready for merging with sca#2
# establish site column from rownames (which are source file names)

#Create season no from season column
gc$sn_no <- ifelse(gc$season=="summer",1,
                      ifelse(gc$season=="autumn",2,
                             ifelse(gc$season=="winter",3,4)))

#convert column class to numeric for year
gc$year <- as.numeric(as.character(gc$year))

#Create syear column with summer years incremented by 1
gc$syear <- ifelse(gc$sn_no==1,gc$year+1,gc$year)

#add yr_season column
gc$yr_season <- paste0(gc$syear,"_",gc$sn_no)

# split file id column into scilapp components
#create df with site name components from gc
scilapp <- c("st","cl","ib","lu","ac","pr","pk")
gc <- data.frame(gc,str_split_fixed(gc$site, "_",7))
colnames(gc)[12:18] <- scilapp
# tidy up columns
gc$ci <- paste0(gc$cl,"_",gc$ib)
gc$pk <- substr(gc$pk,0,3)
gc <- gc[c(12:18,19,10,9,11,3,4,5,6,8,7)]
# rename "percentile columns for brevity
names(gc) <- gsub("percentile_", "pc", names(gc))
head(gc)

*   st cl    ib lu  ac  pr  pk       ci syear sn_no yr_season season pc5
* 1 um 18 BBS10 fo con 000 000 18_BBS10  1988     2    1988_2 autumn  NA
* 2 um 18 BBS10 fo con 000 000 18_BBS10  1988     3    1988_3 winter  NA
* 3 um 18 BBS10 fo con 000 000 18_BBS10  1988     4    1988_4 spring  NA
* 4 um 18 BBS10 fo con 000 000 18_BBS10  1989     1    1989_1 summer  NA
* 5 um 18 BBS10 fo con 000 000 18_BBS10  1989     2    1989_2 autumn  NA
* 6 um 18 BBS10 fo con 000 000 18_BBS10  1989     3    1989_3 winter  NA
*   pc20 pc50 pc95 pc80
* 1   NA   NA   NA   NA
* 2   NA   NA   NA   NA
```

```
* 3    NA    NA    NA    NA
* 4    NA    NA    NA    NA
* 5    NA    NA    NA    NA
* 6    NA    NA    NA    NA
```

Merge groundcover and seasonal climate data

```
#' append seasonal climate data and ratings to gc data
#' based on common ci and yr_season values in sc_ci

# climate data required:
# rain, tmax, tmin, tmean, et, sr, sr2yr
sc_ci$season <- tolower(sc_ci$season) # to match gc$season for merge
gc_sc <- merge(gc,sc_ci,by=c("ci","syear","season","sn_no","yr_season"),
               all.x=TRUE, all.y=FALSE)
head(gc_sc)

#' Export ground cover/seasonal climate (gc_sc) data for future analyses a
nd plotting
#' Data includes gc for project areas by season plus climate summaries and
sr
write.table(gc_sc, file = "gc_sc.txt",append = FALSE, sep = " ",
            eol = "\n",row.names=FALSE,col.names=TRUE)
#' Export data types for ease of future processing
gc_sc_types <- sapply(gc_sc,class)
write.table(gc_sc_types, file = "gc_sc_types.txt",append = FALSE, sep = "
",
            eol = "\n",row.names=FALSE,col.names=F)

*          ci syear season sn_no yr_season st cl    ib lu  ac  pr  pk pc5
* 1 18_BBS10  1988 autumn     2    1988_2 um 18 BBS10 fo con 000 000  NA
* 2 18_BBS10  1988 autumn     2    1988_2 um 18 BBS10 fo prb 580 020  NA
* 3 18_BBS10  1988 autumn     2    1988_2 um 18 BBS10 fo ref 000 000  NA
* 4 18_BBS10  1988 autumn     2    1988_2 um 18 BBS10 fo scp 550 000  NA
* 5 18_BBS10  1988 autumn     2    1988_2 um 18 BBS10 fo scp 580 000  NA
* 6 18_BBS10  1988 autumn     2    1988_2 um 18 BBS10 og con 000 000  NA
*   pc20 pc50 pc95 pc80 rain tmax tmin tmean et   sr sr2yr rainmax rainmin
* 1   NA   NA   NA   NA   NA   NA   NA    NA NA <NA>  <NA>      NA      NA
* 2   NA   NA   NA   NA   NA   NA   NA    NA NA <NA>  <NA>      NA      NA
* 3   NA   NA   NA   NA   NA   NA   NA    NA NA <NA>  <NA>      NA      NA
* 4   NA   NA   NA   NA   NA   NA   NA    NA NA <NA>  <NA>      NA      NA
* 5   NA   NA   NA   NA   NA   NA   NA    NA NA <NA>  <NA>      NA      NA
* 6   NA   NA   NA   NA   NA   NA   NA    NA NA <NA>  <NA>      NA      NA
```

Compile Reference List

```
citations <- function(includeURL = T, includeRStudio = F) {
    if(includeRStudio == TRUE) {
        ref.rstudio <- RStudio.Version()$citation
        #ref.rstudio <- rstudioapi::versionInfo()$citation
        if(includeURL == FALSE) {
            ref.rstudio$url = NULL;
        }
        print(ref.rstudio, style = 'text')
        cat('\n')
    }

    cit.list <- c('base', names(sessionInfo()$otherPkgs))
    for(i in 1:length(cit.list)) {
        ref <- citation(cit.list[i])
        if(includeURL == FALSE) {
```

```
            ref$url = NULL;
        }
        print(ref, style = 'text')
        cat('\n')
    }
}

#call function and tidy up code
prn <- capture.output(citations())
#tidy up output
prn1 <- sub("_", "",prn)
Rprint <- sub("_.", ".",prn1)
# add citation for function used to create citations and for RStudio
cit_func <- paste0("RStudio Team (2018). RStudio: Integrated Development E
nvironment for R. RStudio, Inc., Boston, MA.\n","\n","Reference list produ
ced from adaptation of MS Berends' citations() function accessed from stac
koverflow at: https://stackoverflow.com/questions/15688758/r-stats-citatio
n-for-a-scientific-paper")

# to print references without showing script call in knitted Word file use
:
# ```{r message=FALSE, warnings=FALSE, echo=FALSE comment=NA, results='hol
d'}
# cat(Rprint,sep="\n")
# cat(cit_func,sep="\n")
# ```
```

References

R Core Team (2018). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. <URL: https://www.R-project.org/>.

Xie Y (2018). knitr: A General-Purpose Package for Dynamic Report Generation in R. R package version 1.21, <URL: https://yihui.name/knitr/>.

Xie Y (2015). Dynamic Documents with R and knitr. 2nd edition. Chapman and Hall/CRC, Boca Raton, Florida. ISBN 978-1498716963, <URL: https://yihui.name/knitr/>.

Xie Y (2014). "knitr: A Comprehensive Tool for Reproducible Research in R." In Stodden V, Leisch F, Peng RD (eds.), Implementing Reproducible Computational Research. Chapman and Hall/CRC. ISBN 978-1466561595, <URL: http://www.crcpress.com/product/isbn/9781466561595>.

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Pebesma EJ, Bivand RS (2005). "Classes and methods for spatial data in R." R News. *5*(2), 9-13. <URL: https://CRAN.R-project.org/doc/Rnews/>.

Bivand RS, Pebesma E, Gomez-Rubio V (2013). Applied spatial data analysis with R, Second edition. Springer, NY. <URL: http://www.asdar-book.org/>.

RStudio Team (2018). RStudio: Integrated Development Environment for R. RStudio, Inc., Boston, MA.

Reference list produced from adaptation of MS Berends' citations() function accessed from stackoverflow at: https://stackoverflow.com/questions/15688758/r-stats-citation-for-a-scientific-paper

End of Script

040_aDRCM groundcover scoring

Developed and run by Paul Webb, 2019.

Script to calculate adapted Dynamic Reference Cover Method (aDNRM) scores from combined groundcover and climate data developed in 030_Climate and groundcover data collation.R

Inputs: gc_sc groundcover/seasonal climate data gc_sc_types column data types for previous data

Outputs: adrcm.txt groundcover/seasonal climate data together with groudcover scores D?? from aDRCMethod * WARNING: RF4 AND RF8 IN ADRCM.TXT ARE DYNAMIC BY SEASON NOT SINGLE VALUE PER SYEAR adrcm_types.txt column data types for previous data

Library calls and Operating environment settings

```
#' library calls and directory labelling
library(zoo)
library(R.utils)

* Warning: package 'R.utils' was built under R version 3.5.3

library(ggplot2)
library(knitr)

# Set  wd and datadir (Inputs) directory
# assumes wd is script root directory - need to set in rstudio
# rem out for rmd process as root directory is default
# setwd(dirname(rstudioapi::getActiveDocumentContext()$path))
datadir <- paste0(getwd(),"/Inputs")

#Sart date/time:
startt <- Sys.time()
dt <- format(startt, format = "_%b_%d_%Y")

print(paste("Work Directory:",getwd()))
print(paste("Data Input directory:",datadir))
print("Memory limit set to:")
memory.limit(size=32584)

* [1] "Work Directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCresearchP
roject/PostConfirmationDocs/Thesis/RScripts/040_aDRCM groundcover scoring"
* [1] "Data Input directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCres
earchProject/PostConfirmationDocs/Thesis/RScripts/040_aDRCM groundcover sc
oring/Inputs"
* [1] "Memory limit set to:"
* [1] 32584
```

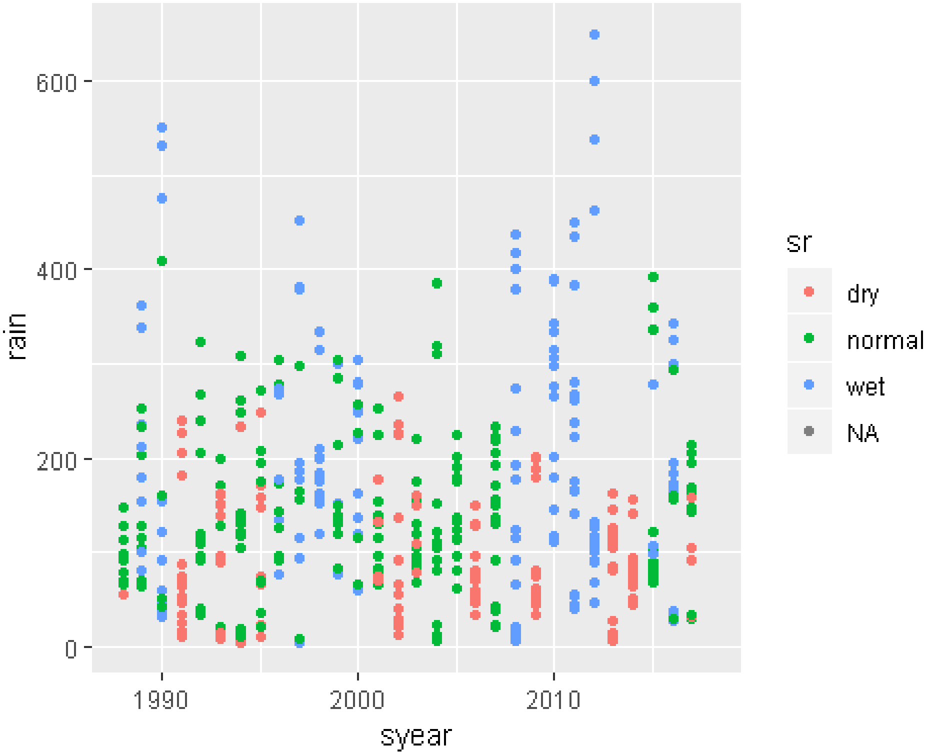
Import seasonal gc/climate archive data

```
# Import data and assign colClasses to maintain integrity
col_types <- read.table(file=paste0(datadir,"/gc_sc_types.txt"), header=F
, sep=" ")
char.types <- as.character(unlist(col_types$V1))
adrcm_wk <- read.table(file=paste0(datadir,"/gc_sc.txt"),header=TRUE,colCl
asses = char.types)

head(adrcm_wk)
```

```
*          ci syear season sn_no yr_season st cl    ib lu  ac  pr  pk pc5
* 1 18_BBS10  1988 autumn     2    1988_2 um 18 BBS10 tg con 000 000  NA
* 2 18_BBS10  1988 autumn     2    1988_2 um 18 BBS10 st scp 490 000  NA
* 3 18_BBS10  1988 autumn     2    1988_2 um 18 BBS10 st ref 000 000  NA
* 4 18_BBS10  1988 autumn     2    1988_2 um 18 BBS10 og ref 000 000  NA
* 5 18_BBS10  1988 autumn     2    1988_2 um 18 BBS10 fo scp 580 000  NA
* 6 18_BBS10  1988 autumn     2    1988_2 um 18 BBS10 tg scp 310 000  NA
*   pc20 pc50 pc95 pc80   rain tmax tmin  tmean     et  sr  sr2yr rainmax
* 1   NA   NA   NA   NA 127.55   35  0.5 17.625 319.35 dry normal   200.7
* 2   NA   NA   NA   NA 127.55   35  0.5 17.625 319.35 dry normal   200.7
* 3   NA   NA   NA   NA 127.55   35  0.5 17.625 319.35 dry normal   200.7
* 4   NA   NA   NA   NA 127.55   35  0.5 17.625 319.35 dry normal   200.7
* 5   NA   NA   NA   NA 127.55   35  0.5 17.625 319.35 dry normal   200.7
* 6   NA   NA   NA   NA 127.55   35  0.5 17.625 319.35 dry normal   200.7
*   rainmin
* 1    73.4
* 2    73.4
* 3    73.4
* 4    73.4
* 5    73.4
* 6    73.4
```

Calculate gc scores

```
# establish ref95 column with ref95 being pc95 value for
# whole ci zone - IDed with matching scil & yr_season plus ac==ref

# create ref95 df for ref sites only
ref95 <- subset(adrcm_wk,(ac=="ref"))
adrcm_wk$ref95 <- with(ref95,pc95[match((paste0(adrcm_wk$ci,adrcm_wk$yr_se
ason,adrcm_wk$lu)),(paste0(ci,yr_season,lu)))])

#Calculate Delta GC scores - from raw GC and ref PC95 data
#eg: Delta20 (score) = 100 - (95% GC (Reference region) - 20% GC (site))
adrcm_wk$D95 <- 100-(adrcm_wk$ref95-adrcm_wk$pc95)
adrcm_wk$D80 <- 100-(adrcm_wk$ref95-adrcm_wk$pc80)
adrcm_wk$D50 <- 100-(adrcm_wk$ref95-adrcm_wk$pc50)
adrcm_wk$D20 <- 100-(adrcm_wk$ref95-adrcm_wk$pc20)
adrcm_wk$D5  <- 100-(adrcm_wk$ref95-adrcm_wk$pc5)

# create scilapp_yrsn column for referencing
adrcm_wk$scilapp_yrsn <- paste(adrcm_wk$st,adrcm_wk$cl,adrcm_wk$ib,adrcm_w
k$lu,
                           adrcm_wk$ac,adrcm_wk$pr,adrcm_wk$pk
                           ,adrcm_wk$yr_season,sep="_")
adrcm_wk <- adrcm_wk[,c(33,1:32)]

head(adrcm_wk)

# check sr ratings sensible
ggplot(data=adrcm_wk,aes(x=syear, y=rain,color=sr,fill=sr))+
  geom_point(data=adrcm_wk,aes(x=syear, y=rain,color=sr,fill=sr))

* Warning: Removed 333 rows containing missing values (geom_point).
```

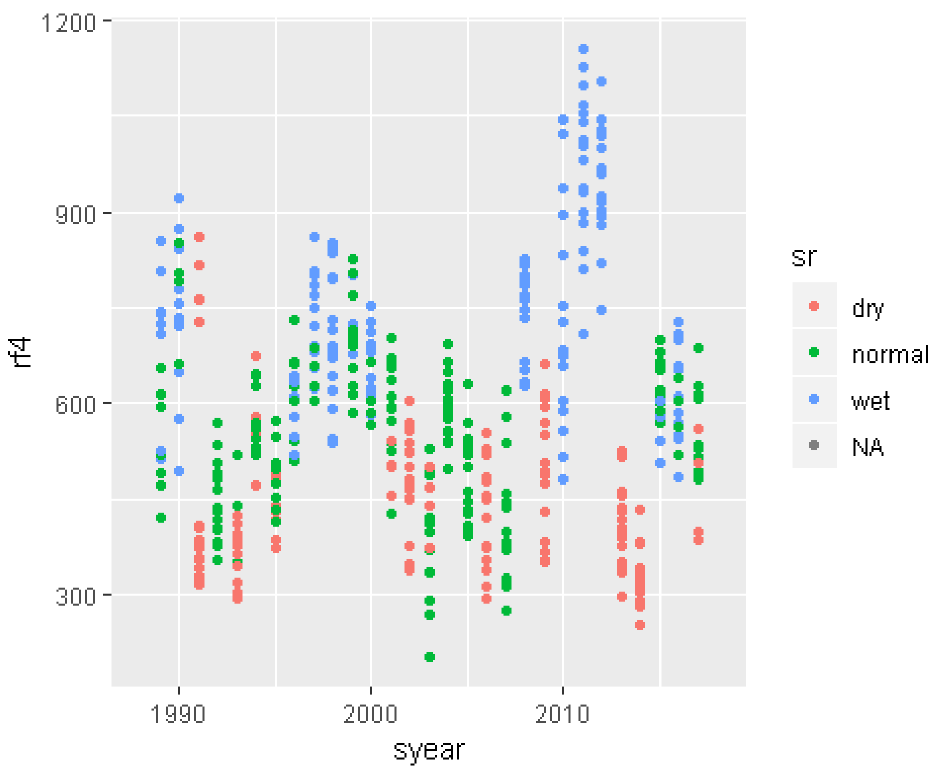



```
*                            scilapp_yrsn       ci syear season sn_no yr_seaso
n
* 1 um_18_BBS10_tg_con_000_000_1988_2 18_BBS10  1988 autumn     2     1988_
2
* 2 um_18_BBS10_st_scp_490_000_1988_2 18_BBS10  1988 autumn     2     1988_
2
* 3 um_18_BBS10_st_ref_000_000_1988_2 18_BBS10  1988 autumn     2     1988_
2
* 4 um_18_BBS10_og_ref_000_000_1988_2 18_BBS10  1988 autumn     2     1988_
2
* 5 um_18_BBS10_fo_scp_580_000_1988_2 18_BBS10  1988 autumn     2     1988_
2
* 6 um_18_BBS10_tg_scp_310_000_1988_2 18_BBS10  1988 autumn     2     1988_
2
*   st cl    ib lu  ac  pr  pk pc5 pc20 pc50 pc95 pc80   rain tmax tmin
* 1 um 18 BBS10 tg con 000 000  NA   NA   NA   NA   NA 127.55   35  0.5
* 2 um 18 BBS10 st scp 490 000  NA   NA   NA   NA   NA 127.55   35  0.5
* 3 um 18 BBS10 st ref 000 000  NA   NA   NA   NA   NA 127.55   35  0.5
* 4 um 18 BBS10 og ref 000 000  NA   NA   NA   NA   NA 127.55   35  0.5
* 5 um 18 BBS10 fo scp 580 000  NA   NA   NA   NA   NA 127.55   35  0.5
* 6 um 18 BBS10 tg scp 310 000  NA   NA   NA   NA   NA 127.55   35  0.5
*    tmean     et  sr  sr2yr rainmax rainmin ref95 D95 D80 D50 D20 D5
* 1 17.625 319.35 dry normal   200.7    73.4    NA  NA  NA  NA  NA NA
* 2 17.625 319.35 dry normal   200.7    73.4    NA  NA  NA  NA  NA NA
* 3 17.625 319.35 dry normal   200.7    73.4    NA  NA  NA  NA  NA NA
* 4 17.625 319.35 dry normal   200.7    73.4    NA  NA  NA  NA  NA NA
* 5 17.625 319.35 dry normal   200.7    73.4    NA  NA  NA  NA  NA NA
* 6 17.625 319.35 dry normal   200.7    73.4    NA  NA  NA  NA  NA NA
```

Create explanatory variables

