Analysis of the Correlation between Curing and Moisture Content in Australia Grasslands with MODIS-based Observations

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Candidate's Declaration

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university. To the best of the author's knowledge, it contains no material previously published or written by another person, except where due reference is made in the text.

Sheng Xuan Date:

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Abstract

Fire is common in Australia grasslands, and it is becoming more frequent and serious due to climate change. Fire has significant impacts upon economy, human-health and ecology, so the management of bushfire is important. Degree of curing (C) and fuel moisture content (FMC) are applied as input variables in different fire prediction models in Australia to evaluate fuel conditions. Indirect satellite observations of FMC are based on the assumption that FMC is related to C. Studying the relationship between C and FMC helps understand fuel dynamics, improve fire prediction model and spectral indices. The relationship between C and FMC has been intensively discussed, despite of different options. Instead of field observation used in previous studies, C and FMC derived from satellite-based observation would be applied in this analysis.

In this thesis, C and FMC estimated at a large-scale with high spatial resolution and temporal resolution were compared to study their relationship. Using satellite-observed C and FMC data, this study investigated the relationship between C and FMC across grasslands in Australia and over a time series. Moreover, this study aimed to investigate the relationship between C and FMC at smaller-scale to examine the influences of grass species, seasonal change, and fire histories on the correlation between C and FMC. It was hypothesised that there would always be a negative linear relationship between C and FMC in Australian grasslands regardless of grass species, fire history, or seasons.

Results of this study confirmed that there were strong negative linear correlations between C and FMC across Australian grasslands; however, in different grasslands the correlation coefficients varied. The correlation between C and FMC was influenced by grass species, previous fire events, and seasonal change. In blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands, temperate tussock grasslands, other tussock grasslands, and non-native grasslands, C and FMC had a very strong negative linear correlation. In other types of grasslands, the correlation between C and FMC was weaker. In areas with frequent fire events and during the extreme dry or rainy seasons, the correlations between C and FMC were also weaker.

This study implicates that the correlation between C and FMC is grass species specific, so fire prediction models should also be developed using various grass species. Strong correlation between C and FMC in southern grasslands except for sedgelands, rushes, or reeds, confirmed that it is suitable to evaluate fuel condition by C. FMC data should be included in fire prediction models for grasslands that do not have very strong significant correlations between C and FMC. Spectral indices that focused on the contrast between red and NIR were questioned by this study because C and FMC were not always very strongly negatively correlated in grasslands in Australia.

Table of Contents

Candidate's Declaration i

Acknowledgements ii

Abstract iii

List of Figures v

List of Tables vii

List of Equations viii

Abbreviations viii

Chapter 1: Introduction 1

1.1 Background 1

1.2 Aims of the study 7

Chapter 2: Literature review 8

2.1 Australian grasslands 8

2.2 Australian fire prediction models 9

2.3 Curing data 12

2.4 FMC data 15

Chapter 3: Methods 19

3.1 Mapping the distribution of different grass species in Australia 19

3.2 Mapping previous fire events in Australian grasslands 24

3.3 Testing the C–FMC relationship in grasslands 25

3.4 Analysing how grass species influence C and FMC relations 27

3.5 Analysing how previous fire events influence C and FMC relations 28

3.6 Analysing how seasonal change influences C and FMC relations 29

Chapter 4: Results 30

4.1 Maps of grassland types and fire history 30

4.2 Fire history map 33

4.3 Relationship between C and FMC in Australian grasslands 35

4.4 Relationship between C and FMC in different regions in Australian grasslands 38

4.5 Relationship between C and FMC in different types of Australian grasslands . 40

4.5.1 Hummock grasslands 40

4.5.2 Mitchell grass (Astrebla) tussock grasslands 44

4.5.3 Blue grass (Dichanthium) and tall bunch grass (Chrysopogon) tussock grasslands 47

4.5.4 Temperate tussock grasslands 51

4.5.5 Other tussock grasslands 55

4.5.6 Wet tussock grasslands with herbs, sedges or rushes, herblands or ferns . 59
4.5.7 Mixed chenopod, samphire, or forbs 62
4.5.8 Sedgelands, rushes, or reeds 65
4.5.9 Non-native grasslands 68
4.6 Relationship between C and FMC in areas with different previous fire events 74
4.6.1 Hummock grasslands 74
4.6.2 Non-native grasslands 81
4.7 Relationship between C and FMC in different seasons 88

Chapter 5: Discussion 90
5.1 C and FMC in different types of grasslands 90
5.2 C and FMC in areas with different fire histories 92
5.3 C and FMC in different seasons 94
5.4 Implications for fire management and fire prediction models 94
5.5 Limitations 96
5.6 Future research 97

Chapter 6: Conclusion 99

References 100

Appendix 1: Python Script Developed For Data Analysis 105

List of Figures

Figure 2.1 McArthur Mark 4 meter (McArthur, 1967) 10
Figure 3.1 Hummock grasslands associated with stony landscapes, Kimberley, WA (Photo: M. Fagg) 22
Figure 3.2 Mitchell tussock grassland, west of Blackall, QLD (Photo: M. Fagg) 22
Figure 3.3 Blue grass (Dichanthium sericeum) tussock grassland, Springsure, QLD (Photo: D.W. Butler) 22
Figure 3.4 Temperate tussock grasslands dominated by Stipa species, Cooma, NSW (Photo: M. Fagg) 22
Figure 3.5 Chenopod shrublands, Hay, NSW (Photo: M. Fagg) 23
Figure 3.6 Samphire shrubland, Murray Sunset National Park, VIC (Photo: M. Fagg) . 23
Figure 3.7 Mire (typically comprising sedges and rushes), Newnes Plateau, NSW (Photo: D. Keith) 23
Figure 3.8 Modified pasture with scattered eucalypts (Photo: M. Fagg) 23
Figure 4.1 Distribution of grasslands in Australia in 2010–2011. 30
Figure 4.2 Distribution of different types of open grasslands in Australia. 31
Figure 4.3 Proportion of covered area of different types of grasslands in Australian grasslands 32

Figure 4.4 Grasslands that were unburned over the 11 years of the study period. 33
Figure 4.5 Fire history map in Australian grasslands. Nine classes were categorised by different previous. 34
Figure 4.6 Average C and FMC values in Australian grasslands on different dates over 11 years (from 2002 to 2014 except 2008 and 2010). 36
Figure 4.7 Scatter plot of average C and corresponding average FMC in Australian grasslands on different date over 11 years (from 2002 to 2014 except 2008 and 2010)..........36
Figure 4.8 Monthly change in average C and FMC. 37
Figure 4.9 Maps of Pearson's correlation coefficient between C and FMC in different years in Australian grasslands. 39
Figure 4.10 Distribution of hummock grasslands (green areas) in Australia. 41
Figure 4.11 Plots of the relationship between average C and FMC in Australian hummock grasslands. 42
Figure 4.12 Distribution of Mitchell grass (Astrebla) tussock grasslands (green areas) in Australia. 44
Figure 4.13 Plots of the relationship between average C and FMC in Mitchell grass (Astrebla) tussock grasslands in Australia. 45
Figure 4.14 Distribution of blue grass (*Dichanthium*) and tall bunch grass *(Chrysopogon*) tussock grasslands (green areas) in Australia. 48
Figure 4.15 Plots of the relationship between average C and average FMC in blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands in Australia. 49
Figure 4.16 Distribution of temperate tussock grasslands (green areas) in Australia.....52
Figure 4.17 Plots of the relationship between average C and FMC in temperate tussock grasslands in Australia. 53
Figure 4.18 Distribution of other tussock grasslands (green areas) in Australia. 56
Figure 4.19 Plots of the relationship between average C and FMC in other tussock grasslands in Australia. 57
Figure 4.20 Distribution of wet tussock grasslands with herbs, sedges or rushes, herblands or ferns (green areas) in Australia..........59
Figure 4.21 Plots of the relationship between average C and FMC in wet tussock grasslands with herbs, sedges or rushes, herblands or ferns in Australia...........60
Figure 4.22 Distribution of mixed chenopod, samphire, or forbs (green areas) in Australia. 62
Figure 4.23 Plots of the relationship between average C and FMC in mixed chenopod, samphire, or forbs in Australia. 63
Figure 4.24 Distribution of sedgelands, rushes, or reeds (green areas) in Australia.......65
Figure 4.25 Plots of the relationship between average C and FMC in sedgelands, rushes, or reeds in Australia. 66
Figure 4.26 Distribution of non-native grasslands (green areas) in Australia. 69
Figure 4.27 Plots of the relationship between average C and FMC in non-native grasslands in Australia. 70

Figure 4.28 Results of Pearson's correlation analysis and Spearman's correlation analysis 73

Figure 4.29 Distribution of hummock grasslands with different fire history classes in Australia. 75

Figure 4.30 Time series plots showing average C and FMC in areas with different fire history classes for Australia hummock grasslands over 12 months. 76

Figure 4.31 Time series plots showing average C and FMC of areas with different fire history classes within Australian hummock grasslands during the entire study period (from 2002 to 2014 except 2008 and 2010). 77

Figure 4.32 Scatter plot showing average C and corresponding average FMC of areas with different fire history classes within Australia hummock grasslands on different dates over the study period (from 2002 to 2014 except 2008 and 2010). 79

Figure 4.33 Results of Pearson's correlation analysis and Spearman's correlation analysis 80

Figure 4.34 Distribution of non-native grasslands with different fire history classes in Australia. 82

Figure 4.35 Time series plot showing the average C and FMC of areas with different fire history classes in Australia non-native grasslands over 12 months. 83

Figure 4.36 Time series plots showing the average C and FMC of areas with different fire history classes in Australia non-native grasslands over 11 years (from 2002 to 2014 except 2008 and 2010) 84

Figure 4.37 Scatter plots showing the average C and corresponding average FMC of areas with different fire history classes in non-native grasslands on different dates over the study period (from 2002 to 2014 except 2008 and 2010). 86

Figure 4.38 Results of Pearson's correlation analysis and Spearman's correlation analysis 87

Figure 4.39 Scatter plot showing the average C and corresponding average FMC of Australia non-native grasslands in different months over 11 years. 88

Figure 4.40 Results of Pearson's correlation analysis and Spearman's correlation analysis 89

List of Tables

Table 1.1 Total quantified losses, total benefits, and net loss for the past five major extreme fire events in Australia (Stephenson *et al.*, 2013) 2

Table 1.2 Bands in MOD09 (Table obtained from Martin et al., 2015) 6

Table 2.1 RMSE of curing estimates derived from several methods based on a time series analysis of the NDVI (Newnham *et al.*, 2010). 14

Table 2.2 RMSE of methods applied to estimate C in Australian grasslands from satellite data (Newnham *et al.*, 2010). 15

Table 2.3 Developed spectral indices for FMC estimation 16

Table 3.1 MVS number and MVS name in NVIS' MVS products included in the present study 19

Table 3.2 Characters of previous fire events with nine fire classes 25

Table 3.3 Description of the strength of the correlation for the absolute value of r.......27

List of Equations

$C = 15.5 + 97e - FMC75.3$ (Equation 1.1)...4

$\boldsymbol{F = 2e - 23.6 + 5.01 \times \ln C + 0.0281 \times T - 0.226 \times \sqrt{H} + 0.633 \times \sqrt{V}}$ (Equation 2.1) 10

$NDVI = NIR - RedNIR + Red$ (Equation 2.2) 12

$SAVI = NIR - RedNIR + Red + L(1 + L)$ (Equation 2.3)..........12

$FMC = -3.7865C + 366.04$ (Equation 4.1) 47

$FMC = -3.9595C + 342.57$ (Equation 4.2)...51

$FMC = -3.2426C + 309.12$ (Equation 4.3) 55

$FMC = -3.8331C + 338.16$ (Equation 4.4) 68

Abbreviations

C	degree of curing
EVI	Enhanced Vegetation Index
FMC	fuel moisture content
GEMI	Global Environmental Monitoring Index
GVMI	Global Vegetation Moisture Index
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	Moisture Stress Index
MVI	Modified Vegetation Index
MVS	Major Vegetation Subgroups
NDII	Normalised Difference Infrared Index
NDVI	Normalised Difference Vegetation Index
NDWI	Normalised Difference Water Index
NIR	near infrared
NVIS	National Vegetation Information System
RTM	Radiative Transfer Models
SAVI	Soil Adjusted Vegetation Index
SIPI	Structural Independent Pigment Index
SR	Simple Ratio
SWIR	short-wave length infrared
VARI	Visible Atmospheric Resistant Index

Chapter 1: Introduction

1.1 Background

Bushfires are a common environmental issue in Australia and have a long history in this country. Currently, approximately 5% of the Australian land surface is burned every year, which consumes up to 10% of net primary productivity (Pittock *et al.*, 2003). Bushfires have major impacts on multiple aspects of Australian society, including the economy, ecology, human health, and heritage. Researchers evaluated the economic loss of the past five major extreme bushfires in Australia (including 1983 Ash Wednesday, 2003 Canberra, 2005/06 Grampians, 2006/07 Great Divide, and 2009 Black Saturday) and found that each of these fires resulted in a net economic loss ranging from AUD 414 million to AUD 3049 million (Table 1.1) (Stephenson *et al.*, 2013). In addition, 825 known civilian and firefighter fatalities have been recorded in 260 bushfires from 1901 to 2011 (Blanchi *et al.*, 2014). In the Australian Capital Territory, water quality in water-supply reservoirs was compromised after fire events due to the erosion of bare soil on slopes and in riparian zones (Worthy and Wasson, 2004). Furthermore, the 2003 Canberra fire destroyed the Mount Stromlo Observatory that was built in 1924, causing a huge loss of heritage and cultural values (Pitman *et al.*, 2007). Because fire events are frequent and can be costly, understanding the fire regime and factors for determining fire regimes are important because it helps predict and manage bushfires in Australia.

Table 1.1 Total quantified losses, total benefits, and net loss for the past five major extreme fire events in Australia (Stephenson *et al.*, 2013**)**

Fire event	1983 Ash Wednesday	2003 Alpine and Canberra	2005/06 Grampians	2006/07 Great Divide	2009 Black Saturday
Total loss (rounded to the nearest $000,000)	1807	3659	455	2216	2939
Net loss (rounded to the nearest $000,000)	1196	3049	414	2038	942

The risks of bushfires are aggravated by climate change. The probability of extreme fire risk is predicted to be consistently increasing to 2100 due to increasing temperatures and decreases in relative humidity (Pitman *et al.*, 2007). Based on McArthur's (1967) forest fire danger index, Beer and Williams (1995) estimated an increase in the frequency of bushfires in Australia because of increasing atmospheric CO_2 concentrations. Overall, the current global climate change increases the risk of bushfires; therefore, understanding the fire regime and factors for determining fire regimes are important for the improvement of fire prediction models and to help fire management in the future.

Grasslands cover a large proportion of land in Australia, are distributed in large areas across different climatic zones, and contain many different grass species. Grasslands have important economic, conservation, tourism, and recreational values (Moore, 1970); therefore, it is important to study grassland fire regime in Australia to ensure better management of bushfires.