```
#' calculate current season plus preceding seasons' rf totals

#order by scilapp_yrsn
```

```
adrcm_wk <- adrcm_wk[order(adrcm_wk$scilapp_yrsn),]
# rf4 as current plus 3 previous
adrcm_wk$rf4 <- rollsumr(adrcm_wk$rain, k=4, fill= NA)
# rf8 as current plus 7 previous
adrcm_wk$rf8 <- rollsumr(adrcm_wk$rain, k=8, fill= NA)

# check sr ratings sensible
ggplot(data=adrcm_wk,aes(x=syear, y=rf4,color=sr,fill=sr)) +
  geom_point(data=adrcm_wk,aes(x=syear, y=rf4,color=sr,fill=sr))

* Warning: Removed 1332 rows containing missing values (geom_point).
```

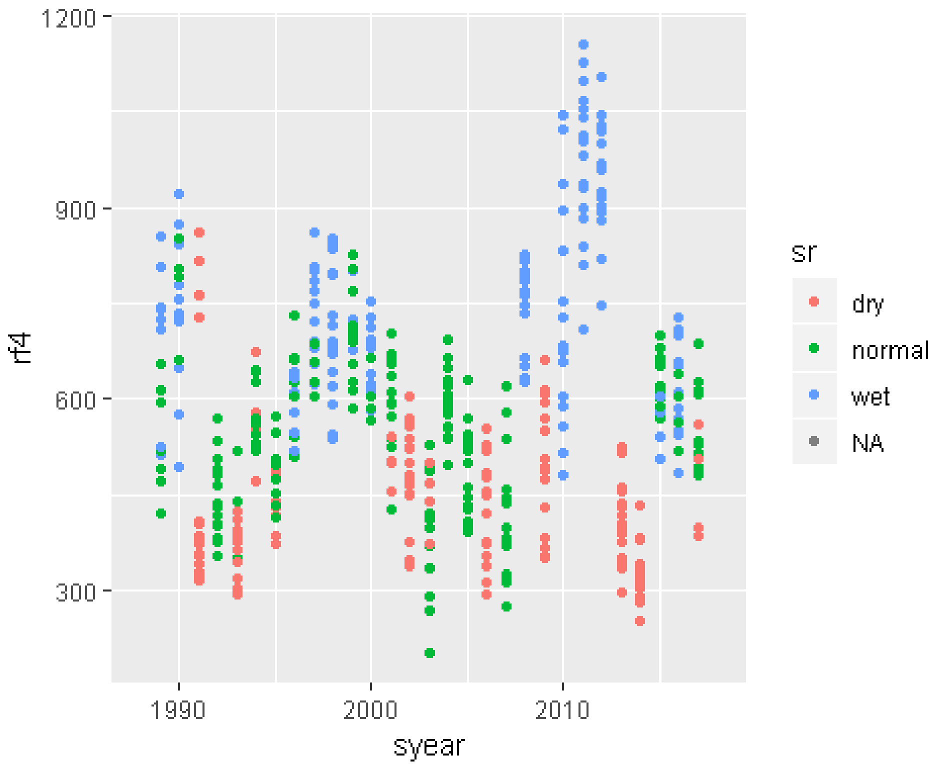



```
#' add area and calculate area weighted D50 scores
# import scilapp_Ha data from csv file
scilapp_Ha <- NULL
scilapp_Ha <- read.csv(file=paste0(datadir,"/scilapp_Ha.csv"), header=TRUE
,
                       colClass=c("factor","numeric","integer"))
scilapp_Ha$Ha <- round(scilapp_Ha$Ha,digits=2)
# create matching qbum_scilapp column in adrcm_wk
adrcm_wk$qbum_scilapp <- substr(adrcm_wk$scilapp_yrsn,0,26)
# create Ha column in adrcm_wk from scilapp_Ha
adrcm_wk$Ha <- scilapp_Ha$Ha[match(adrcm_wk$qbum_scilapp,scilapp_Ha$qbum_s
cilapp)]
adrcm_wk$rainmax <- as.numeric(adrcm_wk$rainmax) # for consistency
head(adrcm_wk)

*                          scilapp_yrsn        ci syear season sn_no
* 12  um_18_BBS10_fo_con_000_000_1988_2 18_BBS10  1988 autumn     2
* 46  um_18_BBS10_fo_con_000_000_1988_3 18_BBS10  1988 winter     3
* 28  um_18_BBS10_fo_con_000_000_1988_4 18_BBS10  1988 spring     4
* 96  um_18_BBS10_fo_con_000_000_1989_1 18_BBS10  1989 summer     1
* 59  um_18_BBS10_fo_con_000_000_1989_2 18_BBS10  1989 autumn     2
* 116 um_18_BBS10_fo_con_000_000_1989_3 18_BBS10  1989 winter     3
```

```
*      yr_season st cl    ib lu  ac  pr  pk pc5 pc20 pc50 pc95 pc80   rain
* 12      1988_2 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 127.55
* 46      1988_3 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  96.35
* 28      1988_4 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  55.25
* 96      1989_1 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 234.45
* 59      1989_2 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 339.05
* 116     1989_3 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  80.70
*      tmax  tmin  tmean     et  sr   sr2yr rainmax rainmin ref95 D95 D80 D5
0
* 12  35.0  0.50 17.625 319.35 dry normal   200.7    73.4    NA  NA  NA  N
A
* 46  29.0 -5.00 12.000 233.50 dry normal   171.8    75.9    NA  NA  NA  N
A
* 28  38.0  1.50 19.500 526.25 dry normal    74.2     7.9    NA  NA  NA  N
A
* 96  37.0 12.50 25.000 525.15 wet normal   413.4   194.3    NA  NA  NA  N
A
* 59  35.0  5.50 20.250 295.00 wet normal   499.2   231.4    NA  NA  NA  N
A
* 116 28.5 -3.75 12.250 213.60 wet normal   127.2    55.7    NA  NA  NA  N
A
*      D20 D5    rf4 rf8              qbum_scilapp       Ha
* 12    NA NA     NA  NA um_18_BBS10_fo_con_000_000 47255.91
* 46    NA NA     NA  NA um_18_BBS10_fo_con_000_000 47255.91
* 28    NA NA     NA  NA um_18_BBS10_fo_con_000_000 47255.91
* 96    NA NA 513.60  NA um_18_BBS10_fo_con_000_000 47255.91
* 59    NA NA 725.10  NA um_18_BBS10_fo_con_000_000 47255.91
* 116   NA NA 709.45  NA um_18_BBS10_fo_con_000_000 47255.91
```

Output and check data

```
#write to txt file for use by other scripts
write.table(adrcm_wk, file = "adrcm.txt", append = FALSE, sep = ",",
            eol = "\n", row.names=FALSE, col.names=TRUE)
#Export data types for ease of future processing
adrcm_types <- sapply(adrcm_wk,class)
write.table(adrcm_types, file = "adrcm_types.txt",append = FALSE, sep = "
",
            eol = "\n",row.names=FALSE,col.names=F)

#check
# Import data and assign colClasses to maintain integrity
col_types <- read.table(file=paste0("adrcm_types.txt"), header=F , sep=" "
)
char.types <- as.character(unlist(col_types$V1))
adrcm <- NULL
adrcm <- read.table(file=paste0(getwd(),"/adrcm.txt"),sep=",", header=TRUE
,colClasses = char.types)
head(adrcm)

# check sr ratings sensible
ggplot(data=adrcm,aes(x=syear, y=rf4,color=sr,fill=sr))+
  geom_point(data=adrcm,aes(x=syear, y=rf4,color=sr,fill=sr))

* Warning: Removed 1332 rows containing missing values (geom_point).
```




```
#  WARNING: RF4 AND RF8 IN ADRCM.TXT ARE DYNAMIC BY SEASON
#  NOT SINGLE VALUE PER SYEAR

#' see script 06 for development of D50 score summaries

*                         scilapp_yrsn       ci syear season sn_no yr_seaso
n
* 1 um_18_BBS10_fo_con_000_000_1988_2 18_BBS10  1988 autumn     2    1988_
2
* 2 um_18_BBS10_fo_con_000_000_1988_3 18_BBS10  1988 winter     3    1988_
3
* 3 um_18_BBS10_fo_con_000_000_1988_4 18_BBS10  1988 spring     4    1988_
4
* 4 um_18_BBS10_fo_con_000_000_1989_1 18_BBS10  1989 summer     1    1989_
1
* 5 um_18_BBS10_fo_con_000_000_1989_2 18_BBS10  1989 autumn     2    1989_
2
* 6 um_18_BBS10_fo_con_000_000_1989_3 18_BBS10  1989 winter     3    1989_
3
*   st cl    ib lu  ac  pr  pk pc5 pc20 pc50 pc95 pc80   rain tmax  tmin
* 1 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 127.55 35.0  0.50
* 2 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  96.35 29.0 -5.00
* 3 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  55.25 38.0  1.50
* 4 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 234.45 37.0 12.50
* 5 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 339.05 35.0  5.50
* 6 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  80.70 28.5 -3.75
*    tmean     et  sr  sr2yr rainmax rainmin ref95 D95 D80 D50 D20 D5     r
f4
* 1 17.625 319.35 dry normal   200.7    73.4    NA  NA  NA  NA  NA NA
NA
* 2 12.000 233.50 dry normal   171.8    75.9    NA  NA  NA  NA  NA NA
NA
* 3 19.500 526.25 dry normal    74.2     7.9    NA  NA  NA  NA  NA NA
NA
```

```
* 4 25.000 525.15 wet normal   413.4   194.3    NA  NA  NA  NA  NA NA 513.
60
* 5 20.250 295.00 wet normal   499.2   231.4    NA  NA  NA  NA  NA NA 725.
10
* 6 12.250 213.60 wet normal   127.2    55.7    NA  NA  NA  NA  NA NA 709.
45
*   rf8              qbum_scilapp       Ha
* 1  NA um_18_BBS10_fo_con_000_000 47255.91
* 2  NA um_18_BBS10_fo_con_000_000 47255.91
* 3  NA um_18_BBS10_fo_con_000_000 47255.91
* 4  NA um_18_BBS10_fo_con_000_000 47255.91
* 5  NA um_18_BBS10_fo_con_000_000 47255.91
* 6  NA um_18_BBS10_fo_con_000_000 47255.91
```

Compile Reference List

```
citations <- function(includeURL = T, includeRStudio = F) {
    if(includeRStudio == TRUE) {
        ref.rstudio <- RStudio.Version()$citation
        #ref.rstudio <- rstudioapi::versionInfo()$citation
        if(includeURL == FALSE) {
            ref.rstudio$url = NULL;
        }
        print(ref.rstudio, style = 'text')
        cat('\n')
    }

    cit.list <- c('base', names(sessionInfo()$otherPkgs))
    for(i in 1:length(cit.list)) {
        ref <- citation(cit.list[i])
        if(includeURL == FALSE) {
            ref$url = NULL;
        }
        print(ref, style = 'text')
        cat('\n')
    }
}

#call function and tidy up code
prn <- capture.output(citations())
#tidy up output
prn1 <- sub("_", "",prn)
Rprint <- sub("_.", ".",prn1)
# add citation for function used to create citations and for RStudio
cit_func <- paste0("RStudio Team (2018). RStudio: Integrated Development E
nvironment for R. RStudio, Inc., Boston, MA.\n","\n","Reference list produ
ced from adaptation of MS Berends' citations() function accessed from stac
koverflow at: https://stackoverflow.com/questions/15688758/r-stats-citatio
n-for-a-scientific-paper")

# to print references without showing script call in knitted Word file use
:
# ```{r message=FALSE, warnings=FALSE, echo=FALSE comment=NA, results='hol
d'}
# cat(Rprint,sep="\n")
# cat(cit_func,sep="\n")
# ```
```

References

R Core Team (2018). R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. <URL: https://www.R-project.org/>.

Xie Y (2018). knitr: A General-Purpose Package for Dynamic Report Generation in R. R package version 1.21, <URL: https://yihui.name/knitr/>.

Xie Y (2015). Dynamic Documents with R and knitr. 2nd edition. Chapman and Hall/CRC, Boca Raton, Florida. ISBN 978-1498716963, <URL: https://yihui.name/knitr/>.

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Reference list produced from adaptation of MS Berends' citations() function accessed from stackoverflow at: https://stackoverflow.com/questions/15688758/r-stats-citation-for-a-scientific-paper

End of Script

050_Groundcover scores and climate data correlation anlyses

Developed and run by Paul Webb, 2019.

Script to test correlations between ground cover and climate variables and between ground cover scores and climate variables. Correlations to be tested for different seasons, grazing land uses and different season conditions (sr)

Inputs: adrcm.txt groundcover/seasonal climate data together with groudcover scores D?? from aDRCMethod adrcm_types.txt column data types for previous data

Outputs: Correlation heatmap plots

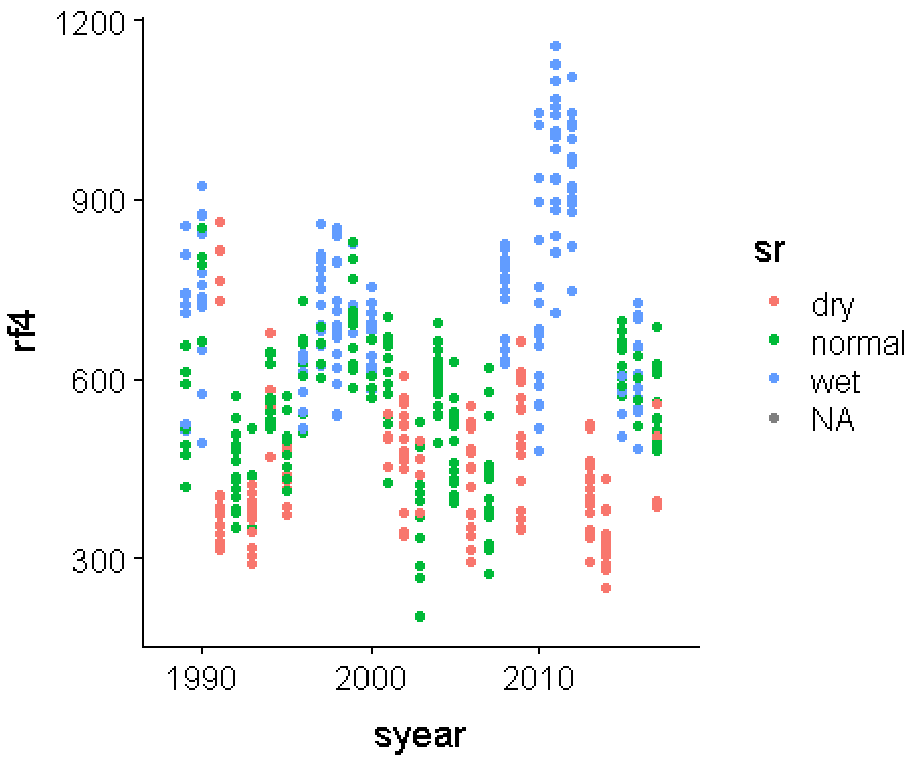
Library calls and Operating environment settings

```
#library calls
library(reshape2)
library(ggplot2)
library(cowplot)

* Warning: package 'cowplot' was built under R version 3.5.3

library(zoo)
library(Hmisc)

* Warning: package 'Hmisc' was built under R version 3.5.3

library(broom)

* Warning: package 'broom' was built under R version 3.5.3

library(corrplot)

* Warning: package 'corrplot' was built under R version 3.5.3

library(dplyr)
library(ggcorrplot)

* Warning: package 'ggcorrplot' was built under R version 3.5.3

library(intrval)

# Set  wd and datadir (Inputs) directory
# assumes wd is script root directory - need to set in rstudio
# rem out for rmd process as root directory is default
#setwd(dirname(rstudioapi::getActiveDocumentContext()$path))
datadir <- paste0(getwd(),"/Inputs")

#Sart date/time:
startt <- Sys.time()
dt <- format(startt, format = "_%b_%d_%Y")

print(paste("Work Directory:",getwd()))
print(paste("Data Input directory:",datadir))
print("Memory limit set to:")
memory.limit(size=32584)
```

```
* [1] "Work Directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCresearchProject/P
ostConfirmationDocs/Thesis/RScripts/050_Groundcover scores and climate data correl
ation anlyses"
* [1] "Data Input directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCresearchPro
ject/PostConfirmationDocs/Thesis/RScripts/050_Groundcover scores and climate data
correlation anlyses/Inputs"
* [1] "Memory limit set to:"
* [1] 32584
```

Import groundcover scores and climate data

```
# Import data and assign colClasses to maintain integrity
col_types <- read.table(file=paste0(datadir,"/adrcm_types.txt"), header=F , sep="
")
char.types <- as.character(unlist(col_types$V1))
adrcm <- NULL
adrcm <- read.table(file=paste0(datadir,"/adrcm.txt"),sep=",", header=TRUE,colClas
ses = char.types)
head(adrcm)

# check sr ratings sensible
ggplot(data=adrcm,aes(x=syear, y=rf4,color=sr,fill=sr))+
  geom_point(data=adrcm,aes(x=syear, y=rf4,color=sr,fill=sr))

* Warning: Removed 1332 rows containing missing values (geom_point).
```




```
*                     scilapp_yrsn      ci syear season sn_no yr_season
* 1 um_18_BBS10_fo_con_000_000_1988_2 18_BBS10  1988 autumn     2    1988_2
* 2 um_18_BBS10_fo_con_000_000_1988_3 18_BBS10  1988 winter     3    1988_3
* 3 um_18_BBS10_fo_con_000_000_1988_4 18_BBS10  1988 spring     4    1988_4
* 4 um_18_BBS10_fo_con_000_000_1989_1 18_BBS10  1989 summer     1    1989_1
```

```
* 5 um_18_BBS10_fo_con_000_000_1989_2 18_BBS10  1989 autumn     2    1989_2
* 6 um_18_BBS10_fo_con_000_000_1989_3 18_BBS10  1989 winter     3    1989_3
*   st cl    ib lu  ac  pr  pk pc5 pc20 pc50 pc95 pc80   rain tmax  tmin
* 1 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 127.55 35.0  0.50
* 2 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  96.35 29.0 -5.00
* 3 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  55.25 38.0  1.50
* 4 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 234.45 37.0 12.50
* 5 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 339.05 35.0  5.50
* 6 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  80.70 28.5 -3.75
*    tmean     et  sr  sr2yr rainmax rainmin ref95 D95 D80 D50 D20 D5    rf4
* 1 17.625 319.35 dry normal   200.7    73.4    NA  NA  NA  NA  NA NA     NA
* 2 12.000 233.50 dry normal   171.8    75.9    NA  NA  NA  NA  NA NA     NA
* 3 19.500 526.25 dry normal    74.2     7.9    NA  NA  NA  NA  NA NA     NA
* 4 25.000 525.15 wet normal   413.4   194.3    NA  NA  NA  NA  NA NA 513.60
* 5 20.250 295.00 wet normal   499.2   231.4    NA  NA  NA  NA  NA NA 725.10
* 6 12.250 213.60 wet normal   127.2    55.7    NA  NA  NA  NA  NA NA 709.45
*   rf8                 qbum_scilapp       Ha
* 1  NA um_18_BBS10_fo_con_000_000 47255.91
* 2  NA um_18_BBS10_fo_con_000_000 47255.91
* 3  NA um_18_BBS10_fo_con_000_000 47255.91
* 4  NA um_18_BBS10_fo_con_000_000 47255.91
* 5  NA um_18_BBS10_fo_con_000_000 47255.91
* 6  NA um_18_BBS10_fo_con_000_000 47255.91
```

__Subset data for comparitive use__

```
#for different combination options
# default all years, seasons and glus

# subset data for comparitive use
scponly <- subset(adrcm,subset=ac %in% "scp") #extension footprint
prbonly <- subset(adrcm,subset=ac %in% "prb") #incentives footprint
refonly <- subset(adrcm,subset=ac %in% "ref") #whole of zones intersected by exten
sion footprint
cononly <- subset(adrcm,subset=ac %in% "con") #intersected zones not in extention
area but in catchment
# for within catchment with no duplicates (scp & con)
catch <- subset(adrcm,subset=ac %in% c("scp","con"))
# use catch as default as this is the most complete with no duplicates
adrcm <- catch

#for seasons
all_seasons <- subset(adrcm,subset=season %in% c("summer","autumn","winter","sprin
g" ))
summer <- subset(adrcm,subset=season %in% "summer")
autumn <- subset(adrcm,subset=season %in% "autumn")
winter <- subset(adrcm,subset=season %in% "winter")
spring <- subset(adrcm,subset=season %in% "spring")

#for lu in spring
spring_og <- subset(spring,subset=lu %in% "og")
spring_st <- subset(spring,subset=lu %in% "st")
```

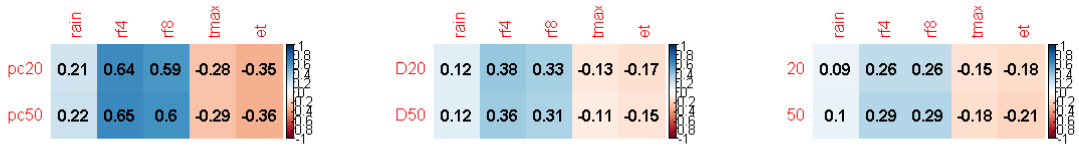
```r
spring_tg <- subset(spring,subset=lu %in% "tg")
spring_fo <- subset(spring,subset=lu %in% "fo")
```

Multi corrplot function development

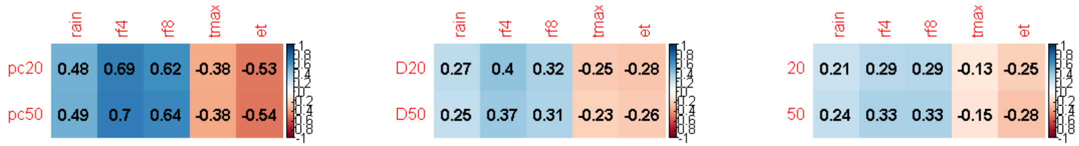
```r
# for(df in c(all_seasons,summer,autumn,winter,spring)) {
multicorrplots <- function (df) {
  #subset data
  #adrcm_option <- adrcm #for testing function
  adrcm_option <- df
  #head(adrcm_option)
  pcM <- cor(na.omit(adrcm_option[,c(19,34,35,20,23,14:18)]))
  pc_p99 <- cor.mtest(na.omit(adrcm_option[,c(19,34,35,20,23,14:18)]),conf.level=0.99)

  #**** work through from here ****
  dcM <- cor(na.omit(adrcm_option[,c(19,34,35,20,23,33:29)]))
  dc_p99 <- cor.mtest(na.omit(adrcm_option[,c(19,34,35,20,23,33:29)]),conf.level=0.99)

  remM <- pcM-dcM
  rownames(remM)[6:10] <- c(5,20,50,80,95)

  #plot median row climate correlations for pcM, dcM and diff50
  # create combo matrix
  #plotcomp <- function (pcM,dcM,remM) {
    pc50 <- corrplot(pcM[7:8,1:5],method="color",addCoef.col = "black",
                     p.mat=pc_p99$p[7:8,1:5],insig ="blank", sig.level = 0.01,pch.cex = 3)[2,]
    D50 <- corrplot(dcM[7:8,1:5],method="color", addCoef.col = "black",
                    p.mat=dc_p99$p[7:8,1:5],insig ="blank", sig.level = 0.01) [2,]
    diff50 <- corrplot(remM[7:8,1:5],method="color",addCoef.col = "black")[2,]
  return(rbind(pc50,D50,diff50))
}
```

Multiplot calls

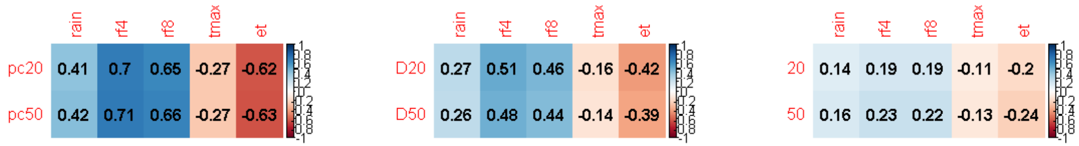
```r
#setting up files
#All seasons and each season - all years and lu
all_seasons_plot <- multicorrplots(all_seasons)
```



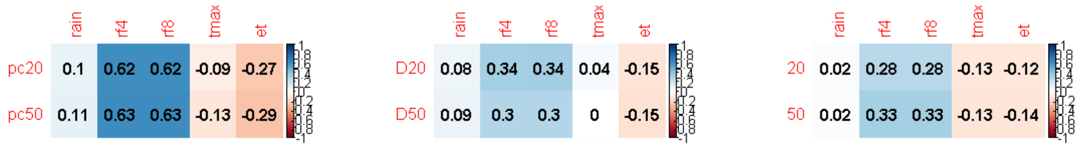

```
summer_plot <- multicorrplots(summer)
```



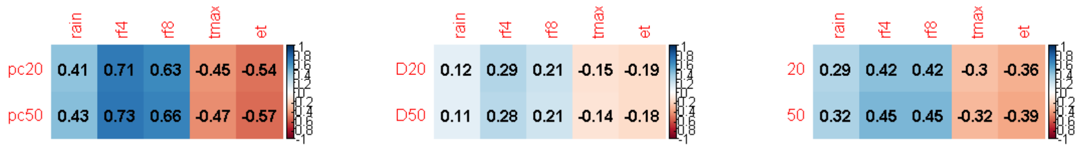

```
autumn_plot <- multicorrplots(autumn)
```



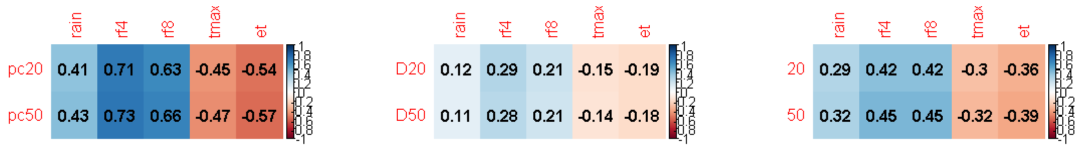

```
winter_plot <- multicorrplots(winter)
```




```
spring_plot <- multicorrplots(spring)
```




```
# Spring only different lu
spring_glu4_plot <- multicorrplots(spring)
```

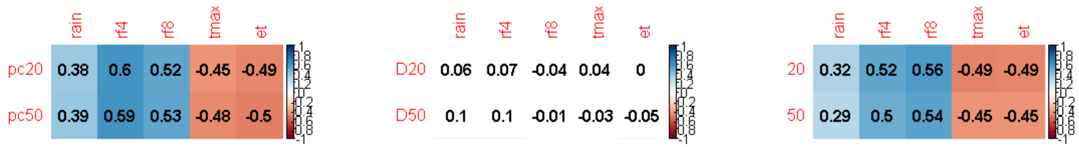


```
spring_og_plot <- multicorrplots(subset(spring,subset=lu %in% "og"))
```

```
spring_st_plot <- multicorrplots(subset(spring,subset=lu %in% "st"))
```

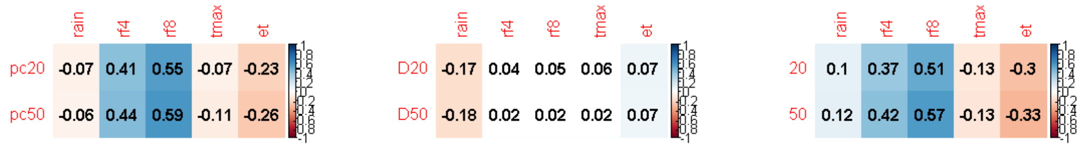
```
spring_tg_plot <- multicorrplots(subset(spring,subset=lu %in% "tg"))
```

```
spring_fo_plot <- multicorrplots(subset(spring,subset=lu %in% "fo"))
```

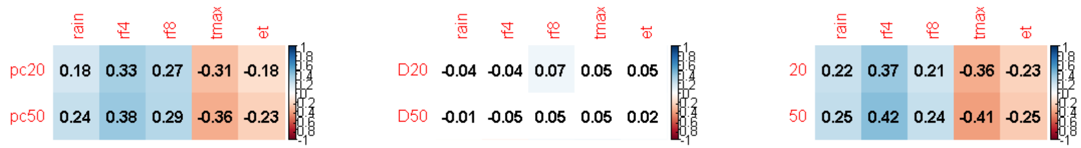


```
# Spring only - all lu (glu4) different season rating (years)
# from previous spring_glu4_plot - spring glu4 all years
spring_glu4_wet_plot <- multicorrplots(subset(spring,subset=sr %in% "wet"))
```

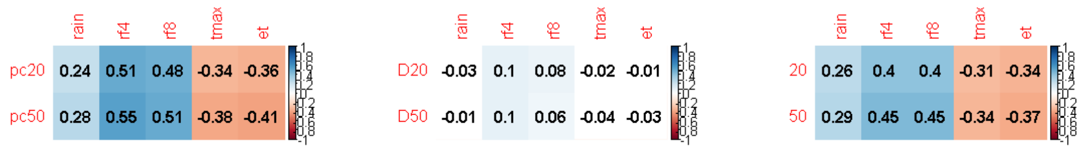

```
spring_glu4_norm_plot <- multicorrplots(subset(spring,subset=sr %in% "normal"))
```



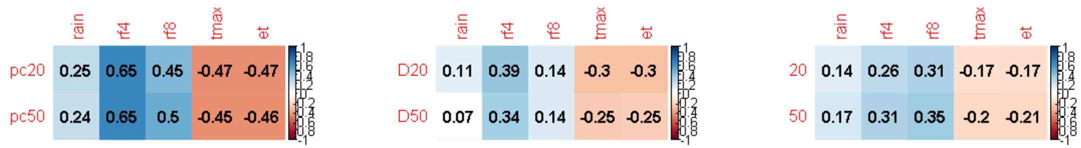

```
spring_glu4_dry_plot <- multicorrplots(subset(spring,subset=sr %in% "dry"))
```




```
spring_glu4_nonwet_plot <- multicorrplots(subset(spring,subset=sr %ni% "wet"))
```

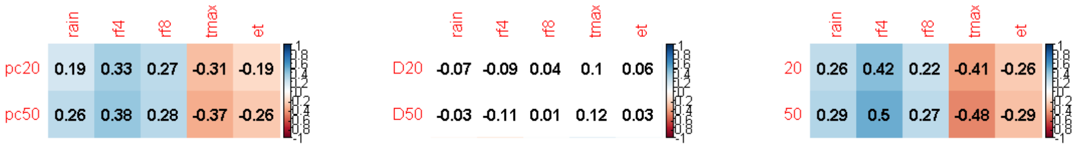



```
# Spring og only different season rating (years)
# from previous spring_og - spring og all years
spring_og_wet_plot <- multicorrplots(subset(spring_og,subset=sr %in% "wet"))
```

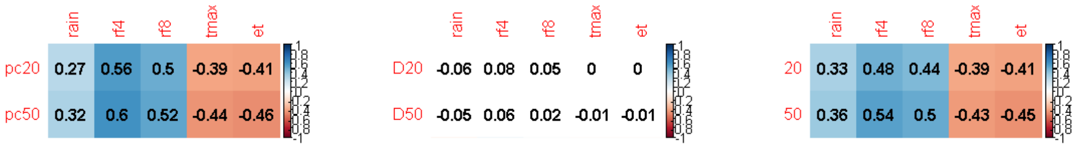



```
spring_og_norm_plot <- multicorrplots(subset(spring_og,subset=sr %in% "normal"))
```


```
spring_og_dry_plot <- multicorrplots(subset(spring_og,subset=sr %in% "dry"))
```

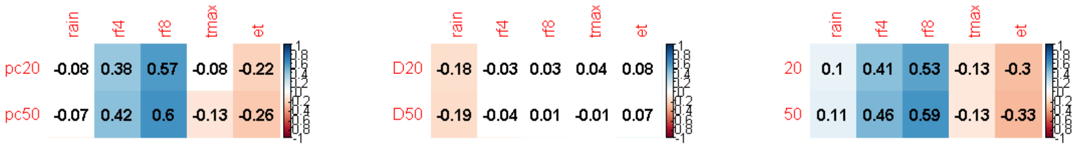



```
spring_og_nonwet_plot <- multicorrplots(subset(spring_og,subset=sr %ni% "wet"))
```

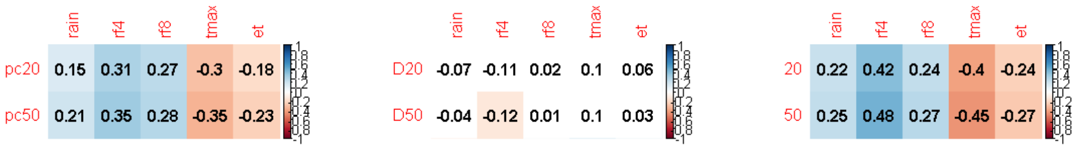



```
# Spring fo only different season rating (years)
# from previous spring_st - spring st all years
spring_st_wet_plot <- multicorrplots(subset(spring_st,subset=sr %in% "wet"))
```


```
spring_st_norm_plot <- multicorrplots(subset(spring_st,subset=sr %in% "normal"))
```




```
spring_st_dry_plot <- multicorrplots(subset(spring_st,subset=sr %in% "dry"))
```



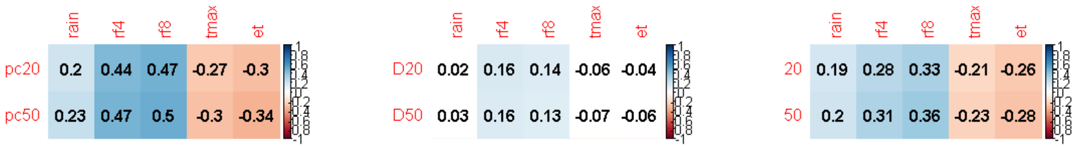

```
spring_st_nonwet_plot <- multicorrplots(subset(spring_st,subset=sr %ni% "wet"))
```


```
# Spring tg only different season rating (years)
# from previous spring_tg - spring tg all years
spring_tg_wet_plot <- multicorrplots(subset(spring_tg,subset=sr %in% "wet"))
```

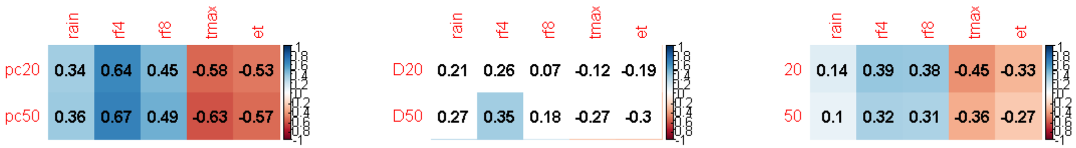

```
spring_tg_norm_plot <- multicorrplots(subset(spring_tg,subset=sr %in% "normal"))
```


```
spring_tg_dry_plot <- multicorrplots(subset(spring_tg,subset=sr %in% "dry"))
```

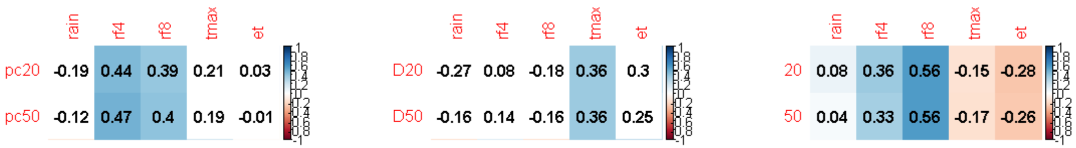

```
spring_tg_nonwet_plot <- multicorrplots(subset(spring_tg,subset=sr %ni% "wet"))
```



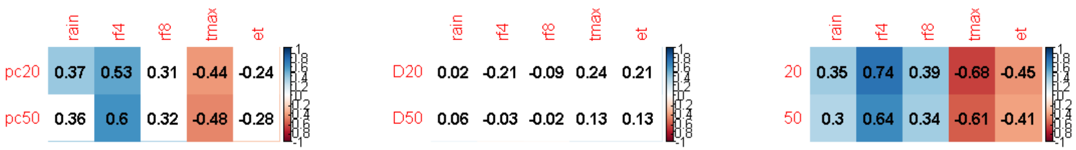

```
# Spring fo only different season rating (years)
# from previous spring_fo - spring fo all years
spring_fo_wet_plot <- multicorrplots(subset(spring_fo,subset=sr %in% "wet"))
```



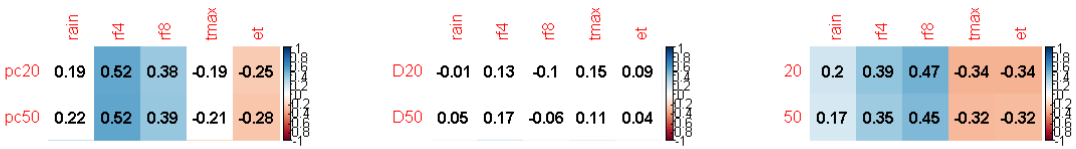

```
spring_fo_norm_plot <- multicorrplots(subset(spring_fo,subset=sr %in% "normal"))
```




```
spring_fo_dry_plot <- multicorrplots(subset(spring_fo,subset=sr %in% "dry"))
```




```
spring_fo_nonwet_plot <- multicorrplots(subset(spring_fo,subset=sr %ni% "wet"))
```




```
col_names <- colnames(all_seasons_plot)
row_names <- rownames(all_seasons_plot)
```

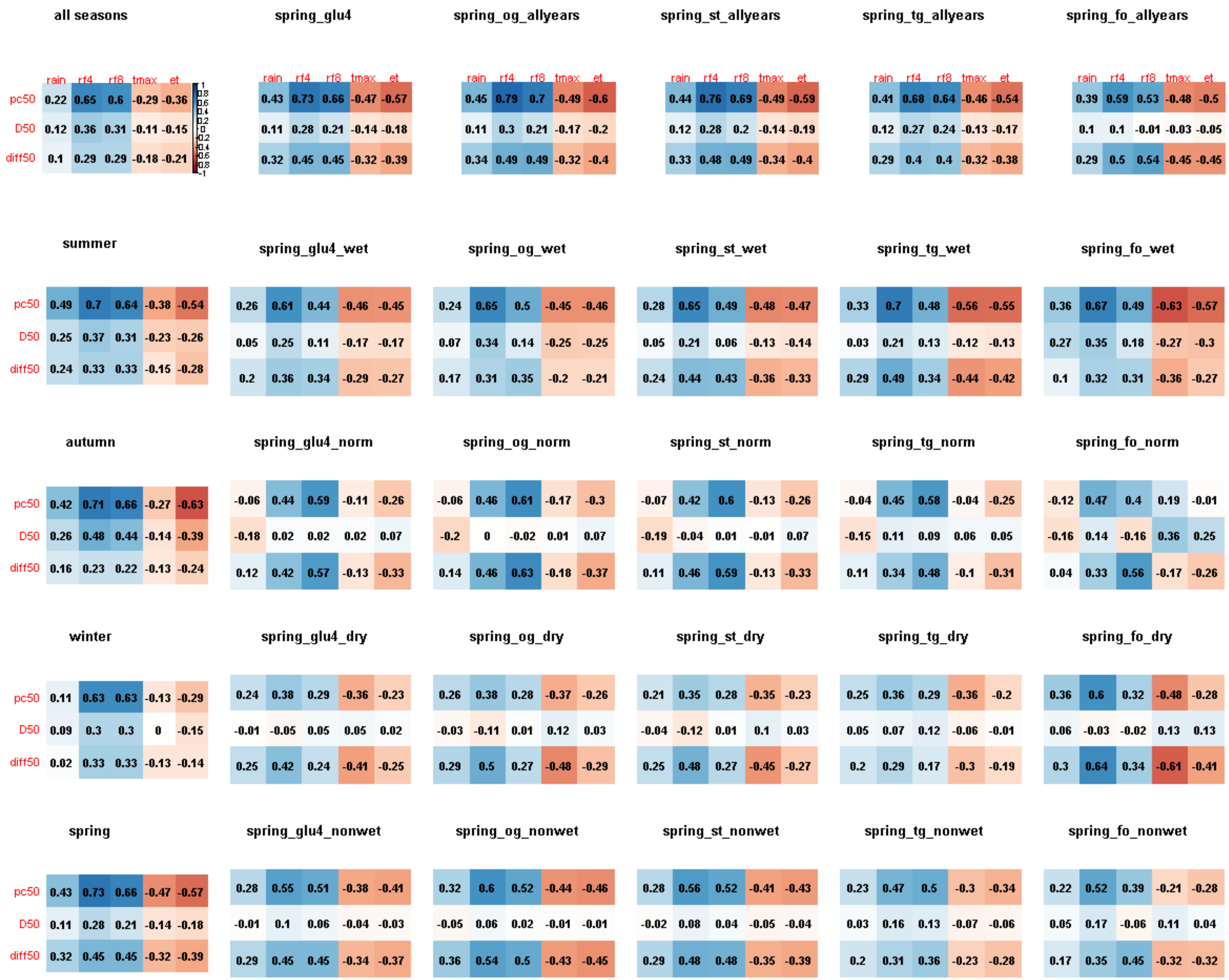
```
#clear plots up to this point
#graphics.off()
```

Plot matrix of plots for comparitive analysis