Due to increasing fire risks in the future, an effective fire prediction model is crucial for fire management and suppression in Australian grasslands because this will help predict fire risks and the rate of fire spread. Two important variables in fire prediction models are the fuel moisture content (FMC) and the degree of curing (C). C refers to the proportion of yellowed or dead material in the total fuel load in a grassland and is applied in fire prediction models to evaluate fuel moisture (Newnham *et al.*, 2010), leading to the estimation of fire spread rate and fire risks (McArthur, 1966; McArthur, 1973; Cheney *et al.*, 1998). Among all ground-based observation of C methods, visual assessment is the simplest and most cost-effective method; however, it also causes errors due to unexperienced observers and a period of "calibration" of the eyes (Anderson and Pearce, 2003). Levy's (1933) method is a more accurate and effective measurement of C in grasslands. FMC is defined as the proportion of water over dry materials (Paltridge and Barber, 1988; Yebra *et al.*, 2008). Ground-based observations of FMC data are collected by plot sampling, weighing, and drying (Chuvieco *et al.*, 2003). Many fire prediction models evaluate fuel conditions to estimate fire risks and fire spread directly from FMC (Burgan and Rothermel, 1984; Griffin and Allan, 1984; Burrows *et al.*, 1991; Burrows *et al.*, 2009). Thus, the relationship between C and FMC is important for assessing fuel conditions and developing fire prediction models. Studies of the relationship between C and FMC provide a better understanding of fuel conditions or fire regimes, so that they help improve fire prediction models. If it could be proven that there was always a clear correlation between C and FMC in grasslands, some fire prediction models that include both C and FMC as variables could be simplified.

Relation between C and FMC are important for satellite based FMC observation. Spectral indices focused on contrast between Red and Near Infrared reflected chlorophyll concentration or C, and they were assumed to relate to FMC, although their association were questioned (Chuvieco *et al.*, 2004; Gond *et al.*, 1999). Indirect observations of FMC were conducted through NDVI in different researches (Rouse Jr *et al.*, 1974; Paltridge and Barber, 1988). Studying relation between C and FMC in grasslands helped test effectiveness of spectral indices that estimated FMC in grasslands.

The relationship between C and FMC had been intensively studied but get conflicting results. It has been hypothesised that there is a negative linear correlation between C and FMC, based on previous studies regarding the relationship between the normalised difference vegetation index (NDVI) and C, and the relationship between NDVI and FMC. NDVI reflects chlorophyll concentration and it is an accurate and effective index in C estimation because there is always a negative linear correlation between NDVI and C (Rouse Jr *et al.*, 1974, Newnham *et al.*, 2010). Data collected in the field-based observation in three sites in Victoria showed positive linear relations between NDVI and FMC; however, the coefficient also varied at different sites (Dilley *et al.*, 2004). A positive correlation between NDVI and FMC was also observed using field sampling data in Canada (Davidson *et al.*, 2006). Therefore, there may be a negative linear relationship between C and FMC.

In contrast, several studies have suggested a negative exponential correlation between C and FMC (Barber, 1990; Dilley *et al.*, 2004). Based on data collected by McArthur (1966), Barber (1990) stated that C and FMC were directly related to a negative monotonic exponential relationship. Dilley *et al.* (2004) expressed the relationship between C and FMC in grasslands in Victoria as Equation 1.1 from Barber's (1990) study:

$$C = 15.5 + 97e^{-\frac{FMC}{75.3}} \qquad \text{(Equation 1.1)}$$

However, other researchers have questioned whether there is a clear relationship between C and FMC. Kidnie *et al.* (2015) studied the relationship between FMC and C in Australian grasslands by classifying grass fuel components into four distinct fuel categories: old dead, new dead, senescing, and green. The four categories had different moisture dynamics. The moisture contents of the old and new dead fuel were more related to environmental conditions, whereas the moisture contents of the senescing and green fuel were relatively stable (Kidnie *et al.*, 2015). Although the change in C may alter the proportion of different fuel categories, it is not directly related to FMC because FMC might also be affected by weather conditions. In addition, previous fire events that changed the proportion of fuel categories in grasslands could influence the relationship between C and FMC. Wittich (2011) classified fuel in grasslands into dead grass and live grass to understand fuel dynamics and found that the FMC of the dead fuel was highly related to atmospheric humidity and it could change rapidly even within one day. For live grass, the relation between C and FMC was different in annual and perennial grasslands, with perennial grasses more tolerant to drought stress and stayed green longer than annual grasses (Wittich, 2011). Thus, the relationship between C and FMC in grasslands is specific to grass species. Gill (2006) stated that the C and FMC relation is species specific. However, Andrews *et al.* (2006) tested 14 sites in Australia and New Zealand and concluded that there was no clear relationship between the moisture content of live fuel and C at the sampling sites. Moreover, in addition to water stress, C is influenced by plant nutrient deficiency, disease, toxicity, and phonological stage (Larcher, 2003); therefore, there is not always a clear correlation between C and FMC in grasslands.

All previous studies that have focused on the C and FMC relationship only tested this relationship at a few experimental sites. To overcome the limited sample size, remote sensing provides a large-scale, non-destructive, and instantaneous observation at various scales (Davidson *et al.*, 2006). MOD09 is a MODIS surface reflectance product that provides reflectance values for every 500-m pixel every 8 days from seven bands (Table 1.2) (Vermote, 2015). Other MODIS surface reflectance products, MCD43A4 and MCD43A2, provide 500-m resolution derived from a 16-day composite (Schaaf and

Wang, 2015). MCD43A4 data are calculated daily from 2000 to present (Schaaf and Wang, 2015).

Table 1.2 Bands in MOD09 (Table obtained from Martin et al., 2015)

Band	Spectral region	Wavelength (nm)
R_1	Red	620–670
R_2	Near-infrared – NIR	841–876
R_3	Blue	459–479
R_4	Green	545–565
R_5	Near-infrared – NIR	1230–1250
R_6	Short-wave infrared – SWIR	1628–1652
R_7	Short-wave infrared – SWIR	2105–2155

1.2 Aims of the study

Based on the literature review, there are controversies regarding the relationship between C and FMC. Thus, the present study aimed to test for the correlation between C and FMC. Using satellite-observed C and FMC data, this study investigated the relationship between C and FMC at a large scale across grasslands in Australia and over a time series. The study also included smaller-scale samples to examine the influences of grass species, seasonal change, and fire histories on the correlation between C and FMC. It was hypothesised that there would always be a negative linear relationship between C and FMC in Australian grasslands regardless of grass species, fire history, or seasons.

To address this hypothesis, two specific aims were studied:

1. Test the correlation between C and FMC across grasslands over the whole of Australia.
2. Investigate factors that might affect the correlation between C and FMC in Australian grasslands, including grass species, fire events, and seasonal climate change.

Chapter 2: Literature review

2.1 Australian grasslands

Moore (1970) defined the term ‘grassland’ as land used for domestic animal feeding and he classified Australian grasslands based on climate, physiognomy, and species. Grass species in Australia vary from tropical tallgrass to sub-alpine tussock grass (Moore, 1970). Various grass species in Australian grasslands were investigated in the present study to test their influence on the relationship between C and FMC. The classification of grasslands and distribution of each grassland type was obtained from the National Vegetation Information System’s (NVIS) Major Vegetation Subgroup (MVS) products (Australian Government Department of the Environment and Energy, 2018). The latest MVS dataset—NVIS Version 5.1—was released in 2018 and it mapped the vegetation types in Australia with a 100 m × 100 m (1 ha) cell size that covered the whole of Australia by dividing the Australian vegetation into 85 subgroups. Native grasslands were classified based on climate, physiognomy, and grass species in this map (Australian Government Department of the Environment and Energy, 2018). NVIS’s MVS products were applied in the analysis because of their spatial and temporal accuracy. To prevent the influence from the canopy layer, only open grassland vegetation types were used (Australian Government Department of the Environment and Energy, 2018). NVIS’s MVS products mainly describe native grasslands and do not clearly map the distribution of non-native grasslands or modified pasture (Australian Government Department of the Environment and Energy, 2018). However, the locations of non-native grasslands were identified by combining NVIS’s MVS products and the Land Use of Australia 2010–11 dataset based on the Australian Bureau of Statistics’ 2010–11 agricultural census data with a 0.01-degree pixel size (Australian Bureau of Agricultural and Resource Economics and Sciences, 2016).

2.2 Australian fire prediction models

An effective, fast, and accurate prediction of fire behaviour is important for the management of bushfires in Australia. To develop effective suppression strategies, it is essential to raise public awareness, implement safely prescribed fires, and undertake fire risk analysis using fast and effective fire prediction models (Plucinski *et al.*, 2017). Prediction methods of fire behaviours in Australian grasslands have been developed for decades. The prediction of fire risks started over 50 years ago with the adaption of the Canadian grassland fire danger tables (Gill *et al.*, 2010). McArthur's meters, which provided fire spread information for tactical and strategic planning, have commonly been used in Australia (McArthur, 1967; Beer, 1990). McArthur's fire danger meters were applied to forecast the possibility of fire ignition, predict the rate of fire spread, and measure the difficulty of fire suppression (Noble *et al.*, 1980). McArthur (1966) stated that C, air temperature, wind velocity, and relative humidity were relevant for estimating the possibility of ignition and the rate of fire spread. He listed fuel or weather conditions and the corresponding fire danger index and rate of fire spread in various tables, known as McArthur's grassland fire danger meter Mark 3 (McArthur, 1966). The McArthur grassland fire danger meter Mark 4 (McArthur, 1973) (listed in Figure 2.1) model was developed from table form to rectangular slide rules and this meter is commonly applied in bushfire prediction in Australian grassland nowadays (Beer, 1991). Noble *et al*. (1980) summarised McArthur's grassland fire danger meter and expressed it as Equation 2.1.

$$\boldsymbol{F} = \boldsymbol{2e}^{-23.6+5.01\times\ln(C)+0.0281\times T-0.226\times\sqrt{H}+0.633\times\sqrt{V}} \quad \textbf{(Equation 2.1)}$$

$$R = 0.13 \times F$$

This equation includes the variables used in the calculation of the fire danger index and the forward spread rate of fire, where F is the fire danger index, C is the degree of curing, T is the air temperature, H is the relative humidity, V is the average wind velocity in the open at a height of 10 m, and R is the forward spread rate of fire.

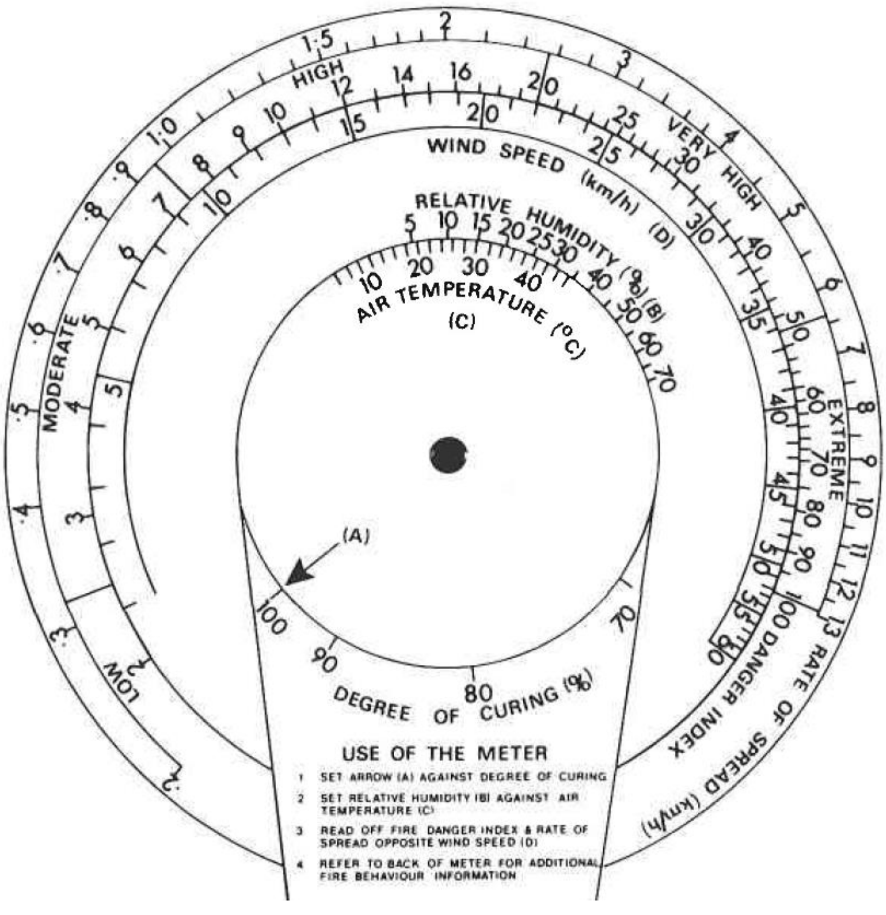


Figure 2.1 McArthur Mark 4 meter (McArthur, 1967)

McArthur's grassland fire danger meter illustrates that fire behaviours are directly determined by fuel conditions and weather conditions. C was a variable used in McArthur's meter to evaluate fuel conditions, which was based on the assumption that C was directly related to both live and dead FMC (Cruz *et al.*, 2015). However, other researchers have shown that the relationship between C and FMC is influenced by other factors, including grass species (Gill, 2006; Wittich, 2011) and the proportion of different fuel categories (Andrews *et al.*, 2006; Kidnie *et al.*, 2015).

Based on the original McArthur grassland fire danger meter Mark 4, the Commonwealth Scientific and Industrial Research Organisation (CSIRO) developed an uncapped grassland fire danger meter (Gill *et al.*, 2010). In the current fire prediction models, Australian grasslands are classified into (i) southern grasslands, (ii) hummock *Spinifex* grassland, and (iii) tropical grassland, woodlands and open forests, with CSIRO recommending different fire prediction models for different grasslands (Cruz *et al.*, 2014).

In southern grasslands, the uncapped grassland fire danger meter was developed based on McArthur's grassland fire danger meter and included C, FMC, and weather conditions as input variables (Cruz *et al.*, 2014). Based on the ground-based data from the Annabarroo experiments (Cheney *et al.*, 1993), a new model was developed to predict the rate of spread in southern grasslands (Cheney *et al.*, 1998). In this model, both dead FMC and C were considered as input variables to evaluate the fuel condition in grasslands.

In hummock *Spinifex* grasslands, models that estimated the rate of spread were developed by Griffin and Allan (1984) and Burrows *et al.* (1991). CSIRO recommends the model described by Burrows *et al.* (2009) for bushfire prediction in hummock *Spinifex* grasslands (Cruz *et al.*, 2014). All the models used in predicting the rate of fire spread in hummock grassland selected FMC and *Spinifex* cover as the input variables to evaluate the fuel condition in hummock grasslands (Cruz *et al.*, 2014).

To predict fire spread in tropical grasslands, woodlands, and open forests, CSIRO recommends the CSIRO Fire Spread Meter for North Australia based on the grassland fire spread model developed by Cheney *et al.* (1998).

Both C and FMC are key input variables in current fire prediction models used for fire prediction and management. The relationship between the two variables, C and FMC, provides a better understanding of fuel dynamic and fire prediction models. The determination of a relationship between C and FMC at different sites can help adjust the application range of a certain fire prediction model or simplify and improve fire prediction models.

2.3 Curing data

Remote sensing has the potential to collect curing data over the whole of Australia and many methods have been developed to collect C in grasslands using satellite data. Different spectral indices must be applied to calculate C from satellite data, including NDVI (Rouse Jr *et al.*, 1974) and the Soil Adjusted Vegetation Index (SAVI) (Huete, 1988). The equations for NDVI and SAVI are listed as Equation 2.2 and Equation 2.3, respectively. The effectiveness of these two different spectral indices in estimating C in grasslands was tested by Newnham *et al.* (2010). NDVI performed the best in natural grasslands or mixed grasslands, while SAVI normalised in time series reduced the influences from bare soil, and thus performed the best in improved pastures.

$$\boldsymbol{NDVI = \frac{NIR - Red}{NIR + Red}} \qquad \textbf{(Equation 2.2)}$$

$$\boldsymbol{SAVI = \frac{NIR - Red}{NIR + Red + L}(1 + L)} \qquad \textbf{(Equation 2.3)}$$

where, L is the value applied to decrease soil noise.