```
#par(mfrow=c(5,2))
##par(mfcol=c(5,6))
layout.matrix <- matrix(c(1:30),nrow=5,ncol=6)
layout(layout.matrix,widths=c(1.2,1,1,1,1,1),heights=c(1.2,1,1,1,1,1))
#layout.show(30)
#for testing individual plots
#par(mfcol=c(1,1))

#All seasons and each season - all years and lu
corrplot(all_seasons_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="all seasons",mar=c(0,0,1,
0))
colnames(summer_plot) <- rep("",NCOL(summer_plot)) # hack to remove column labels
corrplot(summer_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="summer",cl.pos="n",mar=c(0,0,0
.2,0))
colnames(autumn_plot) <- rep("",NCOL(autumn_plot)) # hack to remove column labels
corrplot(autumn_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="autumn",cl.pos="n",mar=c(0,0,1
,0))
colnames(winter_plot) <- rep("",NCOL(winter_plot)) # hack to remove column labels
corrplot(winter_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="winter",cl.pos="n",mar=c(0,0,1
,0))
colnames(spring_plot) <- rep("",NCOL(spring_plot)) # hack to remove column labels
corrplot(spring_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring",cl.pos="n",mar=c(0,0,1
,0))

# Spring only all lu different sr
rownames(spring_glu4_plot) <- rep("",NROW(spring_glu4_plot)) # hack to remove row labels
corrplot(spring_glu4_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_glu4",cl.pos="n",m
ar=c(0,0,1,0))
corrplot(spring_glu4_wet_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_glu4_wet",tl.p
os="n",cl.pos= "n",mar=c(0,0,1,0))
corrplot(spring_glu4_norm_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_glu4_norm",tl
.pos="n",cl.pos="n",mar=c(0,0,1,0))
corrplot(spring_glu4_dry_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_glu4_dry",tl.p
```

```
os="n",cl.pos="n",mar=c(0,0,1,0))
corrplot(spring_glu4_nonwet_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_glu4_nonwet
",tl.pos="n",cl.pos="n",mar=c(0,0,1,0))

# Spring og only different season rating (years)
rownames(spring_og_plot) <- rep("",NROW(spring_og_plot)) # hack to remove row labels
corrplot(spring_og_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_og_allyears",cl.pos=
"n",mar=c(0,0,1,0))
corrplot(spring_og_wet_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_og_wet",tl.pos="
n",cl.pos="n",mar=c(0,0,1,0))
corrplot(spring_og_norm_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_og_norm",tl.pos
="n",cl.pos="n",mar=c(0,0,1,0))
corrplot(spring_og_dry_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_og_dry",tl.pos="
n",cl.pos="n",mar=c(0,0,1,0))
corrplot(spring_og_nonwet_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_og_nonwet",tl
.pos="n",cl.pos="n",mar=c(0,0,1,0))

# Spring st only different season rating (years)
rownames(spring_st_plot) <- rep("",NROW(spring_st_plot)) # hack to remove row labels
corrplot(spring_st_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_st_allyears",cl.pos=
"n",mar=c(0,0,1,0))
corrplot(spring_st_wet_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_st_wet",tl.pos="
n",cl.pos="n",mar=c(0,0,1,0))
corrplot(spring_st_norm_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_st_norm",tl.pos
="n",cl.pos="n",mar=c(0,0,1,0))
corrplot(spring_st_dry_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_st_dry",tl.pos="
n",cl.pos="n",mar=c(0,0,1,0))
corrplot(spring_st_nonwet_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_st_nonwet",tl
.pos="n",cl.pos="n",mar=c(0,0,1,0))

# Spring tg only different season rating (years)
rownames(spring_tg_plot) <- rep("",NROW(spring_tg_plot)) # hack to remove row labels
corrplot(spring_tg_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_tg_allyears",cl.pos=
"n",mar=c(0,0,1,0))
corrplot(spring_tg_wet_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_tg_wet",tl.pos="
n",cl.pos="n",mar=c(0,0,1,0))
corrplot(spring_tg_norm_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_tg_norm",tl.pos
="n",cl.pos="n",mar=c(0,0,1,0))
```

```r
corrplot(spring_tg_dry_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_tg_dry",tl.pos="
n",cl.pos="n",mar=c(0,0,1,0))
corrplot(spring_tg_nonwet_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_tg_nonwet",tl
.pos="n",cl.pos="n",mar=c(0,0,1,0))

# Spring fo only different season rating (years)
rownames(spring_fo_plot) <- rep("",NROW(spring_fo_plot)) # hack to remove row labels
corrplot(spring_fo_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_fo_allyears",cl.pos=
"n",mar=c(0,0,1,0))
corrplot(spring_fo_wet_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_fo_wet",tl.pos="
n",cl.pos="n",mar=c(0,0,1,0))
corrplot(spring_fo_norm_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_fo_norm",tl.pos
="n",cl.pos="n",mar=c(0,0,1,0))
corrplot(spring_fo_dry_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_fo_dry",tl.pos="
n",cl.pos="n",mar=c(0,0,1,0))
corrplot(spring_fo_nonwet_plot,method="color", addCoef.col = "black",tl.srt=0,tl.offset=0.5,title="spring_fo_nonwet",tl
.pos="n",cl.pos="n",mar=c(0,0,1,0))
```


all seasons
rain rf4 rf8 tmax et
pc50 0.22 0.65 0.6 -0.29 -0.36
D50 0.12 0.36 0.31 -0.11 -0.15
diff50 0.1 0.29 0.29 -0.18 -0.21
1 0.8 0.6 0.4 0.2 0 -0.2 -0.4 -0.6 -0.8 -1
spring_glu4
rain rf4 rf8 tmax et
0.43 0.73 0.66 -0.47 -0.57
0.11 0.28 0.21 -0.14 -0.18
0.32 0.45 0.45 -0.32 -0.39
spring_og_allyears
rain rf4 rf8 tmax et
0.45 0.79 0.7 -0.49 -0.6
0.11 0.3 0.21 -0.17 -0.2
0.34 0.49 0.49 -0.32 -0.4
spring_st_allyears
rain rf4 rf8 tmax et
0.44 0.76 0.69 -0.49 -0.59
0.12 0.28 0.2 -0.14 -0.19
0.33 0.48 0.49 -0.34 -0.4
spring_tg_allyears
rain rf4 rf8 tmax et
0.41 0.68 0.64 -0.46 -0.54
0.12 0.27 0.24 -0.13 -0.17
0.29 0.4 0.4 -0.32 -0.38
spring_fo_allyears
rain rf4 rf8 tmax et
0.39 0.59 0.53 -0.48 -0.5
0.1 0.1 -0.01 -0.03 -0.05
0.29 0.5 0.54 -0.45 -0.45
summer
pc50 0.49 0.7 0.64 -0.38 -0.54
D50 0.25 0.37 0.31 -0.23 -0.26
diff50 0.24 0.33 0.33 -0.15 -0.28
spring_glu4_wet
0.26 0.61 0.44 -0.46 -0.45
0.05 0.25 0.11 -0.17 -0.17
0.2 0.36 0.34 -0.29 -0.27
spring_og_wet
0.24 0.65 0.5 -0.45 -0.46
0.07 0.34 0.14 -0.25 -0.25
0.17 0.31 0.35 -0.2 -0.21
spring_st_wet
0.28 0.65 0.49 -0.48 -0.47
0.05 0.21 0.06 -0.13 -0.14
0.24 0.44 0.43 -0.36 -0.33
spring_tg_wet
0.33 0.7 0.48 -0.56 -0.55
0.03 0.21 0.13 -0.12 -0.13
0.29 0.49 0.34 -0.44 -0.42
spring_fo_wet
0.36 0.67 0.49 -0.63 -0.57
0.27 0.35 0.18 -0.27 -0.3
0.1 0.32 0.31 -0.36 -0.27
autumn
pc50 0.42 0.71 0.66 -0.27 -0.63
D50 0.26 0.48 0.44 -0.14 -0.39
diff50 0.16 0.23 0.22 -0.13 -0.24
spring_glu4_norm
-0.06 0.44 0.59 -0.11 -0.26
-0.18 0.02 0.02 0.02 0.07
0.12 0.42 0.57 -0.13 -0.33
spring_og_norm
-0.06 0.46 0.61 -0.17 -0.3
-0.2 0 -0.02 0.01 0.07
0.14 0.46 0.63 -0.18 -0.37
spring_st_norm
-0.07 0.42 0.6 -0.13 -0.26
-0.19 -0.04 0.01 -0.01 0.07
0.11 0.46 0.59 -0.13 -0.33
spring_tg_norm
-0.04 0.45 0.58 -0.04 -0.25
-0.15 0.11 0.09 0.06 0.05
0.11 0.34 0.48 -0.1 -0.31
spring_fo_norm
-0.12 0.47 0.4 0.19 -0.01
-0.16 0.14 -0.16 0.36 0.25
0.04 0.33 0.56 -0.17 -0.26
winter
pc50 0.11 0.63 0.63 -0.13 -0.29
D50 0.09 0.3 0.3 0 -0.15
diff50 0.02 0.33 0.33 -0.13 -0.14
spring_glu4_dry
0.24 0.38 0.29 -0.36 -0.23
-0.01 -0.05 0.05 0.05 0.02
0.25 0.42 0.24 -0.41 -0.25
spring_og_dry
0.26 0.38 0.28 -0.37 -0.26
-0.03 -0.11 0.01 0.12 0.03
0.29 0.5 0.27 -0.48 -0.29
spring_st_dry
0.21 0.35 0.28 -0.35 -0.23
-0.04 -0.12 0.01 0.1 0.03
0.25 0.48 0.27 -0.45 -0.27
spring_tg_dry
0.25 0.36 0.29 -0.36 -0.2
0.05 0.07 0.12 -0.06 -0.01
0.2 0.29 0.17 -0.3 -0.19
spring_fo_dry
0.36 0.6 0.32 -0.48 -0.28
0.06 -0.03 -0.02 0.13 0.13
0.3 0.64 0.34 -0.61 -0.41
spring
pc50 0.43 0.73 0.66 -0.47 -0.57
D50 0.11 0.28 0.21 -0.14 -0.18
diff50 0.32 0.45 0.45 -0.32 -0.39
spring_glu4_nonwet
0.28 0.55 0.51 -0.38 -0.41
-0.01 0.1 0.06 -0.04 -0.03
0.29 0.45 0.45 -0.34 -0.37
spring_og_nonwet
0.32 0.6 0.52 -0.44 -0.46
-0.05 0.06 0.02 -0.01 -0.01
0.36 0.54 0.5 -0.43 -0.45
spring_st_nonwet
0.28 0.56 0.52 -0.41 -0.43
-0.02 0.08 0.04 -0.05 -0.04
0.29 0.48 0.48 -0.35 -0.39
spring_tg_nonwet
0.23 0.47 0.5 -0.3 -0.34
0.03 0.16 0.13 -0.07 -0.06
0.2 0.31 0.36 -0.23 -0.28
spring_fo_nonwet
0.22 0.52 0.39 -0.21 -0.28
0.05 0.17 -0.06 0.11 0.04
0.17 0.35 0.45 -0.32 -0.32

Compile Reference List

```r
citations <- function(includeURL = T, includeRStudio = F) {
    if(includeRStudio == TRUE) {
        ref.rstudio <- RStudio.Version()$citation
        #ref.rstudio <- rstudioapi::versionInfo()$citation
        if(includeURL == FALSE) {
            ref.rstudio$url = NULL;
        }
        print(ref.rstudio, style = 'text')
        cat('\n')
    }

    cit.list <- c('base', names(sessionInfo()$otherPkgs))
    for(i in 1:length(cit.list)) {
        ref <- citation(cit.list[i])
        if(includeURL == FALSE) {
            ref$url = NULL;
        }
        print(ref, style = 'text')
        cat('\n')
    }
}

#call function and tidy up code
prn <- capture.output(citations())
#tidy up output
prn1 <- sub("_", "",prn)
Rprint <- sub("_.", ".",prn1)
# add citation for function used to create citations and for RStudio
cit_func <- paste0("RStudio Team (2018). RStudio: Integrated Development Environment for R. RStudio, Inc., Boston, MA.
<URL: http://www.rstudio.com/.\n","\n","Reference list produced from adaptation of MS Berends' citations() function acc
essed from stackoverflow <URL: https://stackoverflow.com/questions/15688758/r-stats-citation-for-a-scientific-paper")

# to print references without showing script call in knitted Word file use:
# ```{r message=FALSE, warnings=FALSE, echo=FALSE comment=NA, results='hold'}
# cat(Rprint,sep="\n")
# cat(cit_func,sep="\n")
# ```
```

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Reference list produced from adaptation of MS Berends' citations() function accessed from stackoverflow <URL: https://stackoverflow.com/questions/15688758/r-stats-citation-for-a-scientific-paper

End of Script

060_Groundcover scores time series and trend analyses

Developed and run by Paul Webb, 2019.

Script to analyse adapted Dynamic Reference Cover Method (aDNRM) scores from supported and control/reference areas to identify and compare groundcover scores and associate trends with reference to climate data

Inputs: adrcm.txt groundcover/seasonal climate data together with groudcover scores D?? from aDRCMethod adrcm_types.txt column data types for previous data

Outputs: Graphics and tables for method explanations and parameters for catchment model inputs calculations

Library calls and Operating environment settings

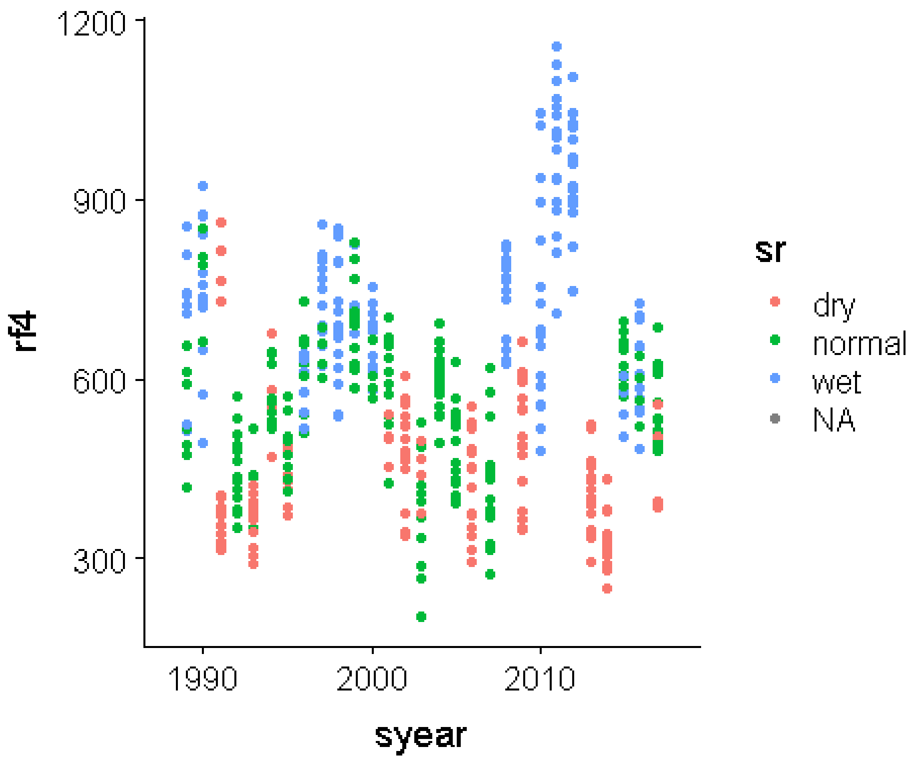
```
#' library calls and directory labelling---
library(reshape2)
library(ggplot2)
library(tidyr)

* Warning: package 'tidyr' was built under R version 3.5.3

library(dplyr)
library(intrval)
library(cowplot)

* Warning: package 'cowplot' was built under R version 3.5.3

library(rcompanion)

* Warning: package 'rcompanion' was built under R version 3.5.3

library(rstudioapi)

* Warning: package 'rstudioapi' was built under R version 3.5.3

library(basicTrendline)

* Warning: package 'basicTrendline' was built under R version 3.5.3

library(knitr)

#check workdirectory datdir (Inputs) directory
datadir <- paste0(getwd(),"/Inputs")

# A colorblind-friendly palette with grey from
# http://www.cookbook-r.com/Graphs/Colors_(ggplot2)/#a-colorblind-friendly
-palette
cbp <- c("#999999", "#E69F00", "#56B4E9",
               "#009E73", "#F0E442", "#0072B2", "#D55E00", "#CC79A7")
#cbp clues (from plotrix::color.id)
#       (grey60, orange2, steelblue2,
#               darkcyan, goldenrod1, dodgerblue3, darkorange, pink3)

# knitr::opts_chunk$set(echo = TRUE)

#Sart date/time:
#startt <- Sys.time()
#dt <- format(startt, format = "_%b_%d_%Y")
```

```
print(paste("Work Directory:",getwd()))
print(paste("Data Input directory:",datadir))
print("Memory limit set to:")
memory.limit(size=32584)

* [1] "Work Directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCresearchP
roject/PostConfirmationDocs/Thesis/RScripts/060_Groundcover scores time se
ries and trend analyses"
* [1] "Data Input directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCres
earchProject/PostConfirmationDocs/Thesis/RScripts/060_Groundcover scores t
ime series and trend analyses/Inputs"
* [1] "Memory limit set to:"
* [1] 32584
```

Load aDRCM groundcover scores and climate data

Import groundcover scores and climate data

```
# Import data and assign colClasses to maintain integrity
col_types <- read.table(file=paste0(datadir,"/adrcm_types.txt"), header=F
, sep=" ")
char.types <- as.character(unlist(col_types$V1))
adrcm <- NULL
adrcm <- read.table(file=paste0(datadir,"/adrcm.txt"),sep=",", header=TRUE
,colClasses = char.types)
head(adrcm)

# check sr ratings sensible
ggplot(data=adrcm,aes(x=syear, y=rf4,color=sr,fill=sr))+
  geom_point(data=adrcm,aes(x=syear, y=rf4,color=sr,fill=sr))

* Warning: Removed 1332 rows containing missing values (geom_point).
```




```
*                          scilapp_yrsn       ci syear season sn_no yr_seaso
n
```