C was derived from satellite data on a regional scale in Australia in many previous studies. Martin *et al.* (2015) compared 500-m MOD09A1 satellite data against field data collected from ground-based observations from October 2005 to January 2013 at 211 grassland sites across Victoria to develop the MapVictoria satellite curing model. Chladil and Nunez (1995) used NDVI to collect C from the National Oceanic Atmospheric Administration/Advanced Very High Resolution Radiometer data in south-eastern Tasmania. In the Northern Territory, Allan *et al.* (2003) compared the relationship between C collected by ground-based observation and NDVI normalised in time series, concluding that there was a strong linear relationship at the black soil site and a strong curvilinear relationship at the red soil site.

C in grasslands can be calculated with NDVI by using different methods. Dilley *et al.* (2004) declared an exponential relation between NDVI and C in south-eastern Australia. Conversely, Newnham *et al.* (2010) proposed a negative linear relationship between C and NDVI after comparing field estimation and satellite data in 25 field sites distributed across five states of Australia. In addition, NDVI collected from MODIS data was placed in time series to eliminate the errors caused by bare soil and evergreen vegetation, and thus to improve the accuracy, which is known as the relative greenness approach (Newnham *et al.*, 2011). The time series should be long enough to include extreme NDVI values, but exclude land use change (Newnham *et al.*, 2011).

The effectiveness of three different methods (listed in Table 2.1) was tested by comparing the results obtained from satellite with field-based observations at 25 grassland sites over 4 years within different climatic zones across Australia (Newnham *et al.*, 2010). The root mean square error (RMSE) of each method was calculated to examine their effectiveness. The relative greenness regression model performed with the highest accuracy for estimating C across Australia, although it tended to underestimate C at high levels (Newnham *et al.*, 2010). C at high levels has high fire risks and rates of spread. Thus, NDVI methods are not suitable for extreme fire prediction because of the underestimation of C at high levels. Newnham *et al.*'s (2010) study also showed that the relationship between C and NDVI was likely to be a negative linear one rather than an exponential one.

Table 2.1 RMSE of curing estimates derived from several methods based on a time series analysis of the NDVI (Newnham *et al.*, 2010).

Method	Formula	RMSE%
Non-linear model	$C = -19.1 + 218e^{-\frac{NDVI}{0.434}}$	18.97
Simple linear model	$C = (1.03 - NDVI) \times 108.11$	16.37
Relative greenness regression model	$C_i = (1.24 - \frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}}) \times 75.36$	15.90

Newnham *et al.* (2010) developed four different methods to calculate C from MODIS MOD09 surface reflectance over the whole of Australia (listed in Table 2.2). The accuracy of these four methods was tested by comparing C derived from satellite and ground observations at sites across Australia over 4 years (Newnham *et al.*, 2010). The results showed that method B, multiple linear regression against NDVI and the ratio of bands 7 and 6, performed the best in estimating C in Australia (Newnham *et al.*, 2010). Thus, C in subsequent analysis was collected from satellite data using method B. The C data product based on method B were downloaded from:

http://opendap.bom.gov.au:8080/thredds/catalog/curing_modis_500m_8-day/aust/netcdf/b/catalog.html.

Table 2.2 RMSE of methods applied to estimate C in Australian grasslands from satellite data (Newnham *et al.*, 2010).

Methods	Formula	RMSE%
Linear regression (NDVI)	$C = 124.71 - 121.4 \times NDVI$	11.90
Multiple linear regression (NDVI, R7/R6)	$C = 237.308 - 190.139 \times NDVI - 142.655 \times \frac{R_7}{R_6}$	10.54
Normalised regression of NDVI	$C = 93.274 - 61.896 \times \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}$	13.26
Normalised regression of SAVI	$C = 93.347 - 73.776 \times \frac{SAVI - SAVI_{min}}{SAVI_{max} - SAVI_{min}}$	12.97

One limitation of satellite-based observations is the potential lack of data in some pixels due to poor atmospheric conditions. In addition, there might be some errors in these observations. NDVI values are underestimated in areas with clouds and aerosols (Feng *et al.*, 2002). Moreover, the atmospheric influences of the zenith angle are more significant when this angle is large (Feng *et al.*, 2002). Method B overestimates C if water is present, whereas it underestimates C if woody vegetation is present (Newnham *et al.*, 2010). Exposed soils reduce the accuracy of C estimation based on NDVI (Huete *et al.*, 1984). The effectiveness of different satellite curing models might change due to vegetation variations because they are fitted for different grass types.

2.4 FMC data

To overcome the limitations of ground-based observations, remote sensing is used to collect instantaneous FMC data (Davidson *et al.*, 2006). Methods used to collect FMC data from satellite data products are well-developed and have been intensively discussed in previous studies. Water content differences are most reflected in near infrared (NIR) and shortwave infrared (SWIR) bands (Tucker, 1980; Bowman, 1989). The contrast between red and NIR bands reflect leaf chlorophyll content, which is assumed to correlate with leaf moisture content (Davidson *et al.*, 2006; Paltridge and Barber, 1988)Different methods have been developed to calculate FMC data in grasslands with these wavelengths, which are listed in Table 2.3.

Table 2.3 Developed spectral indices for FMC estimation

Methods	Formula	Reference
Normalised Difference Vegetation Index (NDVI)	$NDVI = \frac{NIR - Red}{NIR + Red}$	(Rouse Jr *et al.*, 1974)
Soil Adjusted Vegetation Index (SAVI)	$SAVI = \frac{NIR - Red}{NIR + Red + L}(1 + L)$	(Huete, 1988)
Enhanced Vegetation Index (EVI)	$EVI = \frac{2.5(NIR - Red)}{NIR + 6Red - 7.5Blue + 1}$	(Huete *et al.*, 2002))
Global Environmental Monitoring Index (GEMI)	$GEMI = \eta(1 - 0.25\eta) - \frac{\text{Red} - 0.125}{1 - \text{Red}}$ $\eta = \frac{2(NIR^2 - Red^2) + 1.5NIR + 0.5Red}{NIR + Red + 0.5}$	(Pinty and Verstraete, 1992)
Visible Atmospheric Resistant Index (VARI)	$VARI = \frac{Green - Red}{Green + Red - Blue}$	(Gitelson *et al.*, 2002)
Structural Independent Pigment Index (SIPI)	$SIPI = \frac{NIR - Blue}{NIR + Red}$	(Peñuelas and Inoue, 1999)
Modified Vegetation Index (MVI)	$MVI = \frac{NIR - 1.2Red}{NIR + Red}$	(Paltridge and Barber, 1988)
Simple Ratio (SR)	$SR = \frac{NIR}{Red}$	(Jordan, 1969)
Moisture Stress Index (MSI)	$MSI = \frac{SWIR}{NIR}$	(Hunt Jr and Rock, 1989)

Global Vegetation Moisture Index (GVMI)	$$GVMI = \frac{(NIR + 0.1) - (SWIR + 0.02)}{(NIR + 0.1) + (SWIR + 0.02)}$$	(Ceccato *et al.*, 2002)
Normalised Difference Water Index (NDWI)	$$NDWI = \frac{R_2 - R_5}{R_2 - R_5}$$	(Gao, 1996)
Normalised Difference Infrared Index (NDII)	$$NDII = \frac{NIR - SWIR}{NIR + SWIR}$$	(Hunt Jr and Rock, 1989)

Researchers tested the accuracy of spectral indices for collecting FMC from satellite data in grasslands. Davidson *et al.* (2006) compared satellite FMC data with data collected using ground-based sampling in Canadian grasslands, concluding that spectral indices emphasised the contrast between the NIR and SWIR spectral regions (including NDII, MSI, and GVMI) and were more reliable in estimating FMC data than the contrast between red and NIR or between visible and SWIR. Chuvieco *et al.* (2010) suggested that the NIR–SWIR contrast could better reflect FMC change in grasslands and shrublands in Spain. Yebra *et al.* (2008) illustrated that the contrast between red and NIR reflecting the change in chlorophyll content was indirectly related to FMC change. Indices in NIR and SWIR wavelengths including bands with water absorption features had direct links with FMC (Yebra *et al.*, 2008). Furthermore, indices that emphasised the red–NIR contract were related with C. Thus, these indices were not suitable for collecting FMC data in this experiment.

Empirical methods based on fitting ground-observed FMC and satellite reflectance data are site or sensor specific; therefore, they are not suitable for collecting FMC over a large scale (Yebra *et al.*, 2008). Simulation methods based on backwards simulation of radiative transfer models (RTM) had direct links with FMC and the results were not influenced by different sensors or sites (Yebra *et al*., 2008). Spectral indices focus on NIR/SWIR contrast (NDII and GVMI) were selected in these models and an inversion process was achieved by iteratively running the model until a simulated reflectance produced from a set of input parameters was found that closely matched the reflectance values from the satellite data (Yebra *et al.*, 2008). Compared with MOD09, MCD43 improved the accuracy of RTM in estimating the FMC of grasslands (Jurdao *et al.*, 2013). MCD43A4 was applied to estimate FMC, whereas MCD43A2 was used to remove pixels covered by clouds or with low data quality (Yebra *et al.*, 2018). Because of these advantages of the RTM, FMC data in the subsequent analysis were derived from MODIS satellite data using RTM (Yebra *et al.*, 2018), which were downloaded from http://dap.nci.org.au/thredds/remoteCatalogService?catalog=http://dapds00.nci.org.au/thredds/catalog/ub8/au/FMC/c6/mosaics/catalog.xml.

Chapter 3: Methods

3.1 Mapping the distribution of different grass species in Australia

NVIS's MVS products provided information about the attributes of different vegetation types in Australia with a 100 m × 100 m (1 ha) cell size from 2018. This map only reflects the dominant vegetation in a map unit and the less dominant vegetation is neglected (Australian Government Department of the Environment and Energy, 2018). This map differentiates Australia vegetation into 85 categories, 11 of which are related to open grasslands and were applied in subsequent analysis (Table 3.1). NVIS's MVS products were downloaded from:

http://environment.gov.au/fed/catalog/search/resource/downloadData.page?uuid=%7B3F8AD12F-8300-45EC-A41A-469519A94039%7D

Table 3.1 MVS number and MVS name in NVIS' MVS products included in the present study

MVS number	Grasslands types
33	Hummock grasslands
34	Mitchell grass (*Astrebla*) tussock grasslands
35	Blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands
36	Temperate tussock grasslands
37	Other tussock grasslands
38	Wet tussock grasslands with herbs, sedges or rushes, herblands, or ferns
39	Mixed chenopod, samphire, or forbs
41	Saline or brackish sedgelands or grasslands
63	Sedgelands, rushes, or reeds
64	Other native grasslands
99	Cleared, non-native vegetation, buildings

The first 10 types are all native grasslands (Table 3.1) and MVS 99 also includes non-native pasture and other land use types. To separate non-native grasslands from other land use types included in type 11, NVIS's MVS products were combined with the Land Use of Australia 2010–11 dataset based on the Australian Bureau of Statistics' 2010–11 agricultural census data with a 0.01-degree pixel size (Australian Bureau of Agricultural and Resource Economics and Sciences, 2016). The Land Use of Australia 2010–11 dataset was downloaded from:

http://data.daff.gov.au/anrdl/metadata_files/pb_luav5g9abll20160704.xml.

The Land Use of Australia 2010–11 illustrates the distribution of grazing modified pastures and irrigated modified pastures, which help separate the non-native grasslands in type 11. The percentage of coverage by different types of grasslands in the Australian grasslands area was calculated according to the pixels covered by each grassland type.

Hummock grasslands are defined as coarse xeromorphic grass with a mound-like form that is often dead in the middle (NVIS Technical Working Group, 2017) (Figure 3.1). Hummock grasslands are dominated by perennial grasses and a large proportion of the ground surface is bare (Burrows *et al.*, 2009). The discontinuous nature of the vegetation helps accumulate fuel load in hummock grasslands because fire cannot spread when fuel load is low (Burrows *et al.*, 2009). Previous fire events have significant influences on the density, height, and form of hummocks (Burrows *et al.*, 2009).

Tussock grass is defined as discrete and open grasslands consisting of grasses with distinct individual shoots and include different grass species (NVIS Technical Working Group, 2017) (Figure 3.2 and Figure 3.3). Most tussock grass species are perennial, but annual tussock grass does exist (Beadle, 1981). Temperate tussock grasslands in south-eastern Australia are typically dominated by perennial tussock grasses, while forbs, wildflowers, orchids, and other perennial or annual grasses co-exist in inter-tussock spaces (Carter *et al.*, 2003) (Figure 3.4). Grazing of livestock is a major economic activity in tussock grasslands (White *et al.*, 2014). Wet tussock grasslands with herbs, sedges or rushes, and herblands or ferns are dominated by non-woody or herbaceous species such as grasses, sedges, ferns, or a mixture of these, and the vegetation is continuous (Department of the Environment and Energy, 2017).

In mixed chenopod, samphire, or forbs, chenopods are drought and salt tolerant, single or multi-stemmed, semi-succulent annual or perennial herbs, subshrubs or shrubs

(NVIS Technical Working Group, 2017) (Figure 3.5). Samphires are perennial succulent herbs and small shrubs that have articulated branches (Coleman, 1998) (Figure 3.6). Forb is a herbaceous or slightly woody plant that is annual or sometimes perennial (NVIS Technical Working Group, 2017).

Examples of Australian sedgelands, rushes, or reeds are shown in Figure 3.7. Saline or brackish sedgelands are closely associated with coastal saltmarshes (Department of the Environment and Energy, 2017).

Native grasslands under the family *Poaceae*, but without a distinctive tussock nor hummock appearance, are categorised as other grasslands (NVIS Technical Working Group, 2017). This category includes many different species of grasses.

In most Australian temperate grassy ecosystems, grass species changed dramatically after European settlement (Prober and Thiele, 2005). Native kangaroo grass or snow tussock grass have been replaced by secondary native perennial grasses and non-native annual grass (Moore, 1970). Wallaby grass or spear grass communities and many native perennial forbs have been replaced by native and exotic annual grasses due to livestock grazing (Prober and Thiele, 2005). Non-native *Hypochaeris radicata*, *Lolium* spp., *Bromus molliformis, and Echium plantagineum*, and native *Elymus scaber*, *Austrostipa scabra*, *Lomandra filiformis,* and *Bulbine bulbosa* are frequently observed in these grasslands (Prober and Thiele, 2004). Figure 3.8 shows non-native grasslands or modified pasture in Australia.

Figure 3.1 Hummock grasslands associated with stony landscapes, Kimberley, WA (Photo: M. Fagg)

Figure 3.2 Mitchell tussock grassland, west of Blackall, QLD (Photo: M. Fagg)

Figure 3.3 Blue grass (Dichanthium sericeum) tussock grassland, Springsure, QLD (Photo: D.W. Butler)

Figure 3.4 Temperate tussock grasslands dominated by Stipa species, Cooma, NSW (Photo: M. Fagg)

Figure 3.5 Chenopod shrublands, Hay, NSW (Photo: M. Fagg)

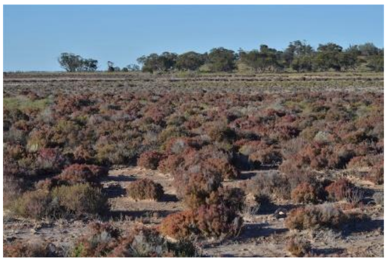


Figure 3.6 Samphire shrubland, Murray Sunset National Park, VIC (Photo: M. Fagg)

Figure 3.7 Mire (typically comprising sedges and rushes), Newnes Plateau, NSW (Photo: D. Keith)

Figure 3.8 Modified pasture with scattered eucalypts (Photo: M. Fagg)

3.2 Mapping previous fire events in Australian grasslands

Previous fire events, including prescribed or natural fires, might affect the relationship between C and FMC in grasslands by changing the fuel load, fuel structure, and grass species (Ruprecht *et al.*, 2013; Underwood and Christian, 2009; Dyer and Smith, 2003); therefore, the understanding of fire behaviour in grasslands is important for subsequent analysis. Fire history maps reflect the frequency and intensity of previous fires because several serious fire events or series of small fire events may have different influences on the relationship between C and FMC.