```
* 1 um_18_BBS10_fo_con_000_000_1988_2 18_BBS10  1988 autumn     2    1988_
2
* 2 um_18_BBS10_fo_con_000_000_1988_3 18_BBS10  1988 winter     3    1988_
3
* 3 um_18_BBS10_fo_con_000_000_1988_4 18_BBS10  1988 spring     4    1988_
4
* 4 um_18_BBS10_fo_con_000_000_1989_1 18_BBS10  1989 summer     1    1989_
1
* 5 um_18_BBS10_fo_con_000_000_1989_2 18_BBS10  1989 autumn     2    1989_
2
* 6 um_18_BBS10_fo_con_000_000_1989_3 18_BBS10  1989 winter     3    1989_
3
*   st cl    ib lu  ac  pr  pk pc5 pc20 pc50 pc95 pc80   rain tmax  tmin
* 1 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 127.55 35.0  0.50
* 2 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  96.35 29.0 -5.00
* 3 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  55.25 38.0  1.50
* 4 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 234.45 37.0 12.50
* 5 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 339.05 35.0  5.50
* 6 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  80.70 28.5 -3.75
*    tmean     et  sr  sr2yr rainmax rainmin ref95 D95 D80 D50 D20 D5    r
f4
* 1 17.625 319.35 dry normal   200.7    73.4    NA  NA  NA  NA  NA NA
NA
* 2 12.000 233.50 dry normal   171.8    75.9    NA  NA  NA  NA  NA NA
NA
* 3 19.500 526.25 dry normal    74.2     7.9    NA  NA  NA  NA  NA NA
NA
* 4 25.000 525.15 wet normal   413.4   194.3    NA  NA  NA  NA  NA NA 513.
60
* 5 20.250 295.00 wet normal   499.2   231.4    NA  NA  NA  NA  NA NA 725.
10
* 6 12.250 213.60 wet normal   127.2    55.7    NA  NA  NA  NA  NA NA 709.
45
*   rf8                 qbum_scilapp       Ha
* 1  NA um_18_BBS10_fo_con_000_000 47255.91
* 2  NA um_18_BBS10_fo_con_000_000 47255.91
* 3  NA um_18_BBS10_fo_con_000_000 47255.91
* 4  NA um_18_BBS10_fo_con_000_000 47255.91
* 5  NA um_18_BBS10_fo_con_000_000 47255.91
* 6  NA um_18_BBS10_fo_con_000_000 47255.91

data <- adrcm
data$lu <- ordered(data$lu, levels=c("og","st","tg","fo","net"))
data$ac <- ordered(data$ac, levels=c("scp","prb","ref","con"))

#create column with control D50 value from ci/lu/yr_season lookup
data$lookup <- paste0(data$ci,"_",data$lu,"_",data$yr_season)
control_data <- data[data$ac=="con",]
data$D50con <- control_data$D50[match(data$lookup,control_data$lookup)]

# remove rows with NA
data <- data %>% drop_na(D50,Ha)
# view data
head(data)

*                          scilapp_yrsn       ci syear season sn_no yr_seas
on
* 9  um_18_BBS10_fo_con_000_000_1990_2 18_BBS10  1990 autumn     2    1990
_2
* 10 um_18_BBS10_fo_con_000_000_1990_3 18_BBS10  1990 winter     3    1990
```

```
_3
* 11 um_18_BBS10_fo_con_000_000_1990_4 18_BBS10  1990 spring     4    1990
_4
* 12 um_18_BBS10_fo_con_000_000_1991_1 18_BBS10  1991 summer     1    1991
_1
* 13 um_18_BBS10_fo_con_000_000_1991_2 18_BBS10  1991 autumn     2    1991
_2
* 14 um_18_BBS10_fo_con_000_000_1991_3 18_BBS10  1991 winter     3    1991
_3
*     st cl    ib lu  ac  pr  pk pc5 pc20 pc50 pc95 pc80   rain tmax tmin
* 9   um 18 BBS10 fo con 000 000  86   91   96  100   99 532.45 35.0  3.5
* 10  um 18 BBS10 fo con 000 000  80   86   92  100   97  31.50 25.5 -3.0
* 11  um 18 BBS10 fo con 000 000  72   77   82   91   86  58.85 40.0  1.0
* 12  um 18 BBS10 fo con 000 000  76   82   86   94   91 239.45 40.0 14.0
* 13  um 18 BBS10 fo con 000 000  80   85   90   97   94  74.25 36.0  3.5
* 14  um 18 BBS10 fo con 000 000  77   83   88   98   94   9.40 29.0 -3.0
*      tmean     et  sr  sr2yr rainmax rainmin ref95 D95 D80 D50 D20 D5
* 9   19.500 289.00 wet    wet   719.6   492.6   100 100  99  96  91 86
* 10  11.250 226.75 wet    wet    46.1    22.5   100 100  97  92  86 80
* 11  20.375 511.30 wet    wet   134.6    33.1    91 100  95  91  86 81
* 12  27.000 500.90 dry normal   315.8   160.9    95  99  96  91  87 81
* 13  19.750 397.75 dry normal   166.3    16.3    97 100  97  93  88 83
* 14  13.000 277.35 dry normal    29.1     0.3    98 100  96  90  85 79
*        rf4     rf8              qbum_scilapp       Ha             lookup
* 9   921.95 1647.05 um_18_BBS10_fo_con_000_000 47255.91 18_BBS10_fo_1990_2
* 10  872.75 1582.20 um_18_BBS10_fo_con_000_000 47255.91 18_BBS10_fo_1990_3
* 11  777.55 1585.80 um_18_BBS10_fo_con_000_000 47255.91 18_BBS10_fo_1990_4
* 12  862.25 1590.80 um_18_BBS10_fo_con_000_000 47255.91 18_BBS10_fo_1991_1
* 13  404.05 1326.00 um_18_BBS10_fo_con_000_000 47255.91 18_BBS10_fo_1991_2
* 14  381.95 1254.70 um_18_BBS10_fo_con_000_000 47255.91 18_BBS10_fo_1991_3
*     D50con
* 9       96
* 10      92
* 11      91
* 12      91
* 13      93
* 14      90
```

Create catch(ment) dataset

including scp and con for spring all lu all years

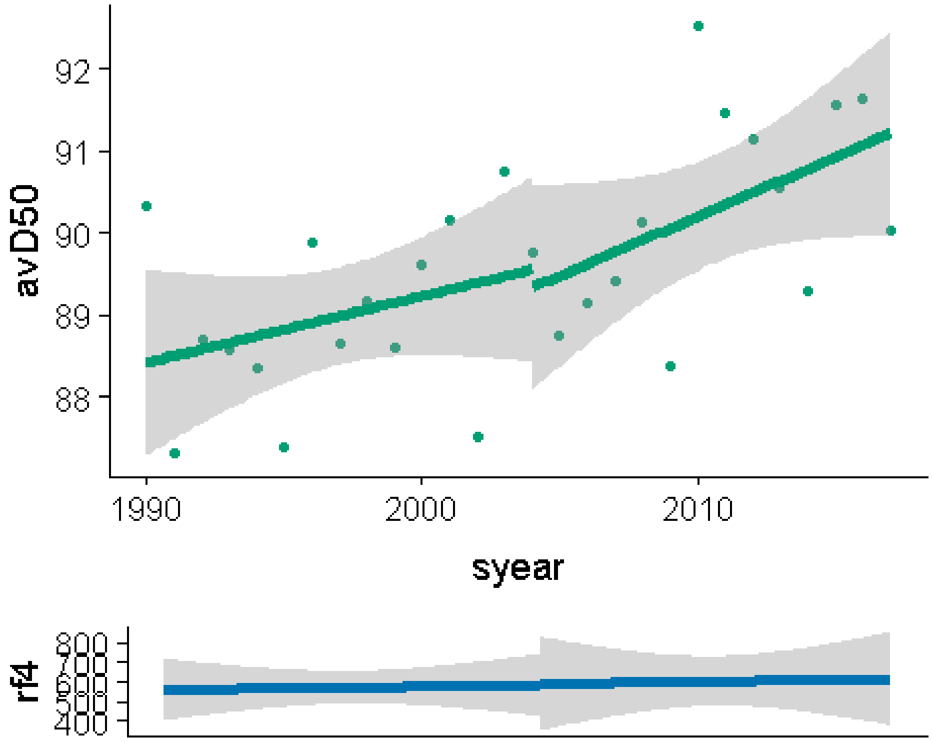
```
catch <- data[data$ac %in% c("scp","con"),]
spr_catch <- catch[catch$sn_no==4,]

#combine all lu and years for spring to show catchment trends
spr_catch_av <- spr_catch %>%
  group_by(syear) %>%
  mutate(avD50 = weighted.mean(D50, Ha),
         avrf4 = weighted.mean(rf4, Ha),
         avpc50 = weighted.mean(pc50, Ha),
         avref95 = weighted.mean(ref95, Ha)
         )
# data has avD50 and avrf4 on each line with values identical for same sye
ar
# now to tidy up so only one line per ci_lu with avD50 and rf4

out=v0=v1=v2=v3=NULL
v0 <- aggregate( avrf4 ~ syear, data = spr_catch_av, mean)
```

```
v1 <- aggregate( avD50 ~ syear, data = spr_catch_av, mean)
v2 <- aggregate( avpc50 ~ syear, data = spr_catch_av, mean)
v3 <- aggregate( avref95 ~ syear, data = spr_catch_av, mean)
#out <- merge(v0,v1,v2,v3, by=c("syear"))
out <- Reduce(merge, list(v0,v1,v2,v3))
out$avD50 <- round(out$avD50,2)
out$avrf4 <- round(out$avrf4,0)
out$avpc50 <- round(out$avpc50,0)
out$avref95 <- round(out$avref95,0)
# delete columns of now dubious data (due to non Ha weighted averaging)

# replace file with tidied up data
spr_catch_av <- out

# set syear as numeric year value
#spr_catch_av$syear <- as.numeric(format(base::as.Date(as.character(spr_ca
tch_av$syear),format="%Y"),"%Y"))

#cleanup
rm(v0,v1,v2,v3,out)
# view data
head(spr_catch_av)

quants <- c(0,0.05,0.20,0.50,0.80,0.95,1)
apply( spr_catch_av[2:5] , 2 , quantile , probs = quants , na.rm = TRUE )

*    syear  avrf4  avD50  avpc50  avref95
* 1   1990    743  90.32      81       91
* 2   1991    353  87.30      75       88
* 3   1992    502  88.69      74       85
* 4   1993    460  88.56      76       88
* 5   1994    505  88.35      77       89
* 6   1995    463  87.38      77       90
*        avrf4    avD50  avpc50  avref95
* 0%    338.00 87.3000  71.00     82.0
* 5%    356.50 87.4255  73.35     85.0
* 20%   406.00 88.5760  75.00     86.0
* 50%   569.50 89.5150  79.50     89.0
* 80%   739.80 90.6700  83.20     92.6
* 95%   894.85 91.6055  86.65     96.0
* 100%  940.00 92.5200  92.00     99.0
```

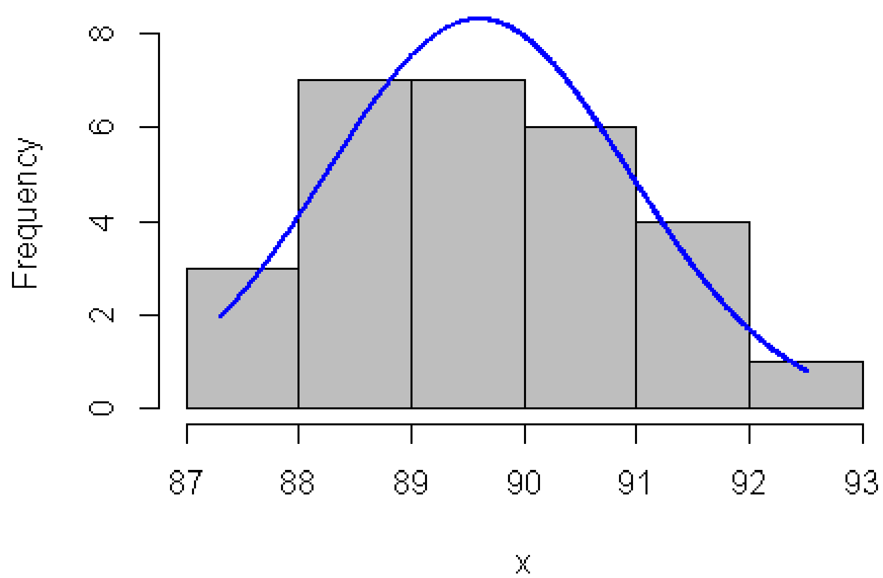
Plot data

```
plot_data <- spr_catch_av

gcs_trend <- ggplot(plot_data,aes(x=syear, y=avD50)) +
  geom_point(data=plot_data,aes(x=syear, y=avD50), color="#009E73") +
  geom_smooth(data=plot_data[plot_data$syear<2005,], aes(x=syear, y=avD50)
, color="#009E73", method="lm",size = 2) +
  geom_smooth(data=plot_data[plot_data$syear>2003,], aes(x=syear, y=avD50)
, color="#009E73", method="lm",size = 2)

rf4 <- ggplot(plot_data,aes(x=syear, y=rf4)) +
  geom_smooth(data=plot_data[plot_data$syear<2005,], aes(x=syear, y=avrf4)
, color="#0072B2", method="lm",size = 2) +
  geom_smooth(data=plot_data[plot_data$syear>2003,], aes(x=syear, y=avrf4)
, color="#0072B2", method="lm",size = 2) +

  theme(plot.title=element_text(plot_data),
```

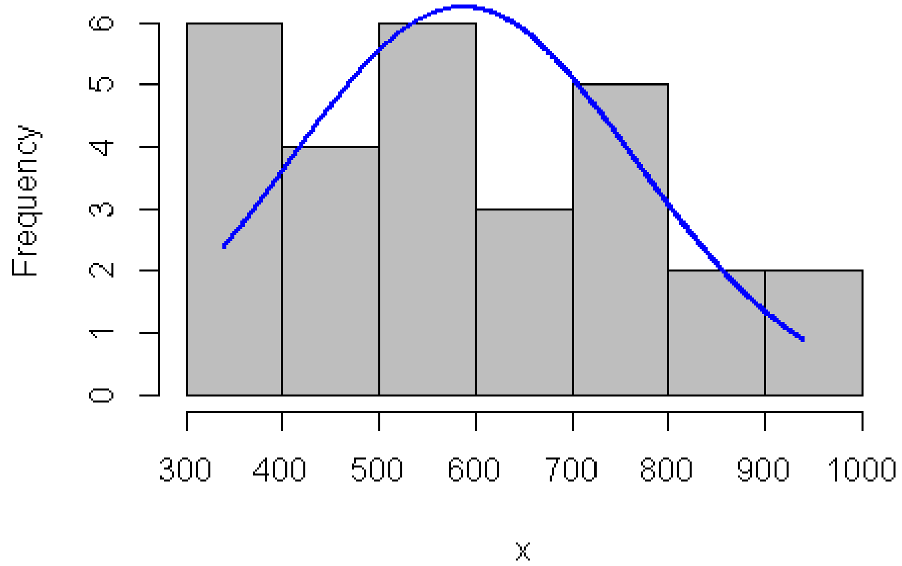
```
        axis.title.x=element_blank(),
        axis.text.x=element_blank(),
        axis.ticks.x=element_blank())

plot_grid(gcs_trend,rf4,nrow=2,rel_heights=c(4,1))
```




```
plotNormalHistogram(spr_catch_av$avD50)
```



```r
plotNormalHistogram(spr_catch_av$avrf4)
```

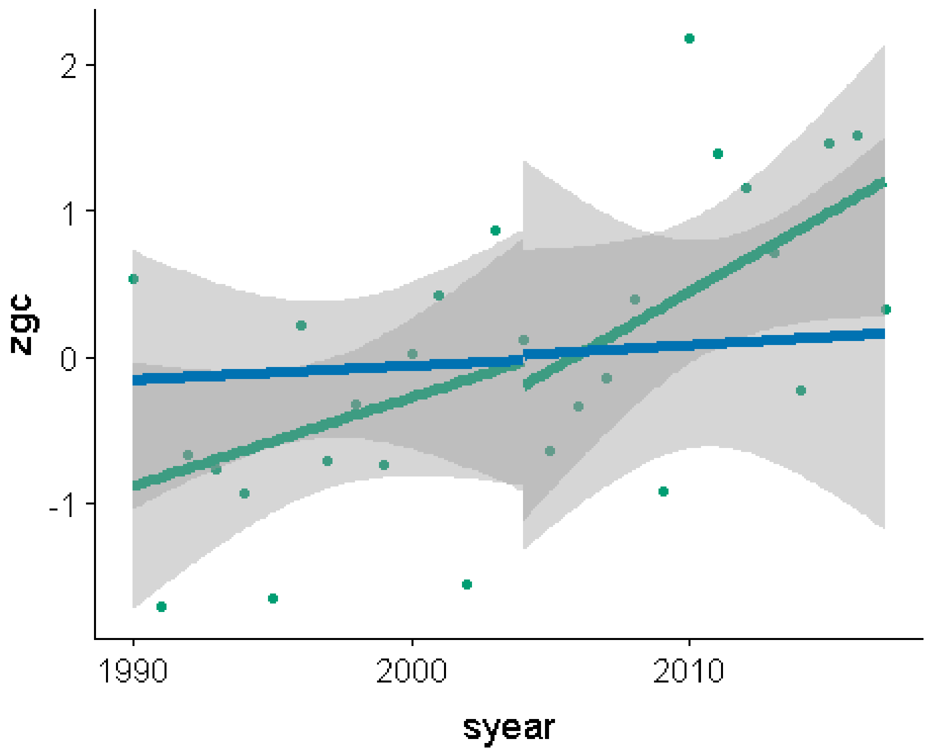



```r
shapiro.test(spr_catch_av$avD50)

##
##  Shapiro-Wilk normality test
##
## data:  spr_catch_av$avD50
## W = 0.97693, p-value = 0.7716

shapiro.test(spr_catch_av$avrf4)

##
##  Shapiro-Wilk normality test
##
## data:  spr_catch_av$avrf4
## W = 0.94624, p-value = 0.1592

# Note: Shapiro-Wilk test Null hypothesis is
# that the data approximates normal distribution
# Null hypothesis rejected if p-value is less than 0.05
# ref Royston 1995

# for catchment modelling ground cover adjustments spr_catch data adopted.
# requires standardisation to adjust for residual climate signal
# to determine slope attributable to grazing land management in LC and NRM
periods
```

Create and Plot standardized data then compute delta slopes and reverse standardisation

```r
# Standardize avD50 and avrf4 data
z_spr <- spr_catch_av
z_spr$zgc <- (z_spr$avD50 - mean(z_spr$avD50)) / sd(z_spr$avD50)
```

```
z_spr$zrf <- (z_spr$avrf4 - mean(z_spr$avrf4)) / sd(z_spr$avrf4)

# plot standardized data split at 2004
catch_ztrend <- ggplot(z_spr,aes(x=syear, y=zgc)) +
  geom_point(data=z_spr,aes(x=syear, y=zgc), color="#009E73") +

  geom_smooth(data=z_spr[z_spr$syear<2005,], aes(x=syear, y=zgc), color="#
009E73", method="lm",size = 2) +
  geom_smooth(data=z_spr[z_spr$syear>2003,], aes(x=syear, y=zgc), color="#
009E73", method="lm",size = 2) +

  geom_smooth(data=z_spr[z_spr$syear<2005,], aes(x=syear, y=zrf), color="#
0072B2", method="lm",size = 2) +
  geom_smooth(data=z_spr[z_spr$syear>2003,], aes(x=syear, y=zrf), color="#
0072B2", method="lm",size = 2)

catch_ztrend
```




```
# split into lc and nrm periods
z_spr_lc <- z_spr[z_spr$syear<2005,]
z_spr_nrm <- z_spr[z_spr$syear>2003,]

#' calculate slopes of z data and
#' difference between zgc and zrf slopes
#' as net slope z value then *sd for net gc score slope

options(digits=2)

coef(lm(z_spr_lc$zgc~z_spr_lc$syear))[2]

## z_spr_lc$syear
##           0.06

coef(lm(z_spr_lc$zrf~z_spr_lc$syear))[2]
```

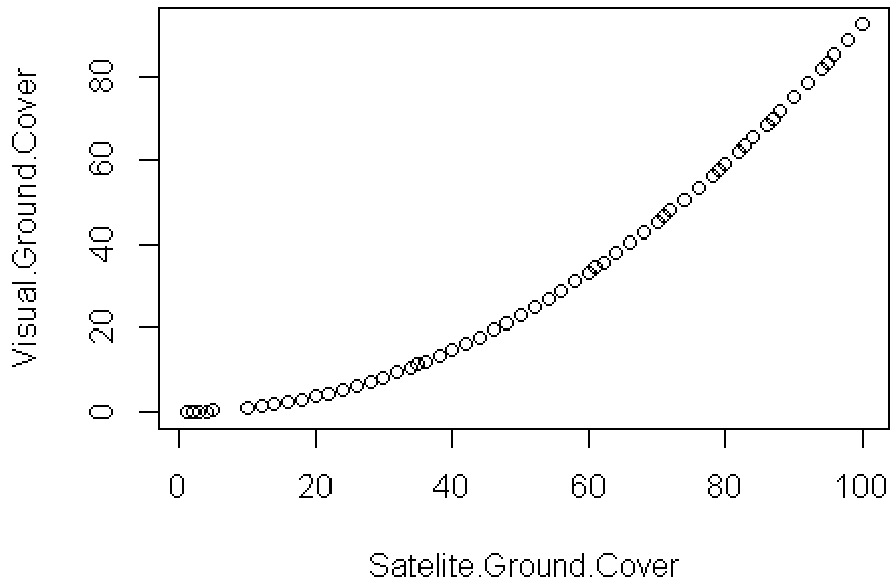
```
## z_spr_lc$syear
##         0.0094

coef(lm(z_spr_nrm$zgc~z_spr_nrm$syear))[2]