Australia's Environment Explorer dataset contains the times of fire occurrence and annual maximum fire intensity in Australia with a 2.5 km cell size from 2000 to 2018 (Van Dijk and Summers, 2016). Fire occurrence and fire intensity data were downloaded from http://wald.anu.edu.au/australias-environment/#Download. Data from 2002 to 2014 except 2008 and 2010 were selected for the present study because there was C data and FMC data every 8 days in these years. In 2008 and 2010, C data were missing in some seasons in the dataset, which might lead to an error in the calculation of the correlation coefficient for the entire year, so these were excluded from the study. The fire occurrence data and fire intensity data over 11 years were selected to create a fire history map. The fire occurrences in each year over a range of Australian grasslands were summarised to calculate the fire occurrence of the 11 years in each pixel. Moreover, the intensity of the most intensive fire event during the study period was regarded as the fire intensity of the research years in each cell. Considering that fire intensity and fire frequency can have distinct influences on the correlation between C and FMC, they were combined to illustrate previous fire behaviour. According to natural breaks, fire intensity and occurrence over the 11 years were classified into three categories. Then, they were combined to create nine fire history classes (Table 3.2) to illustrate the fire history in Australia during these years. Fire frequency was classified as low (1–7 fire events during the study period), middle (7–36 fire events during the study period), and high (36–441 fire events during the study period) fire frequency, whereas fire intensity was classified as low (32–73 °C), middle (73–115 °C), and high (115–234 °C) fire intensity. Thus, fire events were classified as class 1 (low fire intensity/low fire frequency), class 2 (low fire intensity/middle fire frequency), class 3 (low fire intensity/high fire frequency), class 4 (middle fire intensity/low fire frequency), class 5 (middle fire intensity/middle fire frequency), class 6 (middle fire intensity/high fire frequency), class 7 (high fire intensity/low fire frequency), class 8 (high fire intensity/middle fire frequency), and class

9 (high fire intensity/high fire frequency). Grasslands that never burned were identified from the fire occurrence and fire intensity data.

Table 3.2 Characters of previous fire events with nine fire classes

	Fire occurrence (times)	1–7	7–36	36–441
Fire intensity (°C)	Fire classes	Low fire frequency	Middle fire frequency	High fire frequency
32–73	Low fire intensity	Class1	Class2	Class3
73–115	Middle fire intensity	Class4	Class 5	Class 6
115–234	High fire intensity	Class 7	Class 8	Class 9

3.3 Testing the C–FMC relationship in grasslands

The C data in Australia at 500 m resolution every 8 days were derived from MOD09A1 using method B, although the data in several pixels were missing due to atmospheric conditions (Newnham *et al.*, 2010). RTMs estimated FMC data in Australia from MCD43A4; therefore, FMC data was derived from 16-day composites, but FMC was calculated every 4 days (Yebra *et al.*, 2018). C and FMC data derived from method B and RTMs in previous studies were used in the present study. C and FMC data with the same median date were paired to correspondence and subsequently used for the comparison of C and FMC values. The intended study area in this thesis was the grasslands in Australia. During each year in research period (from 2002 to 2014 except 2008 and 2010), 46 pairs of C and FMC values were collected from different pixels of Australian grasslands with an 8-day interval. The spatial resolution of C and FMC data were different; therefore, these two datasets could not be compared directly. To compare the two datasets, C and FMC data were downscaled to 0.05-degree resolution in the range from 10 °S to 44 °S and from 113 °E to 154 °E. Only grids with both validated C data and corresponding FMC data were included in the subsequent comparisons of the C and FMC values.

The average C and FMC values in Australian grasslands on different dates were calculated and plotted in a time series for 11 years (from 2002 to 2014 except 2008 and 2010) to investigate annual change or change in the longer term. Then, corresponding C and FMC values for the entire study period were plotted in a scatter plot to analysis their relationship. There were 46 pairs of average C values and average FMC values in the sample sites in Australian grasslands every year. The average of these 46 pairs of data was calculated covering the 11 years of the study period. Then, the averaged values of these 46 pairs of data that represented the change of C and FMC in Australian grasslands over 12 months were plotted in a time series to observe the seasonal change of C and FMC data. Over 11 years, different dates had various average C values and corresponding average FMC values; therefore, a Pearson's correlation analysis was conducted between average C and FMC values in Australian grasslands to test whether there was a clear linear relationship between C and FMC. C and FMC correlation can also be monotonic but not linear (Barber, 1990); therefore, it was necessary to conduct a Spearman's correlation analysis between all average C and FMC data to test whether there was a monotonic correlation between C and FMC also. Table 3.3 lists the description of the strength of the correlation for the absolute value of *r* based on a guide suggested by (Evans, 1996). Therefore, the changes in average C and average FMC values in Australian grasslands were monitored every 8 days during the study period and the relationship between C and FMC in Australian grasslands was determined.

To identify the regional differences in the C and FMC correlations, these correlations were tested in a time series in different regions and a map of was created of the Pearson's correlation coefficient values in different regions in one year with a resolution of 0.025 degrees. The Pearson's correlation coefficient between corresponding C and FMC values was calculated in a grid on a different date in a single year. To eliminate the influences from limited data, only grids with over 10 pairs of C and FMC data were included. The *r* value, which represented the relationship between C and FMC in a 0.025 grid, was calculated and applied in mapping the C and FMC correlation in Australia. The map of the C and FMC correlation in Australia can help identify the regional differences in the C and FMC relationship.

Table 3.3 Description of the strength of the correlation for the absolute value of *r*

Absolute value of *r*	Description
0.00–0.19	very weak
0.20–0.39	weak
0.40–0.59	moderate
0.60–0.79	strong
0.80–1.00	very strong

3.4 Analysing how grass species influence C and FMC relations

Grasslands with various grass species respond differently to FMC change (Gill *et al.*, 2010; Wittich, 2011). Thus, the influence of grass species on the C and FMC correlation must be tested. Live or dead fuel have different fuel dynamics (Wittich, 2011; Kidnie *et al.*, 2015). The FMC of dead fuel is closely related to atmospheric conditions, whereas the FMC of live fuel is relatively less influenced by weather change (Kidnie *et al.*, 2015). Fire can influence fuel conditions by the removal of dead fuel or live fuel; therefore, unburned areas that conserve complete fuel categories influence dead and live fuel, and thus affect the relationship between C and FMC. Different types of grasslands contain various proportions of fuel categories; therefore, the change in C and FMC correlation among different grasslands is better reflected in unburned areas that preserve all fuel categories. In addition, unburned grasslands help control variables and eliminate the influence of rehabilitation time from the last fire event in grasslands.

Australia's Environment Explorer was used for the identification of unburned areas. The unburned areas in different types of grasslands were identified by clipping the unburnt areas by each type of grassland. This was then used to mask the C and FMC data. Areas covered by saline or brackish sedgelands or grasslands were too small to study. Other native grasslands contained many different grass species that might have different correlations between C and FMC; therefore, these were excluded from this analysis. Thus, the relationship between C and FMC were analysed in nine types of grasslands (Table 3.1) in the present study. Subsequent analysis occurred as described previously.

3.5 Analysing how previous fire events influence C and FMC relations

Earlier fire events can remove dead fuel materials in grasslands, which might result in changes in fire behaviour and correlation between C and FMC. Variation in previous fire events could lead to different fuel conditions in grasslands. Frequent fire events remove dry biomass (old dead fuel or new dead fuel) in grasslands (Ruprecht *et al.*, 2013). Dead fuel and live or senescing fuel might have different moisture dynamics (Kidnie *et al.*, 2015); therefore, the change in fuel composition can lead to a change in the relationship between C and FMC. Thus, it is important to investigate the influence of previous fire events and determine the impacts of different fuel composition on the relationship between C and FMC. However, the influence of fire history can be species specific because different types of grasslands have different fuel dynamics.

In the present study, the influence of earlier fire events on the correlation between C and FMC were evaluated by analysing C and FMC in areas with different fire history classes in various types of grasslands. For this analysis, two major types of grasslands, hummock and non-native, were selected to measure the influence of previous fire events. This was because these two grassland types covered a large proportion of the total grasslands area in Australia and covered areas that have different fire history classes. Pixels with fire history class 3, class 6, and class 9 were very limited in these two types of grasslands; therefore, these three classes were excluded from the present study. Distribution of areas with different fire history and distribution of grassland types were combined to identify areas with different fire history classes in these two types of grasslands. Similar to the previous analysis, C data and corresponding FMC data were selected every 8 days and were downscaled to a 0.05-degree resolution in the study areas. The shapes of the areas with different fire history classes in hummock grasslands or non-native grasslands were applied to mask the C and FMC data to identify the study areas. Average C and FMC of the study areas on different dates were calculated and plotted in a time series and scatter plots to study the relationship between C and FMC in areas with different fire histories. After that, the average C and FMC values in one specific day of a year over 11 years were calculated and plotted in a time series to observe seasonal changes. The correlation between C and FMC in areas with different fire histories were determined by conducting Pearson's and Spearman's correlation analyses. To study how previous fire events influenced the correlation between C and FMC in hummock grasslands and non-native grasslands, the correlation coefficients in different types of grasslands were plotted and compared. Areas with frequent or serious previous fire events, which led to the loss of dead fuel, were compared with never burned grasslands to study the relationship between live FMC and C.

3.6 *Analysing how seasonal change influences C and FMC relations*

Previous studies have confirmed that grass species or previous fire events influence the correlation between C and FMC in Australian grasslands. However, the correlation between C and FMC in grasslands might change over different seasons. Seasonal climate difference might modify the correlation between C and FMC. Additionally, plant nutrient deficiency, disease, toxicity, and phonological stage are related to C (Larcher, 2003), which can all change seasonally.

As shown in Figure 4.27 A, average C and FMC changed seasonally in non-native grasslands, which is a major grassland type in Australia. Additionally, it was confirmed that there was a very strong significant correlation between C and FMC over an entire year ($p < 0.0001$). Thus, the mean C and FMC of non-native grasslands were divided into 12 groups by months. The average C and FMC data of non-native grasslands were plotted in months over 11 years in scatter plots. Pearson’s and Spearman’s correlation analyses were conducted for the correlation between average C and FMC. Comparing the scatter plots and correlation coefficient in different months helped determine any seasonal change in correlation between C and FMC.

Chapter 4: Results

4.1 *Maps of grassland types and fire history*

The distribution of open grasslands in Australia is shown in Figure 4.1 and the distribution of each type of grassland is shown in Figure 4.2. The percentage of areas covered by different grasslands types for the whole of Australia are listed in Figure 4.3. Approximately 50% of grasslands were classified as hummock grasslands, whereas 23% were non-native grasslands. Results suggested that hummock grasslands were the widest distributed grassland type. Non-native grasslands also covered a large area and were the second widest distributed grassland type.

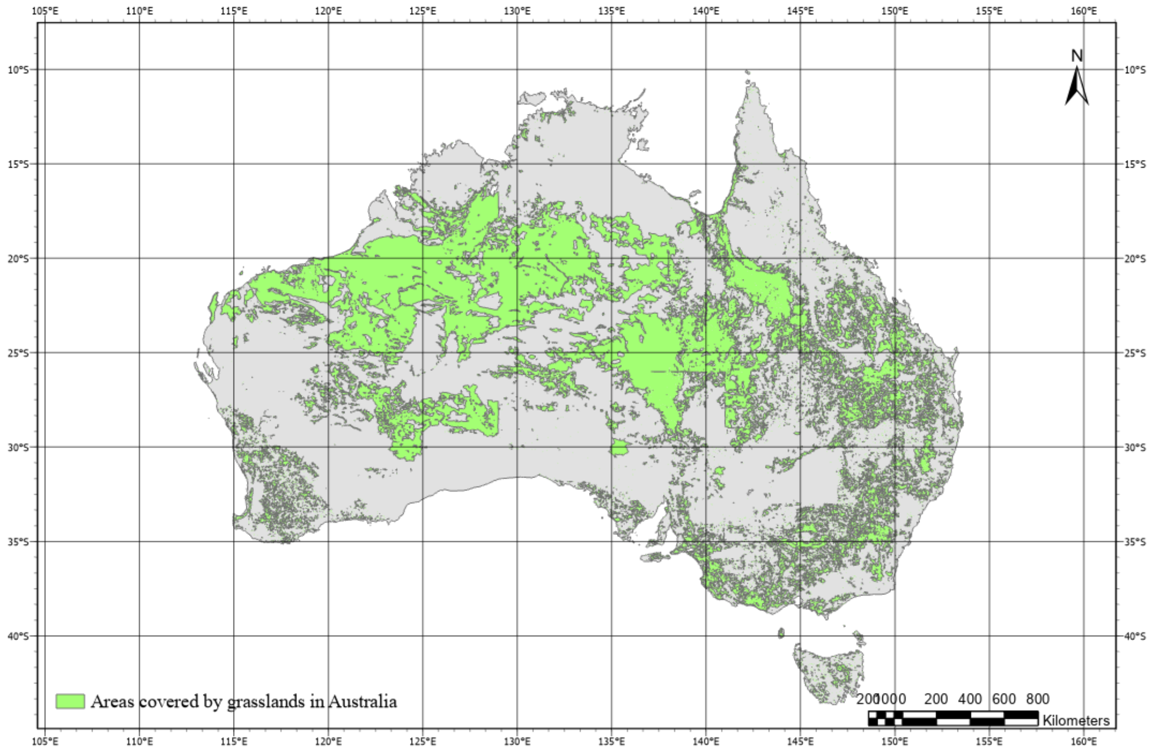


Figure 4.1 Distribution of grasslands in Australia in 2010–2011.

Green areas represent grasslands used in the present study based on the NVIS’s MVS products released in 2018 and the Land Use of Australia 2010–11 dataset.

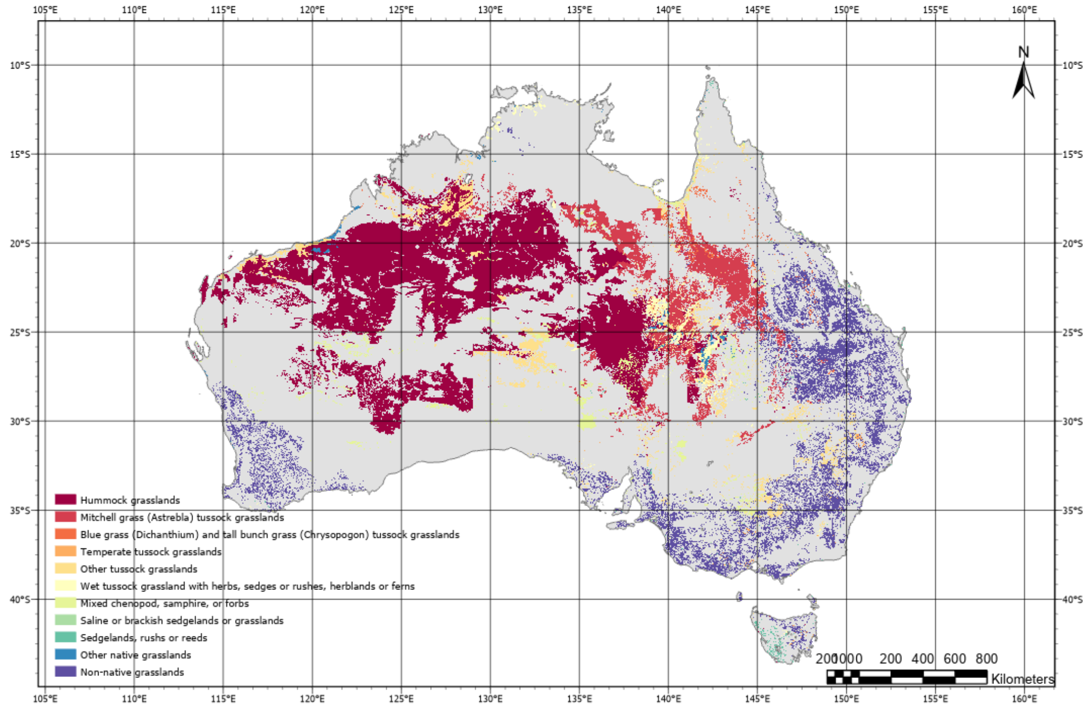


Figure 4.2 Distribution of different types of open grasslands in Australia.