## z_spr_nrm$syear
##            0.11

coef(lm(z_spr_nrm$zrf~z_spr_nrm$syear))[2]

## z_spr_nrm$syear
##           0.011

DeltaGC_z_corr_lc <- (coef(lm(z_spr_lc$zgc~z_spr_lc$syear))[2]-coef(lm(z_s
pr_lc$zrf~z_spr_lc$syear))[2])
DeltaGC_z_corr_nrm <- (coef(lm(z_spr_nrm$zgc~z_spr_nrm$syear))[2]-coef(lm(
z_spr_nrm$zrf~z_spr_nrm$syear))[2])

print(paste("Delta standardised GC score annual increase during Decade of
Landcare =",signif(DeltaGC_z_corr_lc,digits=3)))

## [1] "Delta standardised GC score annual increase during Decade of Landc
are = 0.0511"

print(paste("Delta standardised GC score annual increase during NRM invest
ment period =",signif(DeltaGC_z_corr_nrm,digits=3)))

## [1] "Delta standardised GC score annual increase during NRM investment
period = 0.0963"

DeltaGC_corr_lc <- signif(unname(DeltaGC_z_corr_lc)*sd(z_spr$avD50),digits
=2)
DeltaGC_corr_nrm <- signif(unname(DeltaGC_z_corr_nrm)*sd(z_spr$avD50),digi
ts=2)

print(paste("Delta GC score annual increase during Decade of Landcare =",s
ignif(DeltaGC_corr_lc,digits=3)))

## [1] "Delta GC score annual increase during Decade of Landcare = 0.069"

print(paste("Delta GC score annual increase during NRM investment period =
",signif(DeltaGC_corr_nrm,digits=3)))

## [1] "Delta GC score annual increase during NRM investment period = 0.13
"
```

Adjust Delta GC slopes (from satellite data)

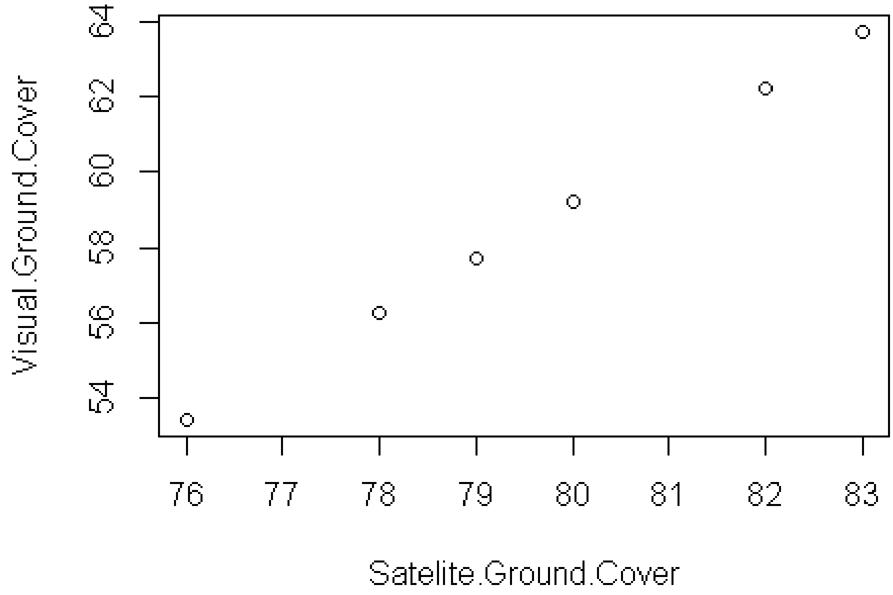
to Visusl Ground Cover (vgc) for Source Model

```
# Load gc/vgc correlation data from Trevethick and Scarth 2013 paper
# data supplied by authors
gc_vgc <- read.csv(file=paste0(datadir,"/","gc_vgc_data.csv"),sep=",", col
Classes="numeric")
gc_vgc <- na.omit(gc_vgc[,1:2])
# plot gc/vgc for 20-80%ile range of source data for DeltaGC trend
# IE avpc50 in spr_catch_av (column [4])
quants <- c(0.20,0.80)
quants.gc <- apply( spr_catch_av[4] , 2 , quantile , probs = quants , na.r
m = TRUE )
```

```r
plot(gc_vgc)
```

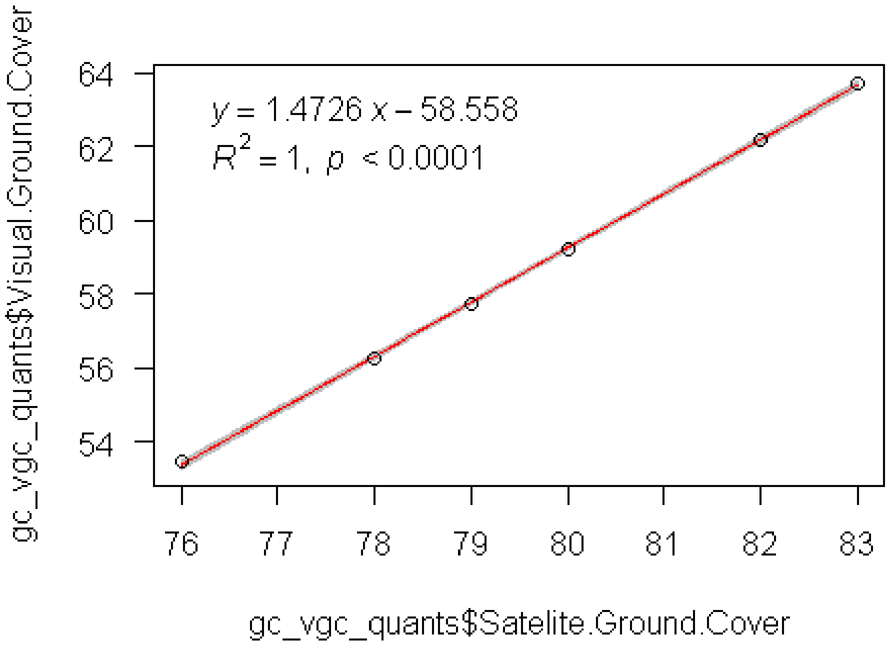



```r
gc_vgc_quants <- gc_vgc[gc_vgc$Satelite.Ground.Cover>=quants.gc[1]&gc_vgc$
Satelite.Ground.Cover<=quants.gc[2],]
plot(gc_vgc_quants)
```



```r
trendline(x=gc_vgc_quants$Satelite.Ground.Cover, y=gc_vgc_quants$Visual.Gr
ound.Cover,model = "line2P", plot = TRUE, linecolor = "red",
          lty = 1, lwd = 1, summary = TRUE)
```

```
##
## Call:
## lm(formula = y ~ x)
##
## Residuals:
##        1        2        3        4        5        6
##  0.06845 -0.02775 -0.04810 -0.04995  0.00185  0.05550
##
## Coefficients:
##                Estimate Std. Error t value  Pr(>|t|)
## (Intercept) -58.558050   0.797446 -73.432 2.061e-07 ***
## x             1.472600   0.010005 147.180 1.278e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.058 on 4 degrees of freedom
## Multiple R-squared:  0.99982,    Adjusted R-squared:  0.99977
## F-statistic:  21662 on 1 and 4 DF,  p-value: 1.2783e-08
##
##
## N: 6 , AIC: -14 , BIC:  -14
## Residual Sum of Squares:  0.013

## Warning in plot.window(...): "plot" is not a graphical parameter

## Warning in plot.xy(xy, type, ...): "plot" is not a graphical parameter

## Warning in axis(side = side, at = at, labels = labels, ...): "plot" is
not
## a graphical parameter

## Warning in axis(side = side, at = at, labels = labels, ...): "plot" is
not
## a graphical parameter

## Warning in box(...): "plot" is not a graphical parameter

## Warning in title(...): "plot" is not a graphical parameter
```




```
# find coefficient (slope) from gc/vgc
vgc_correction <- coef(lm(gc_vgc_quants$Visual.Ground.Cover~gc_vgc_quants$
Satelite.Ground.Cover))[2]

# multiply gc trend due to managemtne by vgc_correction
# to get DeltaVGC_corr_lc & DeltaVGC_corr_nrm
DeltaVGC_corr_lc <- DeltaGC_corr_lc*vgc_correction
DeltaVGC_corr_nrm <- DeltaGC_corr_nrm*vgc_correction

print(paste("Delta VGC annual increase during Decade of Landcare =",signif
(DeltaVGC_corr_lc,digits=3)))

## [1] "Delta VGC annual increase during Decade of Landcare = 0.102"

print(paste("Delta VGC annual increase during NRM investment period =",sig
nif(DeltaVGC_corr_nrm,digits=3)))

## [1] "Delta VGC annual increase during NRM investment period = 0.191"

# for interest, change for 1990-2017
DeltaVGC_corr_por <- DeltaVGC_corr_lc*14+DeltaVGC_corr_nrm*13
signif(DeltaVGC_corr_por,digits=3)

## gc_vgc_quants$Satelite.Ground.Cover
##                                3.9
```

Compile Reference List

```
citations <- function(includeURL = T, includeRStudio = F) {
    if(includeRStudio == TRUE) {
        ref.rstudio <- RStudio.Version()$citation
        #ref.rstudio <- rstudioapi::versionInfo()$citation
        if(includeURL == FALSE) {
            ref.rstudio$url = NULL;
        }
```

```r
        print(ref.rstudio, style = 'text')
        cat('\n')
    }

    cit.list <- c('base', names(sessionInfo()$otherPkgs))
    for(i in 1:length(cit.list)) {
        ref <- citation(cit.list[i])
        if(includeURL == FALSE) {
            ref$url = NULL;
        }
        print(ref, style = 'text')
        cat('\n')
    }
}

#call function and tidy up code
prn <- capture.output(citations())
#tidy up output
prn1 <- sub("_", "",prn)
Rprint <- sub("_.", ".",prn1)
# add citation for function used to create citations and for RStudio
cit_func <- paste0("RStudio Team (2018). RStudio: Integrated Development E
nvironment for R. RStudio, Inc., Boston, MA. <URL: http://www.rstudio.com/
.\n","\n","Reference list produced from adaptation of MS Berends' citation
s() function accessed from stackoverflow <URL: https://stackoverflow.com/q
uestions/15688758/r-stats-citation-for-a-scientific-paper")

# to print references without showing script call in knitted Word file use
:
# ```{r message=FALSE, warnings=FALSE, echo=FALSE comment=NA, results='hol
d'}
# cat(Rprint,sep="\n")
# cat(cit_func,sep="\n")
# ```
```

References


```
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erval of Basic Regression Models to Plot. R package version 2.0.3, <
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```

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org/v21/i12/>.

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R. RStudio, Inc., Boston, MA. <URL: http://www.rstudio.com/.

Reference list produced from adaptation of MS Berends' citations() f
unction accessed from stackoverflow <URL: https://stackoverflow.com/
questions/15688758/r-stats-citation-for-a-scientific-paper
```


End of Script

070_UM_SourceRaster_scenarios_vgc_adjustments

Developed and run by Paul Webb, 2019.

Script developed to adjust each of the 124 visual groundcover files from the base Source catchments model run for the Condamine Balonne 2018 note: For 1990, 2004 & 2017 Scenarios accounting for for underlying improvement in grouncover due to grazing land management in the Upper Maranoa catchment

Inputs: vgc base model rasters (124 scenes) annual adjustment table from TS trend analyses outputs: folders X1990, X2004 & X2017 each with 124 vgc raster with um glu areas only adjusted from base model rasters

Modified from original to process one file only for documentation purposes This version includes a pre and post plot of raster for the single file processed #'###

<u>*Library calls and Operating environment settings*</u>

```
#' make library calls
library(raster)
library(rgdal)
library(tiff)
library(rstudioapi)

* Warning: package 'rstudioapi' was built under R version 3.5.3

library(knitr)

#Set workdirectory (outputs) and data (inputs) directory
# find script root directory
# root <- dirname(getActiveDocumentContext()$path)
datadir <- paste0(getwd(),"/Inputs")
#setwd(paste0(root,"/Outputs"))

# A colorblind-friendly palette with grey from
# http://www.cookbook-r.com/Graphs/Colors_(ggplot2)/#a-colorblind-friendly
-palette
cbp <- c("#999999", "#E69F00", "#56B4E9",
         "#009E73", "#F0E442", "#0072B2", "#D55E00", "#CC79A7")
#cbp clues (from plotrix::color.id)
#       (grey60, orange2, steelblue2,
#               darkcyan, goldenrod1, dodgerblue3, darkorange, pink3)

print(paste("Work Directory:",getwd()))
print(paste("Data Input directory:",datadir))
print("Memory limit set to:")
memory.limit(size=32584)

* [1] "Work Directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCresearchP
roject/PostConfirmationDocs/Thesis/RScripts/070_UM_SourceRaster_scenarios_
vgc"
* [1] "Data Input directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCres
earchProject/PostConfirmationDocs/Thesis/RScripts/070_UM_SourceRaster_scen
arios_vgc/Inputs"
* [1] "Memory limit set to:"
* [1] 32584
```

Read in adjustment table

```
# import correction table for gc by year for each simulation (1990, 2004 a
nd 2017)
corr_table <- read.csv(paste0(datadir,"/vgc_corrections_table.csv"))
modelyrs <- corr_table$year
adjustments <- corr_table[,1:4]
print(
  "Table of adjustments to be applied to visual groundcover raster files f
or Upper Maranoa grazing lands")
print(adjustments)
#print(as.matrix(corr_table[1:19,6:20],quote=F))

* [1] "Table of adjustments to be applied to visual groundcover raster fil
es for Upper Maranoa grazing lands"
*     year  X1990  X2004 X2017
* 1   1986  0.408  1.836 4.319
* 2   1987  0.306  1.734 4.217
* 3   1988  0.204  1.632 4.115
* 4   1989  0.102  1.530 4.013
* 5   1990  0.000  1.428 3.911
* 6   1991 -0.102  1.326 3.809
* 7   1992 -0.204  1.224 3.707
* 8   1993 -0.306  1.122 3.605
* 9   1994 -0.408  1.020 3.503
* 10 1995 -0.510  0.918 3.401
* 11 1996 -0.612  0.816 3.299
* 12 1997 -0.714  0.714 3.197
* 13 1998 -0.816  0.612 3.095
* 14 1999 -0.918  0.510 2.993
* 15 2000 -1.020  0.408 2.891
* 16 2001 -1.122  0.306 2.789
* 17 2002 -1.224  0.204 2.687
* 18 2003 -1.326  0.102 2.585
* 19 2004 -1.428  0.000 2.483
* 20 2005 -1.619 -0.191 2.292
* 21 2006 -1.810 -0.382 2.101
* 22 2007 -2.001 -0.573 1.910
* 23 2008 -2.192 -0.764 1.719
* 24 2009 -2.383 -0.955 1.528
* 25 2010 -2.574 -1.146 1.337
* 26 2011 -2.765 -1.337 1.146
* 27 2012 -2.956 -1.528 0.955
* 28 2013 -3.147 -1.719 0.764
* 29 2014 -3.338 -1.910 0.573
* 30 2015 -3.529 -2.101 0.382
* 31 2016 -3.720 -2.292 0.191
* 32 2017 -3.911 -2.483 0.000
```

Import and adjust raster data

for each season in each year in each of 3 model scenarios

```
# nested loops to import and adjust data for each scenario/year/season
# scenario loop start
#for (syr in c("X1990" ,"X2004", "X2017")) {
#  setwd(paste0("E:/PaulWorking/CondBal Visual Cover_",syr))
  # year loop start
#  for (year in modelyrs) {
```

```
# for rmd sample run use next 4 lines and rem out 3 for loops and closing
"}"
    syr <- "X2017"
    year <- 2004
    season <- "fVC_200312_200402.tif"
    #setwd(paste0(getwd(),syr))
    #end testing lines

    print(paste("model run-",syr,"year-",year)) # for progress check
    # set variable adjustment value v for year/scenario
    v <- corr_table[corr_table$year==year,syr]
    print(paste("adjustment value (v)=",v)) # for progress check

    # find files in vgc directory for computation year
    # list raster files for year
    filenames_year <- list.files(path="E:/CondBal Visual Cover",
                                 pattern=paste0("*",year,"...tif$"))
    print("list of files for year")
    print(filenames_year) # for progress check

    #season loop start
#    for (season in filenames_year) {
      # load um grazing lu pixels
      um_glu <- raster("E:/PaulWorking/um_glu.tif")
      # set values for um glu pixels to adjustment value v
      um_glu[is.finite(um_glu)] <- v # plot(um_glu)
      print(paste("min_max (should both = v)",minValue(um_glu),maxValue(um
_glu)))
      # for progress check

      print(season) # for progress check
      vgc <- raster(paste0("E:/CondBal Visual Cover/",season)) # plot(vgc)

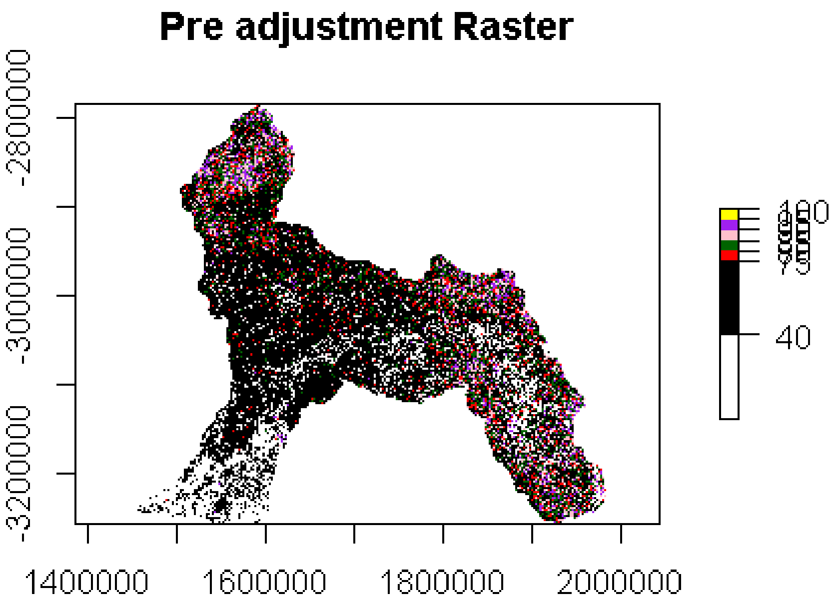
      # Ensure consistent datum and projection GDA95/Australian Albers
      crs(vgc) <- CRS("+init=EPSG:3577 +proj=aea +lat_1=-18 +lat_2=-36 +la
t_0=0 +lon_0=132 +
                          x_0=0 +y_0=0 +ellps=GRS80 +towgs84=0,0,0,0,0,0,0
+units=m +no_defs")
      crs(um_glu) <- CRS("+init=EPSG:3577 +proj=aea +lat_1=-18 +lat_2=-36
+lat_0=0 +lon_0=132 +
                          x_0=0 +y_0=0 +ellps=GRS80 +towgs84=0,0,0,0,0,0,0
+units=m +no_defs")

      # vgc <- crop(vgc,extent(um_glu)) # smaller area for testing only
      vgc_wk <- mosaic(vgc,um_glu,fun=sum,na.rm=T)
      #values(vgc_wk)[is.na(values(um_glu))] <- NA
      values(vgc_wk)[is.na(values(vgc))] <- NA
      vgc_wk[vgc_wk< 0] <- 0

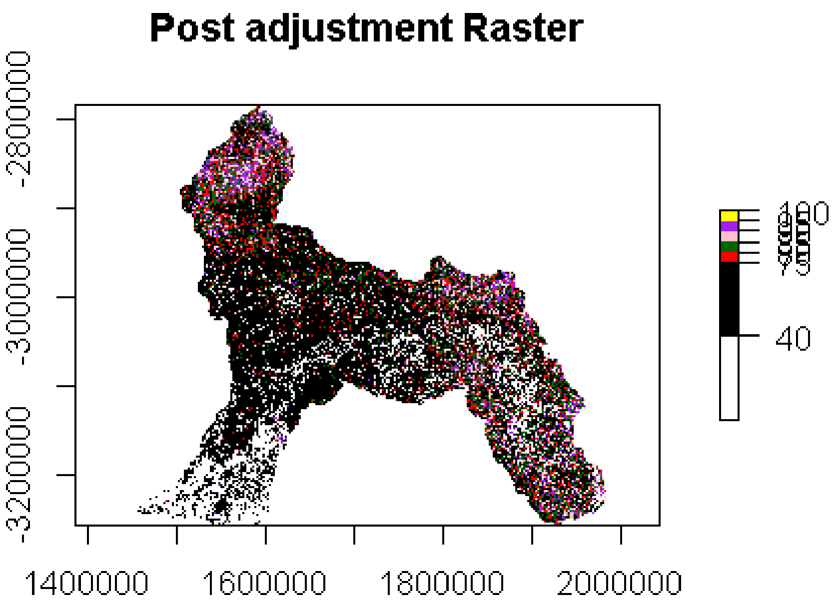
* [1] "model run- X2017 year- 2004"
* [1] "adjustment value (v)= 2.483"
* [1] "list of files for year"
* [1] "fVC_200312_200402.tif" "fVC_200403_200405.tif" "fVC_200406_200408.t
if"
* [4] "fVC_200409_200411.tif"
* [1] "min_max (should both = v) 2.483 2.483"
* [1] "fVC_200312_200402.tif"

      # For plotting in test phases - Plots should show changes in        #
groundcover for Upper Maranoa area only post adjustment
```

```r
# breakpoints <- c(-600,-400,-0.01,0.01,40,95,1100)
breakpoints <- c(40,75,80,85,90,95,100)
colors <- c("black","red","dark green","pink","purple","yellow")
plot(vgc,breaks=breakpoints,col=colors,main="Pre adjustment Raster")
```




```r
plot(vgc_wk,breaks=breakpoints,col=colors,main="Post adjustment Raster")
```



```r
      #end test plot lines

      # output to scenario visual cover directory directory
      writeRaster(vgc_wk, filename=names(vgc), format="GTiff", overwrite=T
) #, options=c('TFW=YES')
      #rm(vgc,vgc_wk) # for memory management
      # clear raster temp files for memory management
      tmpfiles <- list.files(paste0(tempdir(),"/raster"),full.names = T)
      file.remove(tmpfiles)

## [1] TRUE TRUE TRUE TRUE

      # next season
#     }
    # next year
#   }
  # next model scenario
#}
```

Compile Reference List

```r
citations <- function(includeURL = T, includeRStudio = F) {
    if(includeRStudio == TRUE) {
        ref.rstudio <- RStudio.Version()$citation
        #ref.rstudio <- rstudioapi::versionInfo()$citation
        if(includeURL == FALSE) {
            ref.rstudio$url = NULL;
        }
        print(ref.rstudio, style = 'text')
        cat('\n')
    }

    cit.list <- c('base', names(sessionInfo()$otherPkgs))
    for(i in 1:length(cit.list)) {
        ref <- citation(cit.list[i])
        if(includeURL == FALSE) {
            ref$url = NULL;
        }
        print(ref, style = 'text')
        cat('\n')
    }
}

#call function and tidy up code
prn <- capture.output(citations())
#tidy up output
prn1 <- sub("_", "",prn)
Rprint <- sub("_.", ".",prn1)
# add citation for function used to create citations and for RStudio
cit_func <- paste0("RStudio Team (2018). RStudio: Integrated Development E
nvironment for R. RStudio, Inc., Boston, MA. <URL: http://www.rstudio.com/
.\n","\n","Reference list produced from adaptation of MS Berends' citation
s() function accessed from stackoverflow <URL: https://stackoverflow.com/q
uestions/15688758/r-stats-citation-for-a-scientific-paper")

# to print references without showing script call in knitted Word file use
:
# ```{r message=FALSE, warnings=FALSE, echo=FALSE comment=NA, results='hol
d'}
# cat(Rprint,sep="\n")
```

```
# cat(cit_func,sep="\n")
# ```
```

References

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Bivand R, Keitt T, Rowlingson B (2018). rgdal: Bindings for the 'Geospatial' Data Abstraction Library. R package version 1.3-6, <URL: https://CRAN.R-project.org/package=rgdal>.

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Bivand RS, Pebesma E, Gomez-Rubio V (2013). Applied spatial data analysis with R, Second edition. Springer, NY. <URL: http://www.asdar-book.org/>.

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Reference list produced from adaptation of MS Berends' citations() function accessed from stackoverflow <URL: https://stackoverflow.com/questions/15688758/r-stats-citation-for-a-scientific-paper

End of Script

080_UM_SourceRaster_Aspirational_vgc

Developed and run by Paul Webb, 2019.

Script developed to adjust each of the 124 visual groundcover files from the base Source catchments model run for the Condamine Balonne 2018 For an “Aspirational” 2050 visual groundcover for the Upper Maranoa only with values based on 95% values for climate landscapes.

Inputs:

adrcm.txt - adapted Dynamic Reference Cover Method groundcover scores and climate data sca_allyears.txt - seasonal climate archive with climate data including pre 1990 to allow “warmup period for summaries” gc_vgc_data.csv - Trevethick and Scarth, 2013 data for conversion of satellite data to visual gc equivalent. qbum_scil_IDs - list of climate landscape IDs qbum_scil.tif - spatial data for climate landscapes

fVC_startDate_endDate.tif files of observed VGC (from Source catchments base model run)

Outputs:

fVC_startDate_endDate.tif files with data adjusted for Upper Maranoa catchment grazing lands to reflect best possible ground cover

Modified from original to process one file only for documentation purposes This version includes plots of raster for UM and CB for the single file processed

Library calls and Operating environment settings

```
# Increase default memory size for raster data handling
memory.limit(size=32584)

# Make library calls
library(dplyr)
library(RcppRoll)

* Warning: package 'RcppRoll' was built under R version 3.5.3

library(DescTools)

* Warning: package 'DescTools' was built under R version 3.5.3

library(raster)
library(rgdal)
library(tiff)
library(RefManageR)
library(here)

* Warning: package 'here' was built under R version 3.5.3

library(knitr)
library(basicTrendline)

* Warning: package 'basicTrendline' was built under R version 3.5.3

#Set datadir (Inputs) directory
#root <- here::here()
#setwd(paste0(root, "/Outputs"))
#setwd("C:/Users/q9823679/ownCloud/Shared/USQ_QMDCresearchProject/PostConf
irmationDocs/Thesis/RScripts/080_UM_SourceRaster_Aspirational_vgc")
```

```
datadir <- paste0(getwd(), "/Inputs")

# A colorblind-friendly palette with grey from
# http://www.cookbook-r.com/Graphs/Colors_(ggplot2)/#a-colorblind-friendly
-palette
cbp <- c("#999999", "#E69F00", "#56B4E9",
         "#009E73", "#F0E442", "#0072B2", "#D55E00", "#CC79A7")
#cbp clues (from plotrix::color.id)
#       (grey60, orange2, steelblue2,
#               darkcyan, goldenrod1, dodgerblue3, darkorange, pink3)

#knitr::opts_chunk$set(echo = TRUE)
# clear temp diretory function for memory management with knitr
clrmem <- function(x){
  files <- list.files(tempdir(),full.names=T)
  file.remove(files)
}
clrmem

print(paste("Work Directory:",getwd()))
print(paste("Data Input directory:",datadir))
print("Memory limit set to:")
memory.limit(size=32584)

* [1] 32584
* function(x){
*   files <- list.files(tempdir(),full.names=T)
*   file.remove(files)
* }
* [1] "Work Directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCresearchP
roject/PostConfirmationDocs/Thesis/RScripts/080_UM_SourceRaster_Aspiration
al_vgc"
* [1] "Data Input directory: C:/Users/q9823679/ownCloud/Shared/USQ_QMDCres
earchProject/PostConfirmationDocs/Thesis/RScripts/080_UM_SourceRaster_Aspi
rational_vgc/Inputs"
* [1] "Memory limit set to:"
* [1] 32584
```

Import data and assign colClasses to maintain integrity

```
col_types <- read.table(file=paste0(datadir,"/adrcm_types.txt"), header=F
, sep=" ")
char.types <- as.character(unlist(col_types$V1))
adrcm <- NULL
adrcm <- read.table(file=paste0(datadir,"/adrcm.txt"),sep=",", header=TRUE
,colClasses = char.types)
head(adrcm)

# does not include some ci areas - limited to ci s with scp data from QMDC
# Trends assumed to be representative accross the catchment.

# Trim to required data
pc95ref <- adrcm[adrcm$ac=="ref",]
pc95ref$qbum_scil <- substr(pc95ref$qbum_scilapp,1,14)

scil_pc95 <- pc95ref #[,c(38,2,3,5,17,19,34)]

*                        scilapp_yrsn       ci syear season sn_no yr_seaso
n
* 1 um_18_BBS10_fo_con_000_000_1988_2 18_BBS10  1988 autumn     2    1988_
```

```
2
* 2 um_18_BBS10_fo_con_000_000_1988_3 18_BBS10  1988 winter     3    1988_
3
* 3 um_18_BBS10_fo_con_000_000_1988_4 18_BBS10  1988 spring     4    1988_
4
* 4 um_18_BBS10_fo_con_000_000_1989_1 18_BBS10  1989 summer     1    1989_
1
* 5 um_18_BBS10_fo_con_000_000_1989_2 18_BBS10  1989 autumn     2    1989_
2
* 6 um_18_BBS10_fo_con_000_000_1989_3 18_BBS10  1989 winter     3    1989_
3
*   st cl    ib lu  ac  pr  pk pc5 pc20 pc50 pc95 pc80   rain tmax  tmin
* 1 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 127.55 35.0  0.50
* 2 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  96.35 29.0 -5.00
* 3 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  55.25 38.0  1.50
* 4 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 234.45 37.0 12.50
* 5 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA 339.05 35.0  5.50
* 6 um 18 BBS10 fo con 000 000  NA   NA   NA   NA   NA  80.70 28.5 -3.75
*    tmean     et  sr  sr2yr rainmax rainmin ref95 D95 D80 D50 D20 D5    r
f4
* 1 17.625 319.35 dry normal   200.7    73.4    NA  NA  NA  NA  NA NA
NA
* 2 12.000 233.50 dry normal   171.8    75.9    NA  NA  NA  NA  NA NA
NA
* 3 19.500 526.25 dry normal    74.2     7.9    NA  NA  NA  NA  NA NA
NA
* 4 25.000 525.15 wet normal   413.4   194.3    NA  NA  NA  NA  NA NA 513.
60
* 5 20.250 295.00 wet normal   499.2   231.4    NA  NA  NA  NA  NA NA 725.
10
* 6 12.250 213.60 wet normal   127.2    55.7    NA  NA  NA  NA  NA NA 709.
45
*   rf8                qbum_scilapp       Ha
* 1  NA um_18_BBS10_fo_con_000_000 47255.91
* 2  NA um_18_BBS10_fo_con_000_000 47255.91
* 3  NA um_18_BBS10_fo_con_000_000 47255.91
* 4  NA um_18_BBS10_fo_con_000_000 47255.91
* 5  NA um_18_BBS10_fo_con_000_000 47255.91
* 6  NA um_18_BBS10_fo_con_000_000 47255.91
```

Infill startup years and climate landscapes with no cover data

```
# create rows for syear 1986 (sn_no 1:4), 1987 (sn_no 1:4) & 1988 (sn_no 1
)
#  for all unique qbum_scil in scil_pc95

um_scil_ID <- read.csv(paste0(datadir,"/qbum_scil_IDs.csv"))

# to be confirmed
#um_scil_ID <- um_scil_ID[,c(3,1,2)]
colnames(um_scil_ID)[1] <- "ID"

scil.list <- unique(as.character(um_scil_ID$QBUM_SCIL))
um_scil_ID$ci <- substr(um_scil_ID$QBUM_SCIL,4,11)
#scil.list <- unique(as.character(um_scil_ID$QBUM_SCIL))
#um_scil_ID$ci <- substr(um_scil_ID$QBUM_SCIL,4,11)
ci.list <- unique(um_scil_ID$ci)
vgc.list <- list.files("E:/CondBal Visual Cover/",pattern = "\\.tif$") #re
quires external hard disc connected
```

```
# split scil.list for sites with pc95 data and those without
scil.list.with <- as.character(unique(scil_pc95$qbum_scil))
scil.list.without <- as.character(scil.list[scil.list %nin% scil.list.with
])

# create blank rows for years pre 1990
#scil_pc95 <- scil_pc95[,c(38,2,3,5,17,19,34)]
scil_pc95 <- scil_pc95[,c("qbum_scil","ci","syear","sn_no","pc95","rain","
rf4")]

# this is to infill pc95 from rf4 for missing years
for (scil in scil.list.with) {
  scil_pc95 <- rbind(data.frame(qbum_scil=c(rep(scil,9)),
                                ci=c(rep(substr(scil,4,11))),
                                syear=as.integer(c(rep(1986,4),rep(1987,4),1988)
),
                                sn_no=as.integer(c(1:4,1:4,1)),
                                pc95=c(rep(NA,9)),
                                rain=c(rep(NA,9)),
                                rf4=c(rep(NA,9))),
                          scil_pc95)
}

# create blank rows for all years for scil s with no data
# this is to infill pc95 from rf4 for missing years
for (scil in scil.list.without) {
  for (syear in c(1986:2017)) {
    for (sn_no in c(1:4)) {
      scil_pc95 <- rbind(data.frame(qbum_scil=scil,
                                    ci=substr(scil,4,11),
                                    syear=as.integer(syear),
                                    sn_no=as.integer(sn_no),
                                    pc95=NA,
                                    rain=NA,
                                    rf4=NA),
                              scil_pc95)
    }
  }
}

# to ensure columns present in appropriate order
scil_pc95$qbum_scil <- as.character(scil_pc95$qbum_scil)
scil_pc95$ci <- as.character(scil_pc95$ci)

# create season based filename column with label as per vgc files
scil_pc95$startyr <- ifelse(scil_pc95$sn_no==1,strtoi(scil_pc95$syear, 10L
)-1,strtoi(scil_pc95$syear, 10L))
scil_pc95$endyr <- strtoi(scil_pc95$syear, 10L)
scil_pc95$startm <- ifelse(scil_pc95$sn_no==1,12,ifelse(scil_pc95$sn_no==2
,3,ifelse(scil_pc95$sn_no==3,6,9)))
scil_pc95$startm <-formatC(scil_pc95$startm,width=2,flag=0)
scil_pc95$endm <- ifelse(scil_pc95$sn_no==1,2,ifelse(scil_pc95$sn_no==2,5,
ifelse(scil_pc95$sn_no==3,8,11)))
scil_pc95$endm <-formatC(scil_pc95$endm,width=2,flag=0)
scil_pc95$fileID <- paste0("fVC_",scil_pc95$startyr,scil_pc95$startm,"_",s
cil_pc95$endyr,scil_pc95$endm,".tif")

scil_pc95$syear<- as.numeric(as.character(scil_pc95$syear))
scil_pc95$sn_no <- as.numeric(as.character(scil_pc95$sn_no))
```

```
scil_pc95$rf4 <- as.numeric(as.character(scil_pc95$rf4))

head(scil_pc95)

#' Infill pc95 from RF4 correlation for missing years (pre 1990)
#' And missing ci areas (areas in UM with no QMDC works so no
#' data accessed in previous work)

# Import seasonal climate data for all years from "sca_allyears.txt"
#  created in 03_um_gc_climate_analyses.R (and copied to wd)
sca <- read.table(file=paste0(datadir,"/sca_allyears.txt"),sep=" ", header
=TRUE,
                    colClass=c("factor","numeric","factor","numeric","fact
or","numeric",
                               "numeric","numeric","numeric","numeric","nu
meric","numeric","factor")
)

# Average Rain by ci Syear Season
sca_ci <- sca %>%
  group_by(ci,Syear,Sn_No) %>%
  summarise(Rain=mean(Rain))

* Warning: Factor `ci` contains implicit NA, consider using
* `forcats::fct_explicit_na`

# will have na values but not for ci in UM so ignore warning

# filter on ci in scil.list
sca_ci_um <- sca_ci[which(sca_ci$ci %in% ci.list),]
# filter to data from 1985 - to allow for rf4 for 1986 on
sca_ci_um <- sca_ci_um[sca_ci_um$Syear>1984,]

# tidy up to manage memory
rm(adrcm,sca,sca_ci,pc95ref)

# Create RF4 column from current plus 3 preceding seasons total

sca_ci_um <- sca_ci_um %>%
  group_by(ci) %>%
  mutate(rf4=roll_sum(Rain,4,fill = NA,align="right"))

head(sca_ci_um)

names(scil_pc95) <- tolower(names(scil_pc95))
names(sca_ci_um) <- tolower(names(sca_ci_um))

scil_pc95_sca <- merge(scil_pc95,sca_ci_um,by=c("ci","syear","sn_no"))
# note Rain and rf4 for 1988 impacted by stats startup effect
# use the sca sourced data ahead of scil data which was
# initially culled for gc data anlysis with gc data from 1990
# slight variations post 1988 are due to sca data lumped on ci
# and scil data averaged on cil
# combined using sca dat up to the end of 1988

scil_pc95_sca$rain <- ifelse(scil_pc95_sca$syear<1989|is.na(scil_pc95_sca$
rain.x),scil_pc95_sca$rain.y,scil_pc95_sca$rain.x )
scil_pc95_sca$rf4 <- ifelse(scil_pc95_sca$syear<1989|is.na(scil_pc95_sca$r
f4.x),scil_pc95_sca$rf4.y,scil_pc95_sca$rf4.x )
```

```
scil_pc95_sca <- scil_pc95_sca[,-c(6,7,13,14)]

# now need to calculate missing pc95 values
# from lm of rf4~pc95 grouped by scil for scil.list.with
#  for pre available groundcover period in zones with groundcover data
# from lm of rf4~pc95 grouped by lu for scil.list.without
#  for estimating groundcover in parts of the study catchment where
#  groundcover data was not accessed for this project

for (scil in scil.list.with) { # scil <- "um_17_BBS10_fo"
  #create lm from available data filtered on scil
  # exclude pre 1989 data for which rf4 not accurate
  print(scil)

  data <- scil_pc95_sca[scil_pc95_sca$qbum_scil==scil,]
  #na_data <- scil_pc95_sca[is.na(scil_pc95_sca$pc95)&scil_pc95_sca$qbum_s
cil==scil,5]
  model <- lm(pc95~rf4,data[data$syear>1988,])
  scil_pc95_sca[is.na(scil_pc95_sca$pc95)&scil_pc95_sca$qbum_scil==scil,5]
<-
   predict(model,newdata=data[is.na(data$pc95),])
}

# for lm for scil.list.without create lu column
scil_pc95_sca$lu <- substr(scil_pc95_sca$qbum_scil,13,14)

for (lu in unique(scil_pc95_sca$lu)) {
  print(lu)
  lm.data <- scil_pc95_sca[scil_pc95_sca$lu==lu,]
  model <- lm(pc95~rf4,lm.data[lm.data$syear>1988,])
  scil_pc95_sca[is.na(scil_pc95_sca$pc95)&scil_pc95_sca$lu==lu,5] <-
    predict(model,newdata=lm.data[is.na(lm.data$pc95),])
}

scil_pc95_sca[,c("pc95","rain","rf4")] <- round(scil_pc95_sca[,c("pc95","r
ain","rf4")])

head(scil_pc95_sca)

rm(data,lm.data,sca_ci_um,scil_pc95,scil,scil.list,scil.list.with,scil.lis
t.without,
   sn_no,syear,ci.list,lu,model)