Coloured areas represent the distribution of 11 types of open grasslands based on the NVIS's MVS products released in 2018 and the Land Use of Australia 2010–11 dataset.

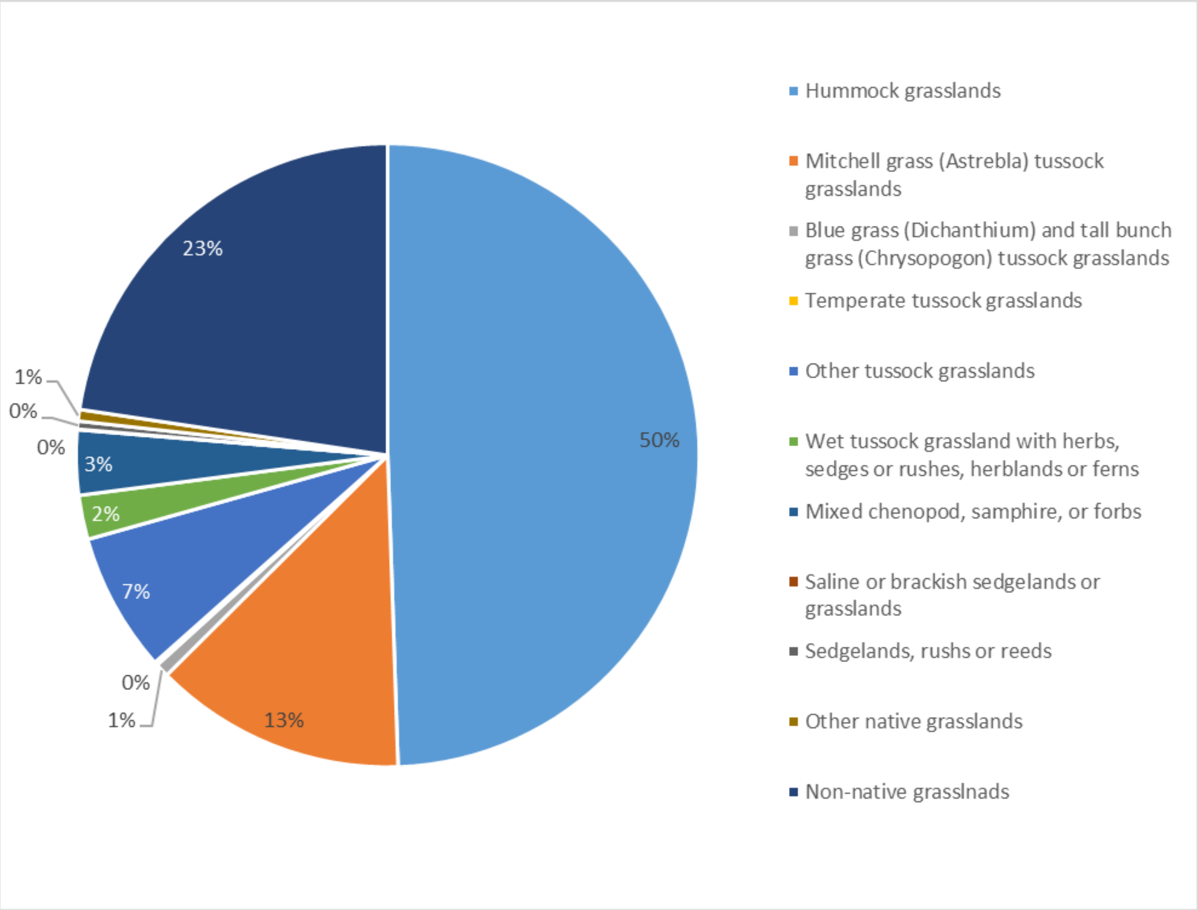


Figure 4.3 Proportion of covered area of different types of grasslands in Australian grasslands

4.2 Fire history map

Grasslands that never burned during the 11 years of the study period are plotted in Figure 4.4. A fire history map showing previous fire events during the entire study period in Australian grasslands by classifying fire history into nine classes is shown in Figure 4.5.

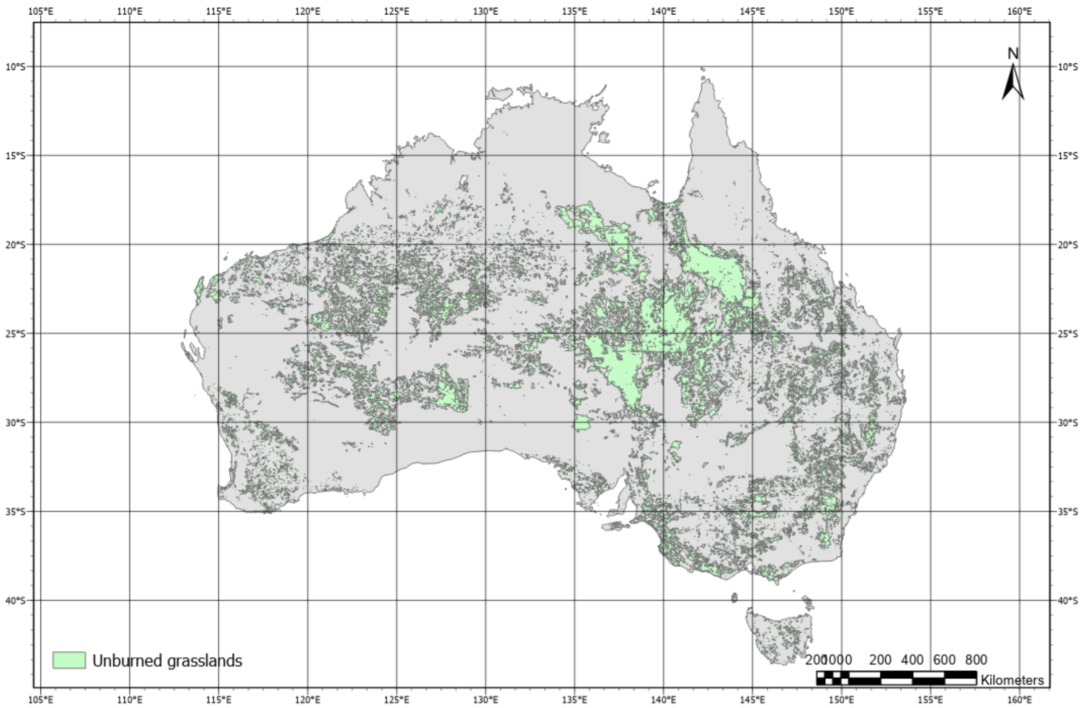


Figure 4.4 Grasslands that were unburned over the 11 years of the study period.

Green areas represent areas that never burned in Australian grasslands

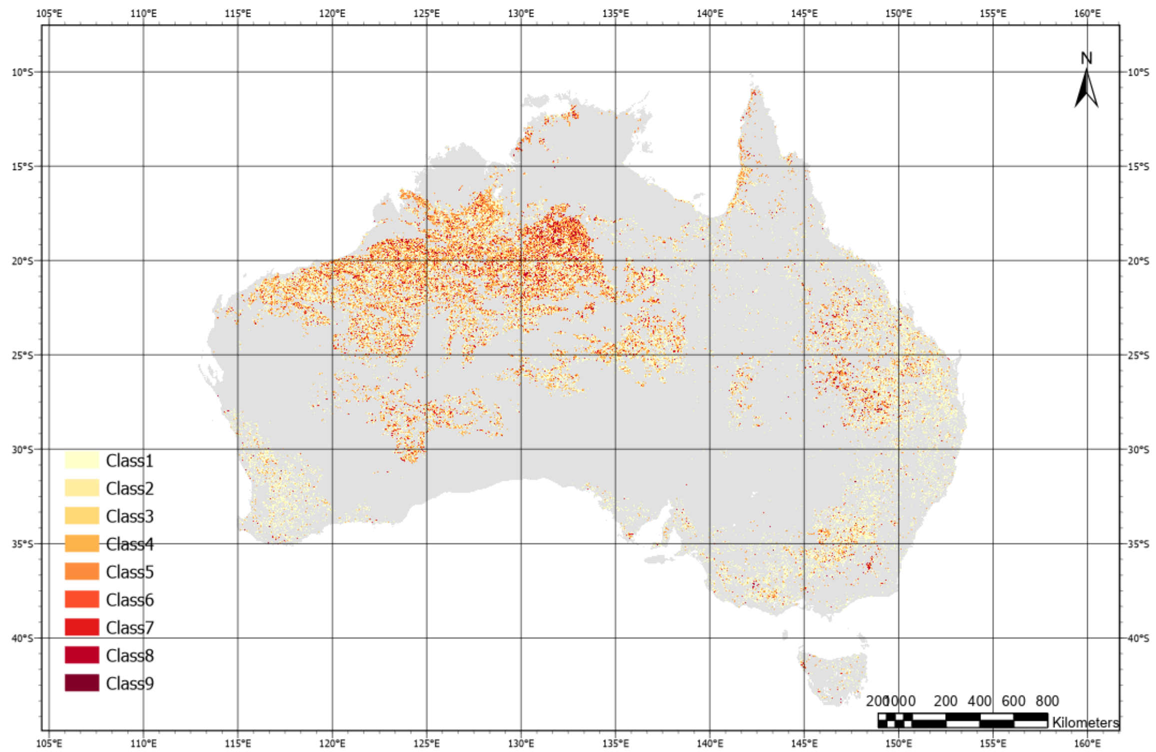


Figure 4.5 Fire history map in Australian grasslands. Nine classes were categorised by different previous.

Fire intensities and fire frequencies represented by the different coloured areas

4.3 Relationship between C and FMC in Australian grasslands

Average C and FMC in Australian grasslands over the 11 years of the study period are plotted in Figure 4.6. Results showed that both average C and FMC changed throughout the years. In March or September, average FMC was relatively low whereas average C was relatively high. The two peaks in average FMC were possibly caused by distinct monthly climate in different districts because precipitation was high in March in tropical areas but the highest precipitation in temperate areas occurs in September. Both C and FMC changed consistently within each year. Time and amplitude of average C and average FMC change changed in different years. The changes in average C always corresponded with changes in the opposite direction of average FMC.

To more clearly visualise the relationship between C and FMC, average C and FMC in Australian grasslands were plotted in a scatter plot (Figure 4.7). The results showed that average C and FMC of Australian grasslands were negatively correlated.

Average C and FMC of different months over the 11 years were calculated and plotted in a time series to observe seasonal changes of C and FMC in Australian grasslands (Figure 4.8). The results showed that seasonal change of average C of the entire Australian grasslands was slight, whereas the average FMC showed a more obvious seasonal change. Average FMC increased from June to September, or from December to March of the next year, but it decreased in other months. Oppositely, average C decreased slightly from June to September, or from December to March of the next year. Different types of grasslands or grasslands in different districts may have different average C and FMC values at different times, which led to two peaks in the average FMC during different seasons.

Pearson's and Spearman's correlation analyses were conducted between pairs of average C and FMC in the entire Australian grasslands over 11 years. Results confirmed that there was a significantly strong negative linear correlation between C and FMC ($r = -0.73314$) and there was a significantly strong negative monotonical correlation between C and FMC ($r = -0.73224$) in Australian grasslands ($p < 0.0001$).

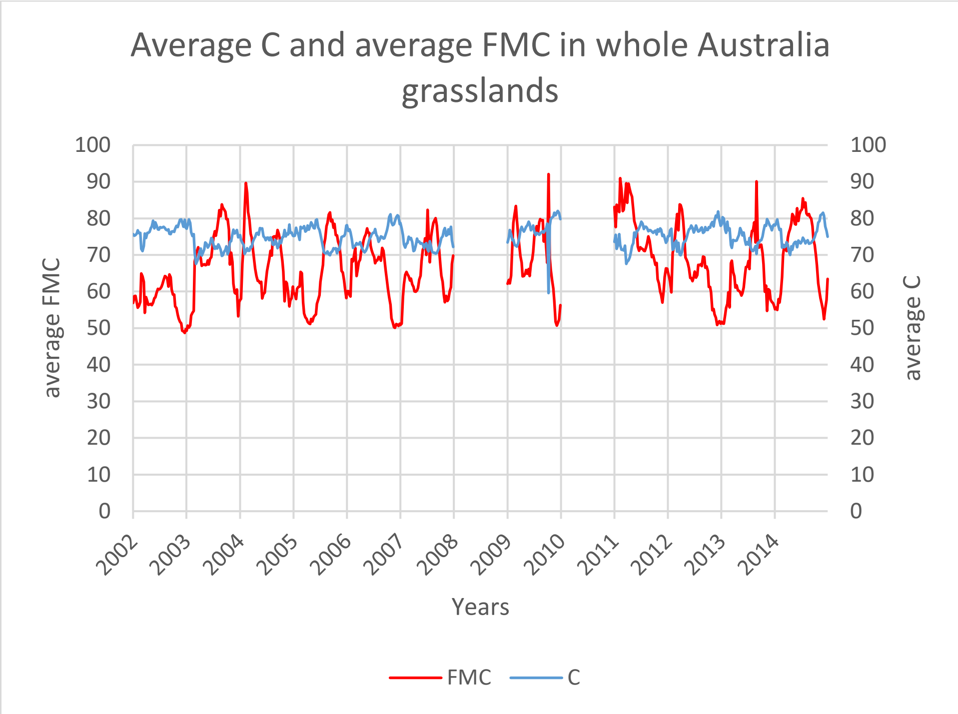


Figure 4.6 Average C and FMC values in Australian grasslands on different dates over 11 years (from 2002 to 2014 except 2008 and 2010).

Years are shown on the horizontal axis and average FMC (blue line) and C (red line) values are shown on the left and right vertical axes, respectively.

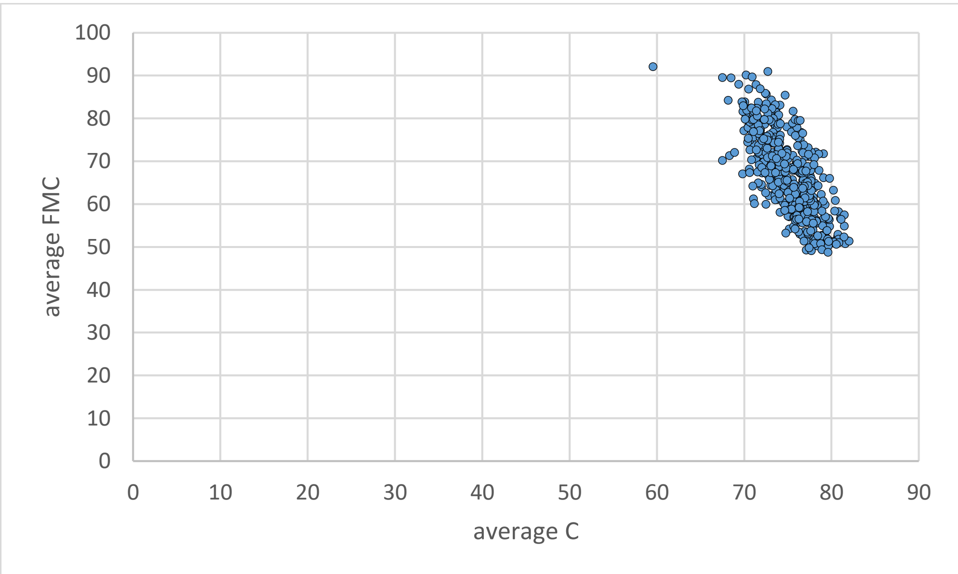


Figure 4.7 Scatter plot of average C and corresponding average FMC in Australian grasslands on different date over 11 years (from 2002 to 2014 except 2008 and 2010)

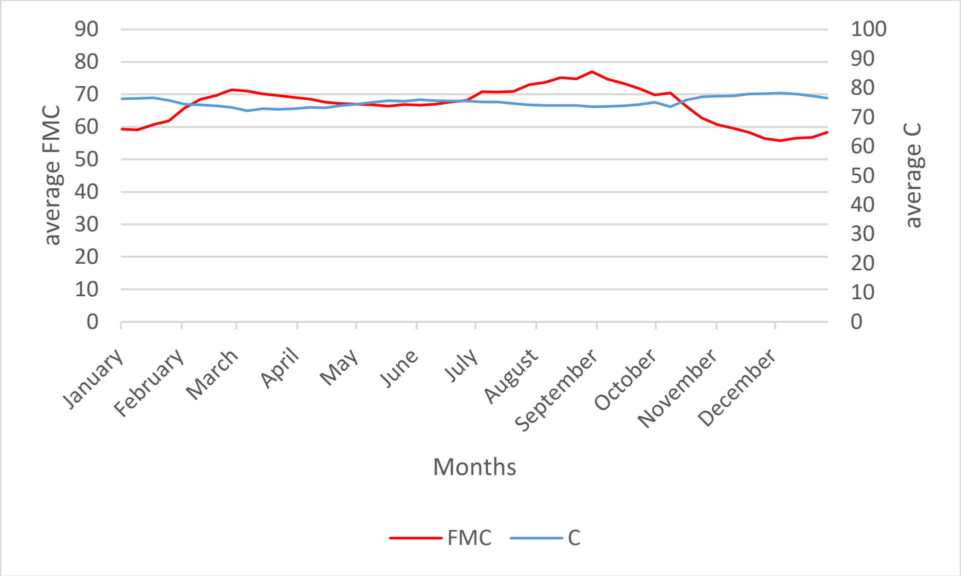


Figure 4.8 Monthly change in average C and FMC.

Months are shown on the horizontal axis and average FMC (blue line) and C (red line) values are shown on the left and right vertical axes, respectively.

4.4 Relationship between C and FMC in different regions in Australian grasslands

The results of Pearson's correlation analysis between the C and corresponding FMC values at sample sites in grids covered by grasslands on different days in a single year over the 11 years of the study period are shown in different maps (Figure 4.9). The C and FMC correlation in different years were slightly different, but they also contained many common features. Different regions showed a changing relationship between C and FMC. There were always strong negative linear relationships between C and FMC in south-eastern Australia, south-western Australia, and north-eastern Australia. In central Australia, which is covered by hummock grasslands, the correlation between C and FMC was weak, whereas in other areas in this region, C and FMC values were positively correlated. Therefore, the correlations between C and FMC were region specific, which was influenced by factors including various grass species, differences in previous fire events, and climatic variations. Thus, it is necessary to study the possible parameters that might influence C and FMC through more detailed studies. In addition, the C and FMC correlations changed among different years, confirming the existence of yearly variation, which must be tested in long-term studies (Figure 4.9).

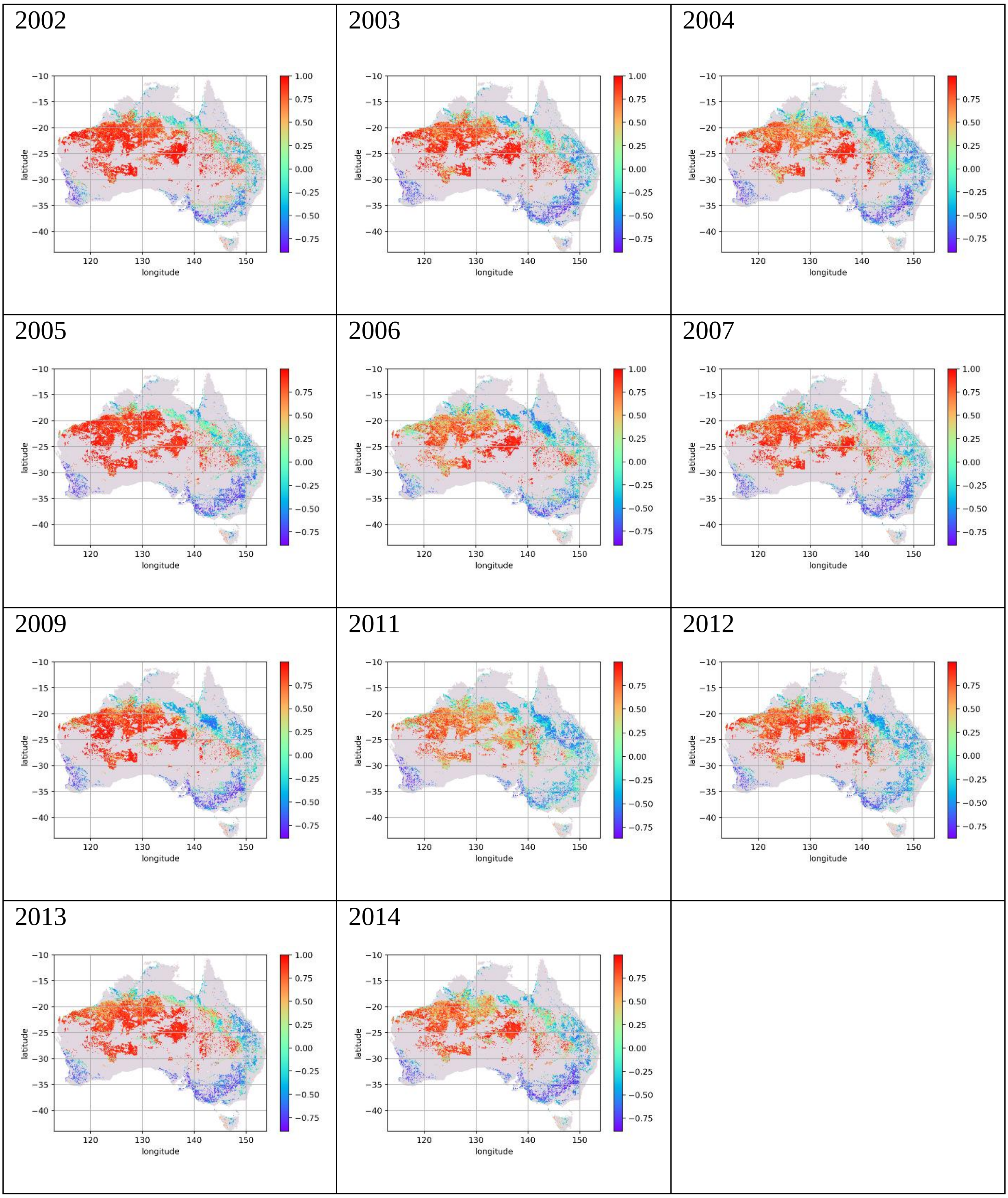


Figure 4.9 Maps of Pearson’s correlation coefficient between C and FMC in different years in Australian grasslands.

Different colours represent the variation in the correlation between C and FMC as listed in colour bars.

4.5 Relationship between C and FMC in different types of Australian grasslands

Unburned areas in different types of Australian grasslands that preserve complete fuel structures were used to evaluate the relationship between C and FMC. The correlations between C and FMC in the nine types of grasslands over the 11 years studied varied. There was a significantly strong negative linear correlation between C and FMC in Blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands, temperate tussock grasslands, other tussock grasslands, and non-native grasslands. In these grasslands, compared with exponential functions, linear functions could better explain the relation between C and FMC. In other types of grasslands, the correlation between C and FMC was weaker.

4.5.1 Hummock grasslands

The areas covered by hummock grasslands are shown in Figure 4.10. The average FMC and C values in hummock grasslands over the 11 years studied were plotted in a time series plot and scatter plot (Figure 4. 11).

Hummock grasslands are mainly distributed in central Australia (Figure 4.10). In hummock grasslands, the average FMC and C values were shown to have seasonal changes, although the amplitude was relatively small (Figure 4.11 A). The lowest average C appeared around March and increased gradually until December. The average FMC data reached the highest value around June and then decreased until November. In hummock grasslands, the average C ranged from 74.14% to 78.50% and the average FMC ranged from 59.44% to 64.72%.

There were also variations in the changes in average C and FMC in the different years and the dates with extreme average C or FMC values did not correlate in each year (Figure 4.11 B). Therefore, the average C and FMC values during the study period underestimated the changes in C and FMC in hummock grasslands. The scatter plot did not show a clear relation between C and FMC in Australian hummock grasslands (Figure 4.11 C). Both C and FMC changed slightly in hummock grasslands and their relationship was not clear. Overall, the results of Pearson's ($r = -0.48662$) and Spearman's ($r = -0.48625$) correlation analyses illustrated that there was a significant moderate linear or monotonic correlation between average C and FMC of hummock grasslands during the study period ($p < 0.0001$).

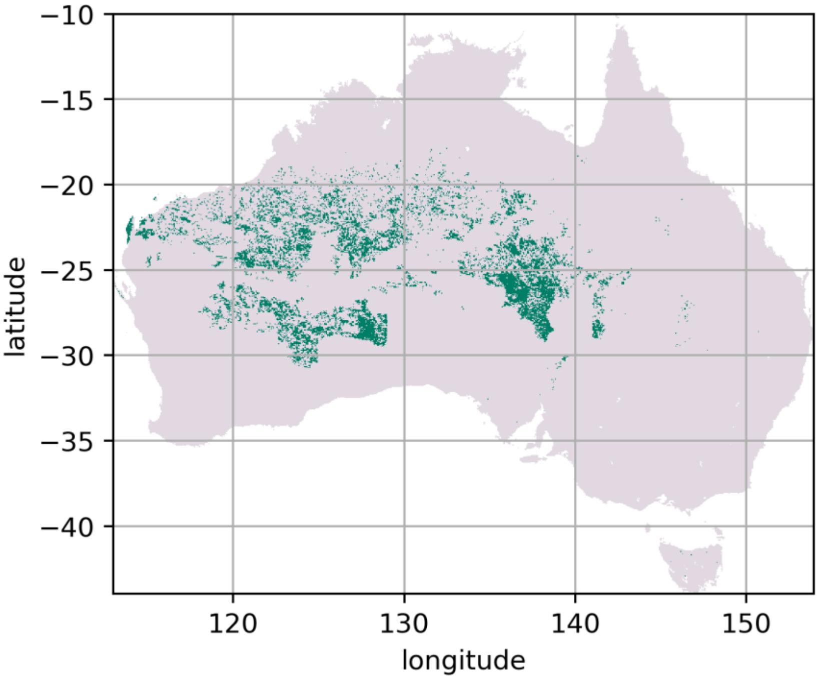


Figure 4.10 Distribution of hummock grasslands (green areas) in Australia.

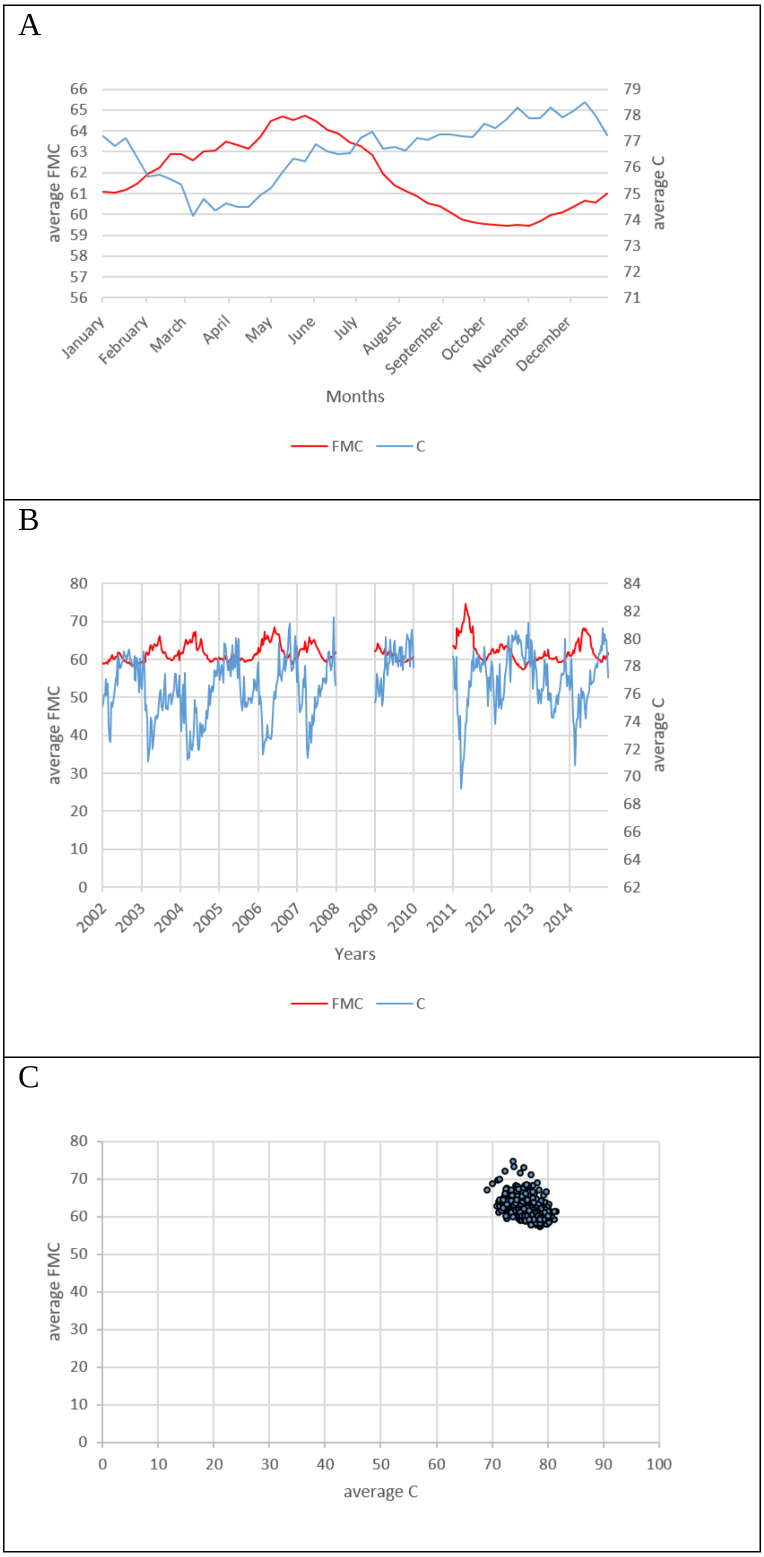


Figure 4.11 Plots of the relationship between average C and FMC in Australian hummock grasslands.

(A) Time series plot of average C and FMC over 12 months. Average C and FMC were calculated from the data obtained from 2002 to 2014, except 2008 and 2010. The X-axis represents different months and the Y-axis represents average C (blue line) and

FMC (red line) values. (B) Time series plot of average C and FMC over 11 years (from 2002 to 2014 except 2008 and 2010). X-axis represents years and Y-axis represents average C (blue line) and FMC (red line) values. (C) Scatter plot of average C and corresponding average FMC on different dates over 11 years (from 2002 to 2014 except 2008 and 2010). Average C is shown on the X-axis and average FMC is shown on the Y-axis. Blue dots represent average C and FMC on different dates.

4.5.2 Mitchell grass (Astrebla) tussock grasslands

The distribution of Mitchell grass in Australia is shown in Figure 4.12. Figure 4.13 A shows a time series plot reflecting the monthly change in average C and FMC in different years. The average FMC and C of Mitchell grass tussock grasslands over 11 years are shown in a time series plot and scatter plot (Figure 4.13 B and C, respectively).