*             qbum_scil       ci syear sn_no pc95 rain rf4 startyr endyr
* 1     um_24_BBS10_tg 24_BBS10  2017     4   NA   NA  NA    2017  2017
* 11917 um_24_BBS10_tg 24_BBS10  2017     3   NA   NA  NA    2017  2017
* 11916 um_24_BBS10_tg 24_BBS10  2017     2   NA   NA  NA    2017  2017
* 11915 um_24_BBS10_tg 24_BBS10  2017     1   NA   NA  NA    2016  2017
* 11914 um_24_BBS10_tg 24_BBS10  2016     4   NA   NA  NA    2016  2016
* 11913 um_24_BBS10_tg 24_BBS10  2016     3   NA   NA  NA    2016  2016
*       startm endm                fileID
* 1         09   11 fVC_201709_201711.tif
* 11917     06   08 fVC_201706_201708.tif
* 11916     03   05 fVC_201703_201705.tif
* 11915     12   02 fVC_201612_201702.tif
* 11914     09   11 fVC_201609_201611.tif
* 11913     06   08 fVC_201606_201608.tif
* # A tibble: 6 x 5
* # Groups:   ci [1]
```

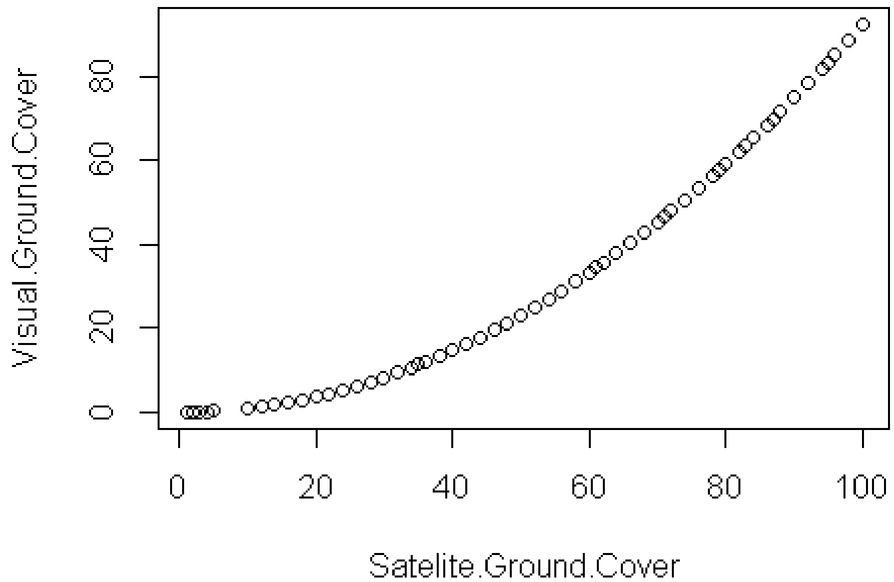
```
*    ci        Syear Sn_No  Rain   rf4
*    <fct>     <dbl> <dbl> <dbl> <dbl>
* 1 17_BBS10  1985     1 185.     NA
* 2 17_BBS10  1985     2  34.7    NA
* 3 17_BBS10  1985     3 145.     NA
* 4 17_BBS10  1985     4 152.    517.
* 5 17_BBS10  1986     1 296.    628.
* 6 17_BBS10  1986     2  50.6   644.
* [1] "um_18_BBS10_fo"
* [1] "um_18_BBS10_og"
* [1] "um_18_BBS10_st"
* [1] "um_18_BBS10_tg"
* [1] "um_18_BBS12_og"
* [1] "um_18_BBS12_st"
* [1] "um_18_BBS12_tg"
* [1] "um_19_BBS12_fo"
* [1] "um_19_BBS12_og"
* [1] "um_19_BBS12_st"
* [1] "um_19_BBS12_tg"
* [1] "um_24_BBS12_og"
* [1] "um_24_BBS12_st"
* [1] "um_24_BBS12_tg"
* [1] "tg"
* [1] "fo"
* [1] "st"
* [1] "og"
*         ci syear sn_no      qbum_scil pc95 startyr endyr startm endm
* 1 17_BBS10  1986     1 um_17_BBS10_tg   94    1985  1986     12   02
* 2 17_BBS10  1986     1 um_17_BBS10_fo   93    1985  1986     12   02
* 3 17_BBS10  1986     1 um_17_BBS10_st   94    1985  1986     12   02
* 4 17_BBS10  1986     1 um_17_BBS10_og   94    1985  1986     12   02
* 5 17_BBS10  1986     2 um_17_BBS10_st   94    1986  1986     03   05
* 6 17_BBS10  1986     2 um_17_BBS10_og   95    1986  1986     03   05
*                fileid rain rf4 lu
* 1 fVC_198512_198602.tif  296 628 tg
* 2 fVC_198512_198602.tif  296 628 fo
* 3 fVC_198512_198602.tif  296 628 st
* 4 fVC_198512_198602.tif  296 628 og
* 5 fVC_198603_198605.tif   51 644 st
* 6 fVC_198603_198605.tif   51 644 og
```

Spatial data correction value derivation

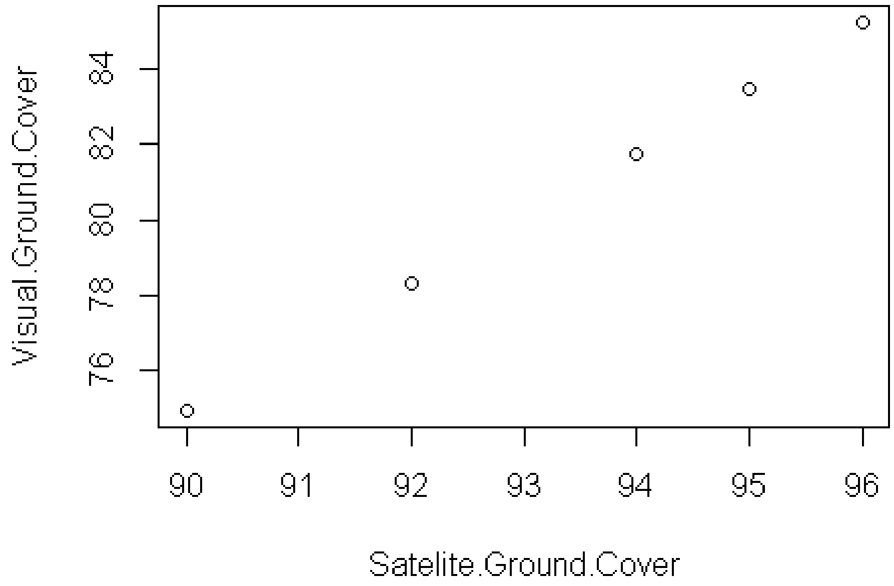
scil_pc95_sca contains pc95 values for scil units per season These values now need to be used to replace existing vgc values for each season - as per vgc.list

```
# create scil areas template for um
um_scil <- raster(paste0(datadir,"/qbum_scil.tif"), RAT=T)
crs(um_scil) <- CRS("+init=EPSG:3577 +proj=aea +lat_1=-18 +lat_2=-36 +lat_0=0 +lon_0=132 +
                          x_0=0 +y_0=0 +ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +units=m +no_defs")
um_scil <- ratify(um_scil)
levels(um_scil) <- um_scil_ID
# um_scil is a raster file with 1:27 ID alligning with
# scil codes in um_scil_ID

# correct for vgc from remote sensing gc
# Assess data to see range of data to be used for correlation
```

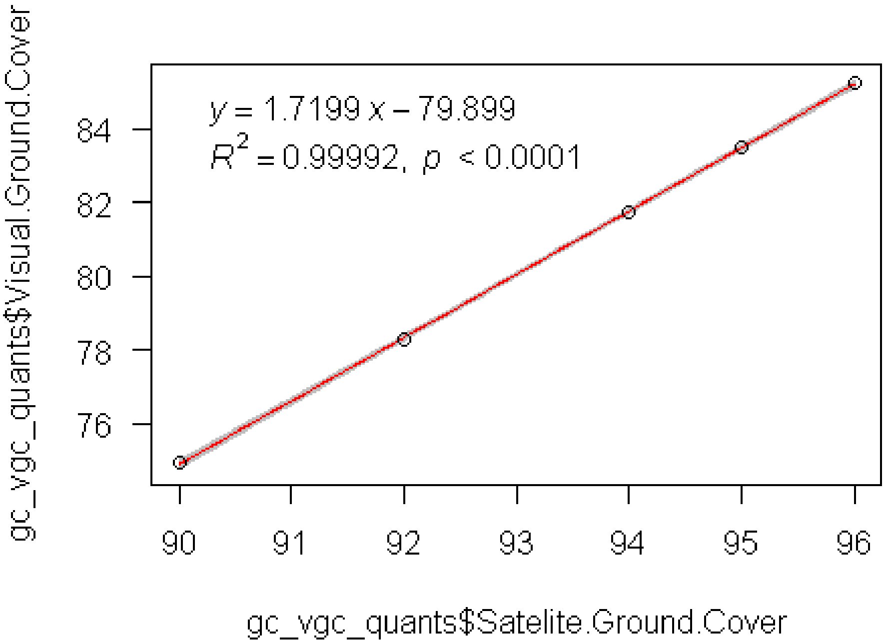
```
quants <- c(0,0.05,0.20,0.50,0.80,0.95,1)
apply( scil_pc95_sca[5] , 2 , quantile , probs = quants , na.rm = TRUE )

clrmem # clear temp files
# Load gc/vgc correlation data from Trevethick and Scarth 2013 paper
# data supplied by authors
gc_vgc <- read.csv(file=paste0(datadir,"/","gc_vgc_data.csv"),sep=",", col
Classes="numeric")
gc_vgc <- na.omit(gc_vgc[,1:2])
# plot gc/vgc for 20-80%ile range of source data for DeltaGC trend
# IE avpc50 in spr_catch_av (column [4])
quants <- c(0.20,0.80)
#quants.gc <- apply( spr_catch_av[4] , 2 , quantile , probs = quants , na.
rm = TRUE )
# quants.gc <- apply( scil_pc95_sca[5] , 2 , quantile , probs = c(0,1) , n
a.rm = TRUE )
quants.gc <- apply( scil_pc95_sca[5] , 2 , quantile , probs = quants , na.
rm = TRUE )

plot(gc_vgc)
```




```
gc_vgc_quants <- gc_vgc[gc_vgc$Satelite.Ground.Cover>=quants.gc[1]&gc_vgc$
Satelite.Ground.Cover<=quants.gc[2],]
plot(gc_vgc_quants)
```




```
trendline(x=gc_vgc_quants$Satelite.Ground.Cover, y=gc_vgc_quants$Visual.Gr
ound.Cover,model = "line2P", plot = TRUE, linecolor = "red",
          lty = 1, lwd = 1, summary = TRUE)

* Warning in plot.window(...): "plot" is not a graphical parameter

* Warning in plot.xy(xy, type, ...): "plot" is not a graphical parameter

* Warning in axis(side = side, at = at, labels = labels, ...): "plot" is n
ot
* a graphical parameter

* Warning in axis(side = side, at = at, labels = labels, ...): "plot" is n
ot
* a graphical parameter

* Warning in box(...): "plot" is not a graphical parameter

* Warning in title(...): "plot" is not a graphical parameter
```



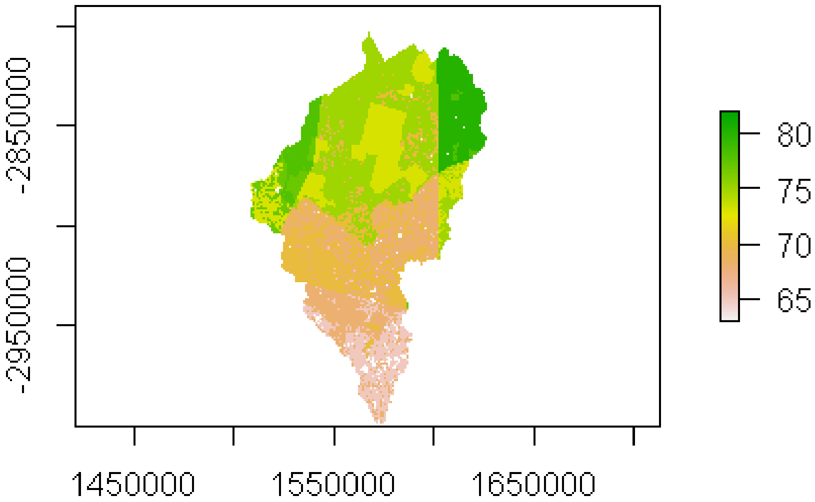

```
# find coefficient slope and offset from gc/vgc
vgc_correction_m <- coef(lm(gc_vgc_quants$Visual.Ground.Cover~gc_vgc_quant
s$Satelite.Ground.Cover))[2]
vgc_correction_c <- coef(lm(gc_vgc_quants$Visual.Ground.Cover~gc_vgc_quant
s$Satelite.Ground.Cover))[1]

# create vgc data from scil_pc95_sca and apply
# gc-vgc coeff to pc95 so pc95 is vgc equivalent
scil_pc95_vgc <- scil_pc95_sca
scil_pc95_vgc$pc95 <- round((vgc_correction_m*scil_pc95_sca$pc95+vgc_corre
ction_c),digits=0)
# check
quants.gc <- apply( scil_pc95_sca[5] , 2 , quantile , probs = quants , na.
rm = TRUE )
quants.vgc <- apply( scil_pc95_vgc[5] , 2 , quantile , probs = quants , na
.rm = TRUE )
print(paste0("satellite gc pc95 20%ile ",quants.gc[1]," satellite gc pc95
80%ile ",quants.gc[2]))
print(paste0("visual gc pc95 20%ile ",quants.vgc[1]," visual gc pc95 80%il
e ",quants.vgc[2]))
clrmem # clear temp files

*       pc95
* 0%      73
* 5%      86
* 20%     90
* 50%     93
* 80%     97
* 95%    100
* 100%   110
* function(x){
*   files <- list.files(tempdir(),full.names=T)
*   file.remove(files)
* }
```

```
*
* Call:
* lm(formula = y ~ x)
*
* Residuals:
*          1          2          3          4          5
*  0.0366810 -0.0360431 -0.0347672 -0.0063793  0.0405086
*
* Coefficients:
*                Estimate  Std. Error t value  Pr(>|t|)
* (Intercept) -79.8992672   0.8331379 -95.902 2.499e-06 ***
* x             1.7198621   0.0089177 192.859 3.074e-07 ***
* ---
* Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
*
* Residual standard error: 0.042953 on 3 degrees of freedom
* Multiple R-squared:  0.99992, Adjusted R-squared:  0.99989
* F-statistic:  37194 on 1 and 3 DF,  p-value: 3.0741e-07
*
*
* N: 5 , AIC: -13.841 , BIC:  -15.013
* Residual Sum of Squares:  0.005535
* [1] "satellite gc pc95 20%ile 90 satellite gc pc95 80%ile 97"
* [1] "visual gc pc95 20%ile 75 visual gc pc95 80%ile 87"
* function(x){
*   files <- list.files(tempdir(),full.names=T)
*   file.remove(files)
* }
```

Spatial data adjustment for Source Model period

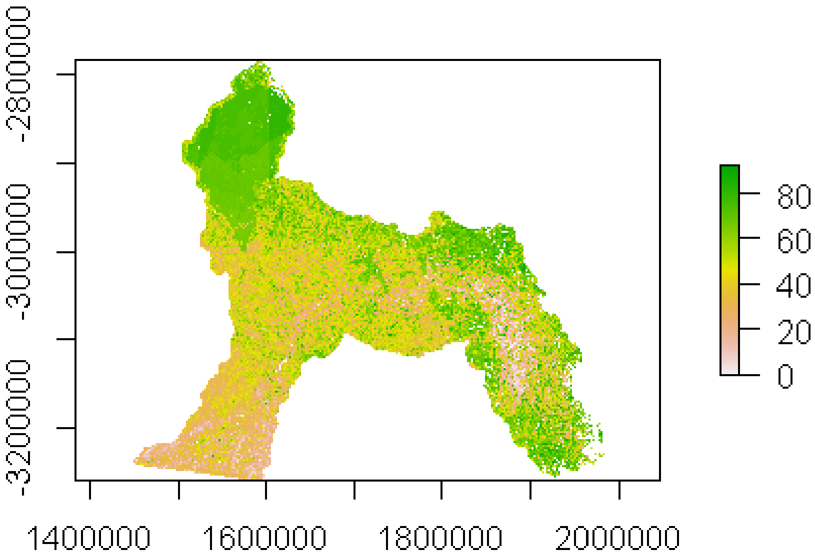
Assign pc95 values for each season Assign values by season based on tiff file name

```
# for full dataset use loop
#for (ssn in vgc.list) { # [n1>0:n2<125] for subset
  # for single file import to demonstrate process use single ssn file assi
gnment
ssn <- "fVC_201709_201711.tif"
  # load pc95 values for each scil and filter for selected season
  scil_ssn <- scil_pc95_vgc[scil_pc95_vgc$fileid==ssn,]
  levels(um_scil) <- um_scil_ID # to reset after loop actions
  rat <- as.data.frame(levels(um_scil))
  colno <- which(colnames(rat)=="QBUM_SCIL")
  colnames(rat)[colno] <- tolower(colnames(rat)[colno])
  um_scil_pc95 <- left_join(rat,scil_ssn,by="qbum_scil")

* Warning: Column `qbum_scil` joining factor and character vector, coercin
g
* into character vector

  um_scil_pc95 <- um_scil_pc95[,c(1:3,8)]
  levels(um_scil) <- um_scil_pc95
  pc95 <- deratify(um_scil,"pc95")
  plot(pc95) # check
```




```r
  # Load vgc for MB for selected season
  vgc <- raster(paste0("E:/CondBal Visual Cover/",ssn)) # plot(vgc)

  out <- merge(pc95,vgc)
  values(out)[is.na(values(vgc))] <- NA
  crs(out) <- CRS("+init=EPSG:3577 +proj=aea +lat_1=-18 +lat_2=-36 +lat_0=
0 +lon_0=132 +
                  x_0=0 +y_0=0 +ellps=GRS80 +towgs84=0,0,0,0,0,0,0 +units=
m +no_defs")
  # output to scenario visual cover directory directory
  writeRaster(out, filename=ssn, format="GTiff", overwrite=T) #, options=c
('TFW=YES')
  print(paste0(ssn," completed"))
  plot(out) # check
```




```
  # clear raster temp files for memory management
  tmpfiles <- list.files(paste0(tempdir(),"/raster"),full.names = T)
  file.remove(tmpfiles)
  rm(pc95,vgc,um_scil_pc95)
  # next season
#}

* [1] "fVC_201709_201711.tif completed"
* [1] TRUE TRUE TRUE TRUE
```

Compile Reference List

```
citations <- function(includeURL = T, includeRStudio = F) {
    if(includeRStudio == TRUE) {
        ref.rstudio <- RStudio.Version()$citation
        #ref.rstudio <- rstudioapi::versionInfo()$citation
        if(includeURL == FALSE) {
            ref.rstudio$url = NULL;
        }
        print(ref.rstudio, style = 'text')
        cat('\n')
    }

    cit.list <- c('base', names(sessionInfo()$otherPkgs))
    for(i in 1:length(cit.list)) {
        ref <- citation(cit.list[i])
        if(includeURL == FALSE) {
            ref$url = NULL;
        }
        print(ref, style = 'text')
        cat('\n')
    }
}
```

```
#call function and tidy up code
prn <- capture.output(citations())
#tidy up output
prn1 <- sub("_", "",prn)
Rprint <- sub("_.", ".",prn1)
# add citation for function used to create citations and for RStudio
cit_func <- paste0("RStudio Team (2018). RStudio: Integrated Development E
nvironment for R. RStudio, Inc., Boston, MA. <URL: http://www.rstudio.com/
.\n","\n","Reference list produced from adaptation of MS Berends' citation
s() function accessed from stackoverflow <URL: https://stackoverflow.com/q
uestions/15688758/r-stats-citation-for-a-scientific-paper")

# to print references without showing script call in knitted Word file use
:
# ```{r message=FALSE, warnings=FALSE, echo=FALSE comment=NA, results='hol
d'}
# cat(Rprint,sep="\n")
# cat(cit_func,sep="\n")
# ```
```

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```


End of Script