Mitchell grasses grow in north-eastern inland Australia (Figure. 4.12). There were clear seasonal changes in average C and FMC of Mitchell grass tussock grasslands (Figure 4.13 A). Average FMC increased rapidly after December and reached a peak around March. After that, average FMC decreased rapidly until July and remained relatively stable during the following months. In contrast, average C was low in March and it changed the opposite to average FMC. FMC in Mitchell grass tussock grasslands ranged from approximately 35.18% to 96.74% in a year (Figure 4.13 A). In different years, the values and dates of the average FMC peak were slightly different (Figure 4.13 B). The scatter plot (Figure 4.13 C) indicated that C and FMC were negatively correlated. Pearson's correlation coefficient (r = -0.71705) and Spearman's correlation coefficient (r = -0.44728) indicated that there was a significantly strong negative linear correlation between C and FMC in Mitchell grass (*Astrebla*) tussock grasslands ($p < 0.0001$).

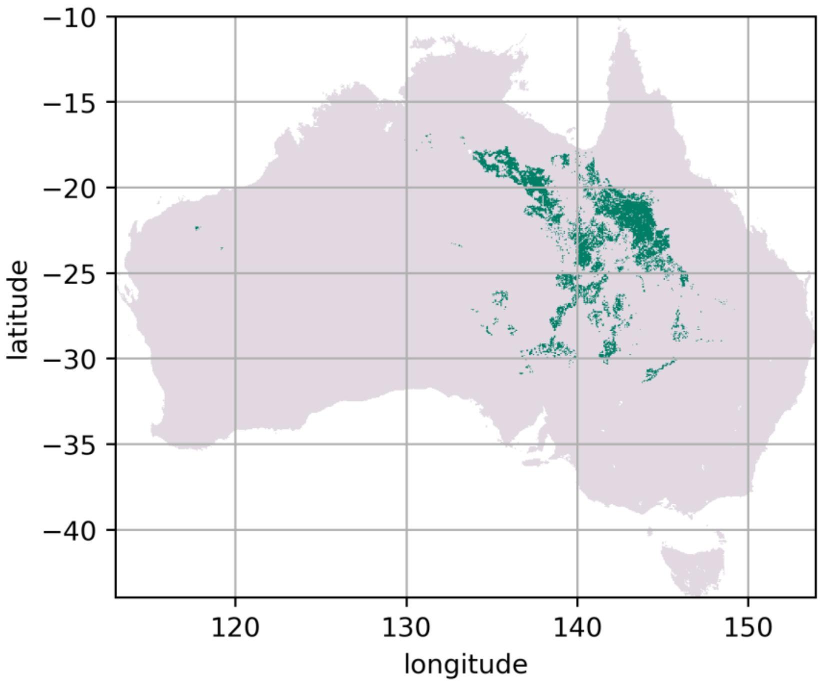


Figure 4.12 Distribution of Mitchell grass (Astrebla) tussock grasslands (green areas) in Australia.

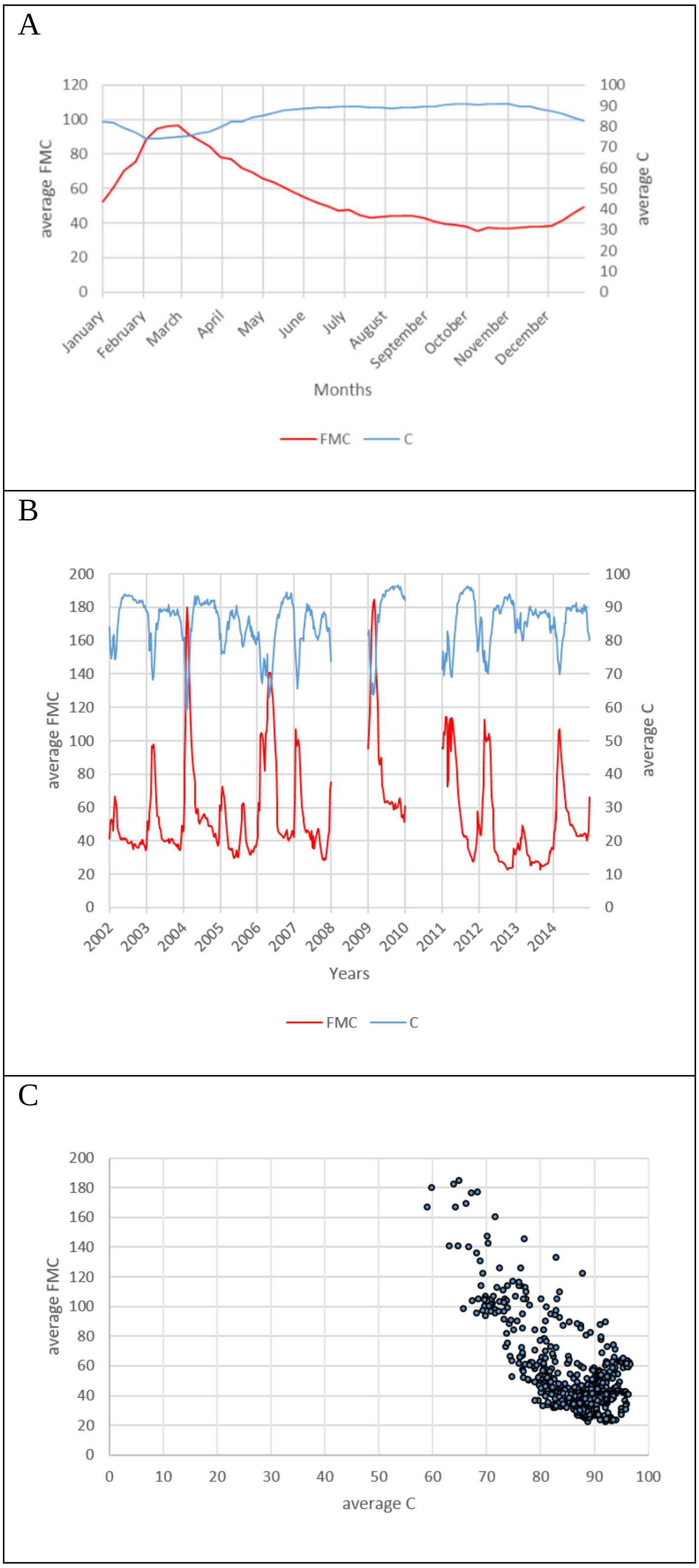


Figure 4.13 Plots of the relationship between average C and FMC in Mitchell grass (Astrebla) tussock grasslands in Australia.

(A) Time series plot of average C and FMC over 12 months. Average C and FMC were calculated from the data obtained from 2002 to 2014, except 2008 and 2010. The

X-axis represents different months and average C (blue line) and FMC (red line) values were plotted on the Y-axis. (B) Time series plot of average C and FMC over 11 years (from 2002 to 2014 except 2008 and 2010). The X-axis represents years and the Y-axis represents the average C (blue line) and FMC (red line) values. (C) Scatter plot of average C and corresponding average FMC on different dates over 11 years (from 2002 to 2014 except 2008 and 2010). Average C is shown on the X-axis and average FMC is shown on the Y-axis. Blue dots represent average C and FMC on different dates.

4.5.3 Blue grass (Dichanthium) and tall bunch grass (Chrysopogon) tussock grasslands

Figure 4.14 shows the distribution of blue and tall bunch grass tussock grasslands in Australia. Yearly average C and FMC changes in blue and tall bunch grass tussock grasslands were plotted in time series plots shown in Figure 4.15 A. The average C and FMC of Australian blue and tall bunch grass tussock grasslands over the study period were plotted in a time series plot and in scatter plot (Figure 4.15 B and Figure 4.15 C).

This type of grasslands is located in north-eastern Australia (Figure 4.14). The seasonal changes in average C and FMC was similar to that of Mitchell grass tussock grasslands (Figure 4.15 A). However, the amplitude of both average C and FMC change was larger in this type of grasslands than that in Mitchell grass tussock grasslands (Figure 4.15 A). The average FMC in a year ranged from approximately 28.57% to 133.83%. Figure 4.15 B shows the regular seasonal change of average C and FMC, but the amplitude of change was different in different years. The scatter plot shows a negative correlation between C and FMC (Figure 4.15 C). There was a significantly very strong negative linear relationship between C and FMC in blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands (Pearson's: r = -0.82362, Spearman's: r = -0.62493) ($p < 0.0001$). Compared with an exponential function, the linear function could better represent the relationship between C and FMC in blue and tall bunch grass tussock grasslands because it had a smaller R^2 value. The relationship between C and FMC can be shown as Equation 4.1.

$$\boldsymbol{FMC = -3.7865C + 366.04} \qquad \textbf{(Equation 4.1)}$$

$$R^2 = 0.6784$$

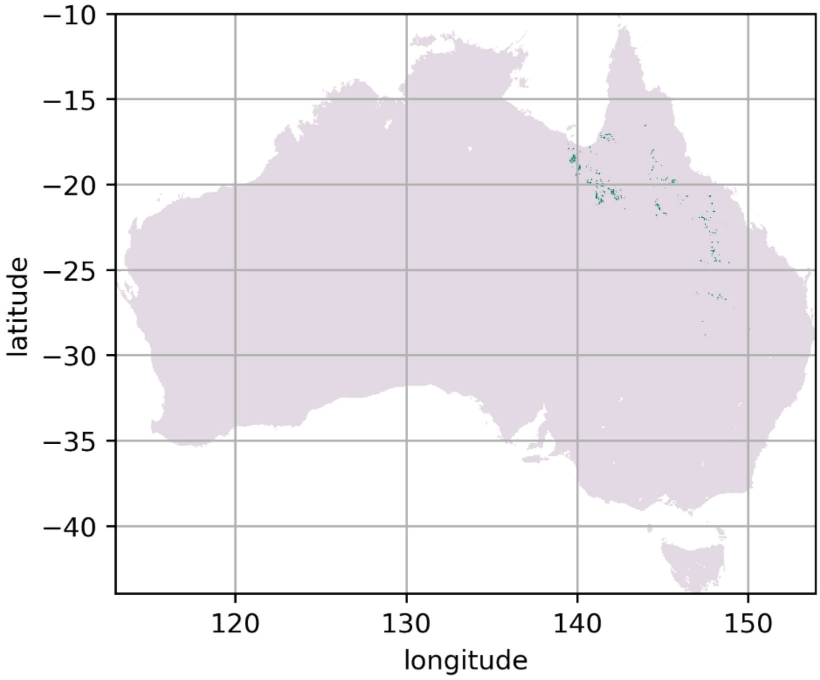


Figure 4.14 Distribution of blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands (green areas) in Australia.

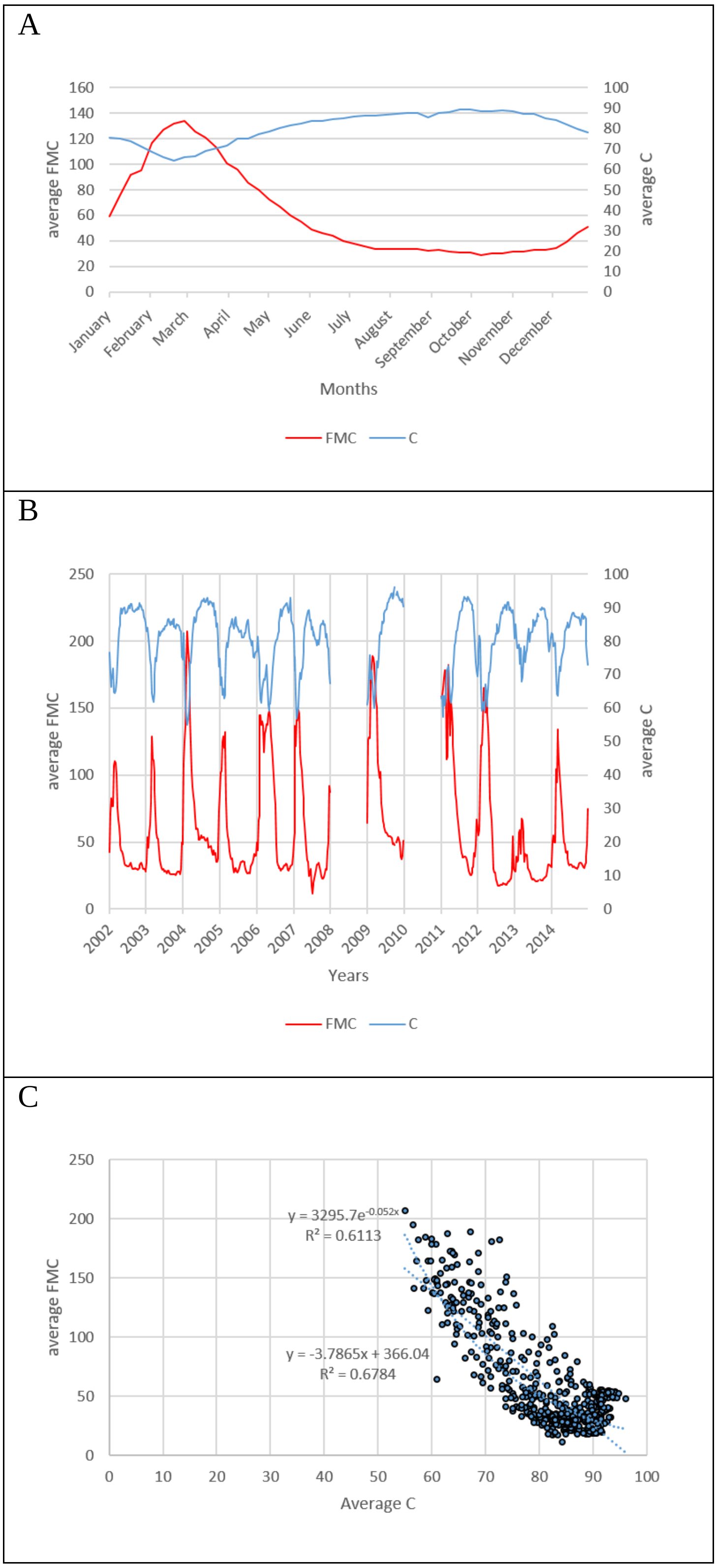


Figure 4.15 Plots of the relationship between average C and average FMC in blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands in Australia.

(A) Time series plot of average C and FMC over 12 months. Average C and FMC were calculated from the data obtained from 2002 to 2014, except 2008 and 2010. The

X-axis represents different months and the average C (blue line) and FMC (red line) values are plotted on the Y-axis. (B) Time series plot of average C and FMC over 11 years (from 2002 to 2014 except 2008 and 2010). The X-axis represents the years and the average C (blue line) and FMC (red line) values are plotted on the Y-axis. (C) Scatter plot of average C and corresponding average FMC on different dates over 11 years (from 2002 to 2014 except 2008 and 2010). Average C is shown on the X-axis and average FMC is shown on the Y-axis. Blue dots represent average C and FMC on different dates.

4.5.4 Temperate tussock grasslands

Temperate tussock grasslands were mainly located in south-eastern Australia and Tasmania, as shown in Figure 4.16. Monthly average C and FMC of temperate tussock grasslands periods were plotted in time series plots (Figure 4.17 A) and average FMC and C in temperate tussock grasslands over the study period were plotted in a time series plot and scatter plot in Figure 4.17 B and Figure 4.17 C, respectively.

In temperate tussock grasslands, average C and FMC changed seasonally. Average FMC was low in summer and increased rapidly after February, reaching a peak of 152.36% around September. After that, the average FMC decreased rapidly until February in the next year (Figure 4.17 A). In contrast, the average C was low in winter and high in summer (Figure 4.17 A). The amplitude of the C and FMC change in temperate tussock grasslands was larger than the change in other types of grasslands mentioned above (Figure 4.17 A). In temperate tussock grasslands, the average FMC ranged from approximately 46.88% to 152.36% in a year (Figure 4.17 A). In different years, the change in the amplitude and time of average FMC and C was slightly different (Figure 4.17 B). The scatter plot showed that C and FMC were negatively correlated (Figure 4.17 C). Results of the correlation coefficient indicated that there was a significantly very strong negative linear correlation between C and FMC in temperate tussock grasslands (Pearson's: r = -0.92919, Spearman's: r = -0.91371) ($p < 0.0001$). The trend line in the scatter plot confirmed that a linear function could better explain the relationship between C and FMC in temperate tussock grasslands, which can be expressed as Equation 4.2.

$$\boldsymbol{FMC = -3.9595C + 342.57} \qquad \textbf{(Equation 4.2)}$$

$$R^2 = 0.8634$$

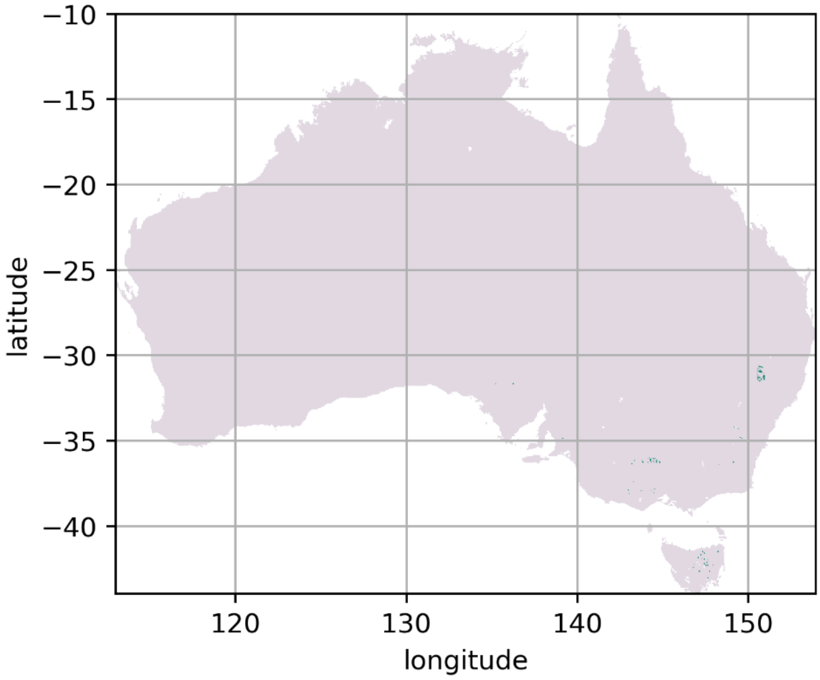


Figure 4.16 Distribution of temperate tussock grasslands (green areas) in Australia.

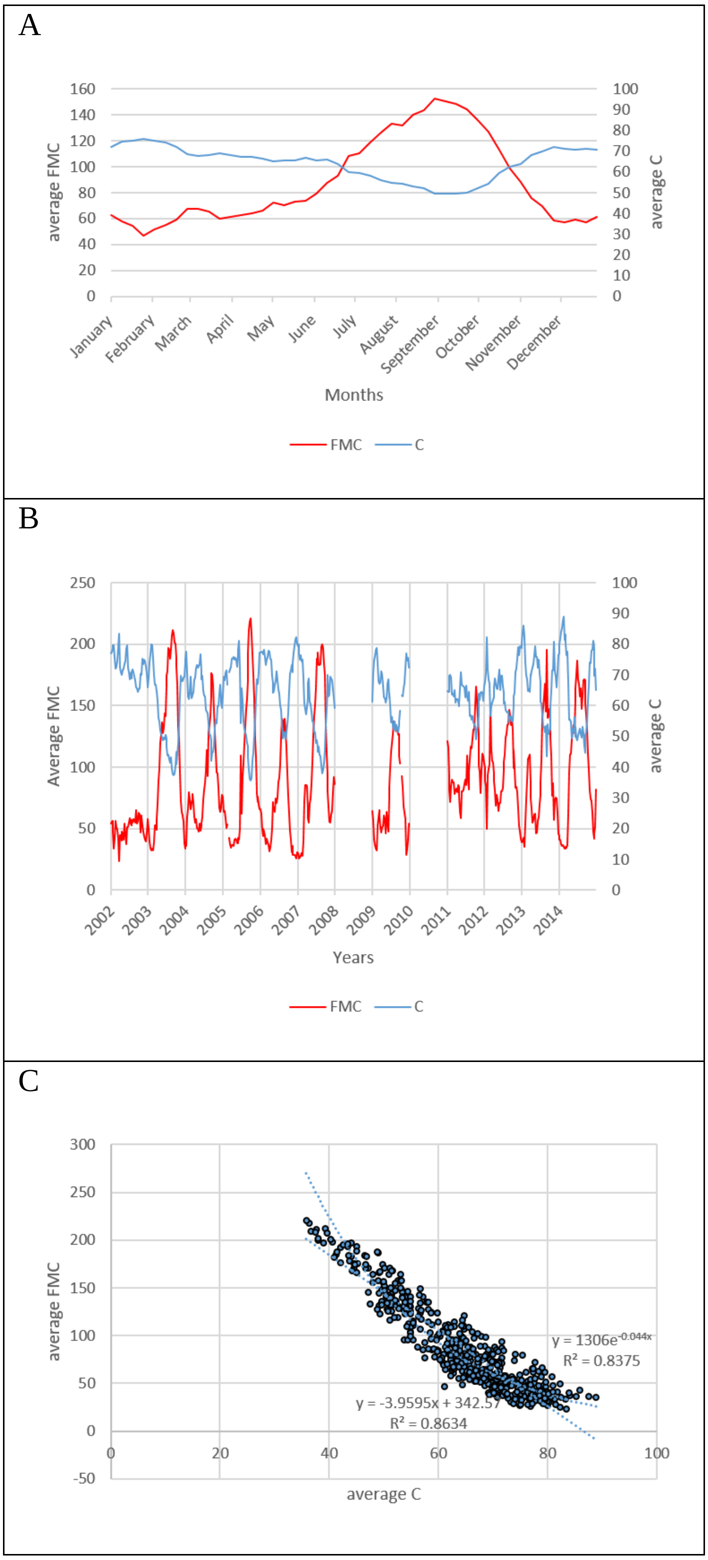


Figure 4.17 Plots of the relationship between average C and FMC in temperate tussock grasslands in Australia.

(A) Time series plot of average C and FMC over 12 months. Average C and FMC were calculated from the data obtained from 2002 to 2014, except 2008 and 2010. The

X-axis represents different months and the average C (blue line) and FMC (red line) values are plotted on the Y-axis. (B) Time series plot of average C and FMC over 11 years (from 2002 to 2014 except 2008 and 2010). The X-axis represents years and the average C (blue line) and FMC (red line) values are plotted on the Y-axis. (C) Scatter plot of average C and corresponding average FMC in temperate tussock grasslands in Australia on different dates over 11 years (from 2002 to 2014 except 2008 and 2010). Average C is shown on the X-axis and average FMC is shown on the Y-axis. Blue dots represent average C and FMC on different dates.

4.5.5 Other tussock grasslands

Other tussock grasslands contained different tussock grass species and their location is mapped in Figure 4.18. The monthly average C and FMC of other tussock grasslands were plotted in a time series plot for each year (Figure 4.19 A). The average FMC and C values of the other tussock grasslands measured during the study period are plotted in a time series plot and scatter plot (Figure 4.19 B and Figure 4.19 C, respectively).

Other tussock grasslands, which included grasslands dominated by different tussock grass species, cover large areas of Australia (Figure 4.18). There were two peaks in the average FMC value of other tussock grasslands in March and September, with C and FMC values changing in opposite directions (Figure 4.19 A). Other tussock grasslands in various regions and dominated by different grass species might have a different seasonal change in the C and FMC values. In different years, the seasonal change in average C and FMC was different (Figure 4.19 B). The scatter plot indicated that C and FMC were negatively correlated (Figure 4.19 C) and results of the correlation coefficient indicated that there was a significantly very strong negative linear correlation between C and FMC in temperate tussock grasslands (Pearson's: r = -0.85214, Spearman's: r = -0.84781) ($p < 0.0001$). Equation 4.3 can be used to better explain the relation between C and FMC in other tussock grasslands than that of exponential functions. However, there were different grass species in other tussock grasslands, which might have different correlations between C and FMC. Thus, further study is required to determine the relation between C and FMC in grasslands dominated by different tussock grass species.

$$\boldsymbol{FMC = -3.2426C + 309.12}$$ **(Equation 4.3)**

$R^2 = 0.7261$

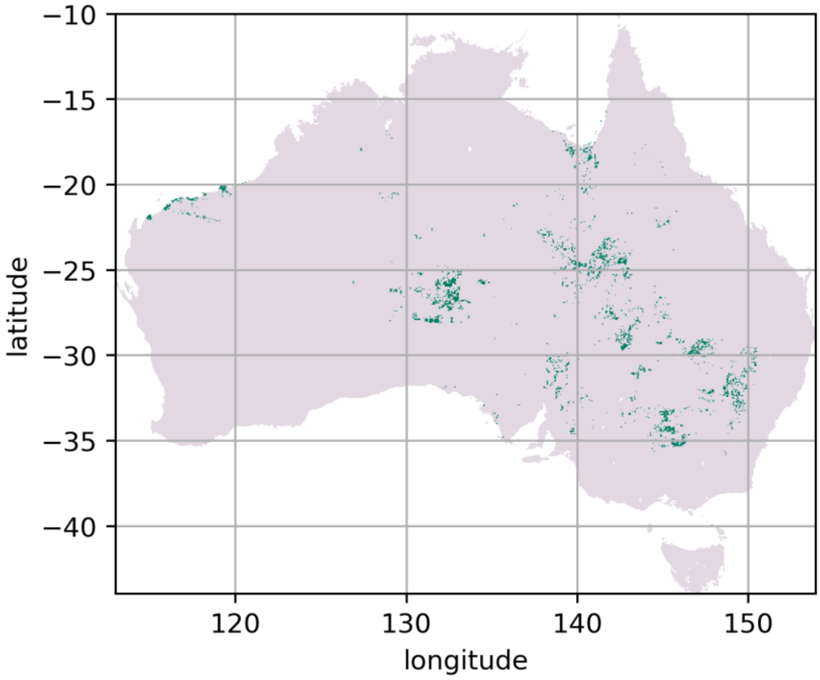


Figure 4.18 Distribution of other tussock grasslands (green areas) in Australia.

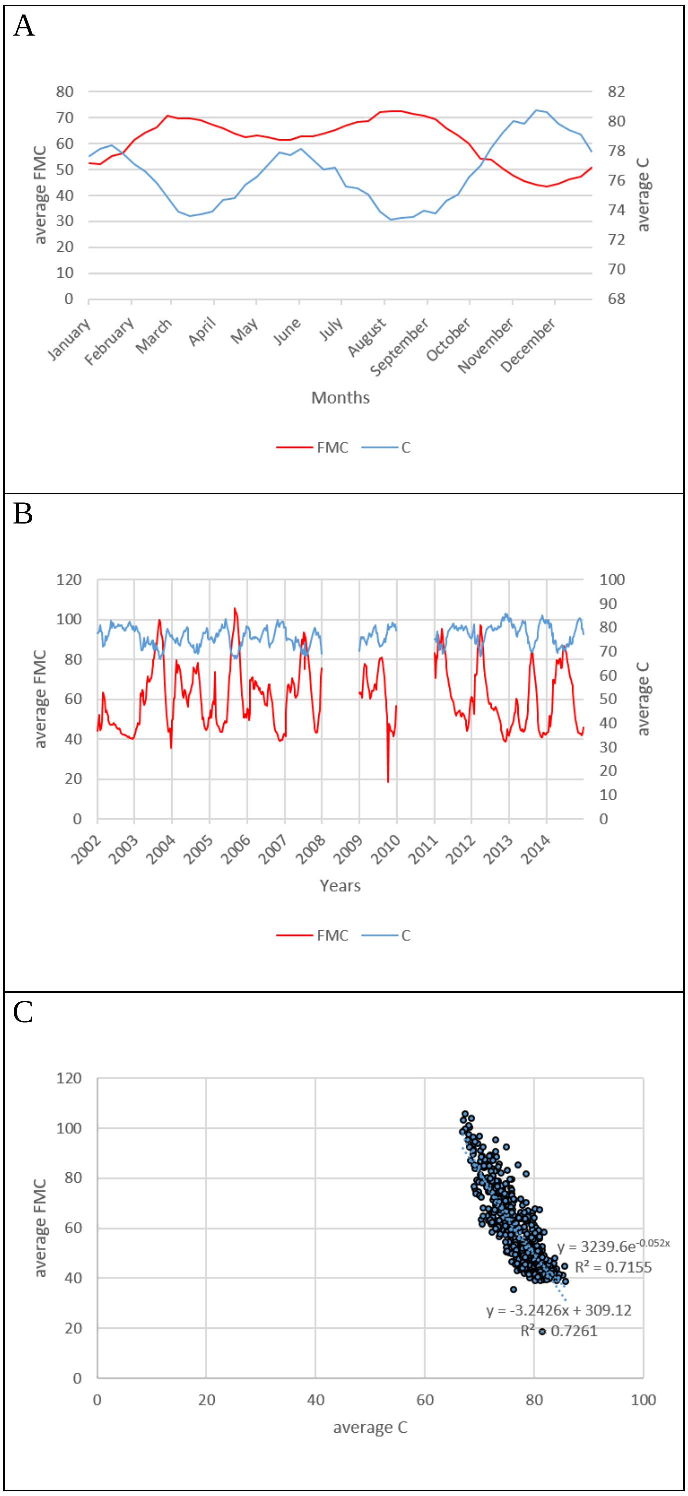


Figure 4.19 Plots of the relationship between average C and FMC in other tussock grasslands in Australia.

(A) Time series plot of average C and FMC over 12 months. Average C and FMC were calculated from the data obtained from 2002 to 2014, except 2008 and 2010. The X-axis represents different months and the average C (blue line) and FMC (red line)

values are plotted on the Y-axis. (B) Time series plot of average C and FMC over 11 years (from 2002 to 2014 except 2008 and 2010). The X-axis represents years and the average C (blue line) and FMC (red line) values are plotted on the Y-axis. (C) Scatter plot of average C and corresponding average FMC in temperate tussock grasslands in Australia on different dates over 11 years (from 2002 to 2014 except 2008 and 2010). Average C is shown on the X-axis and average FMC is shown on the Y-axis. Blue dots represent average C and FCM on different dates

4.5.6 Wet tussock grasslands with herbs, sedges or rushes, herblands or ferns

Figure 4.20 shows the distribution of wet tussock grasslands with herbs, sedges or rushes, herblands or ferns in Australia. Monthly average C and FMC values of this type of grasslands are plotted in time series plots (Figure 4.21 A) and average FMC and C during the study period are plotted in a time series plot and scatter plot (Figure 4.21 B and Figure 4.21 C, respectively).

This type of grasslands is usually located in north-eastern Australia or central Australia (Figure 4.20). Average FMC values reached a peak around March and then decreased constantly until November (Figure 4.21 A). Average C changed in the opposite direction; however, the amplitude of change was small (Figure 4.21 A). The amplitude of the average FMC change was significantly distinct over different years (Figure 4.21 B). The scatter plot showed a negative correlation between C and FMC in these grasslands (Figure 4.21 C). Results of the correlation analyses indicate that there was a significantly strong negative linear relationship between C and FMC in wet tussock grasslands with herbs, sedges or rushes, herblands or ferns in Australia (Pearson's: $r = -0.64729$, Spearman's: $r = -0.64163$) ($p < 0.0001$).

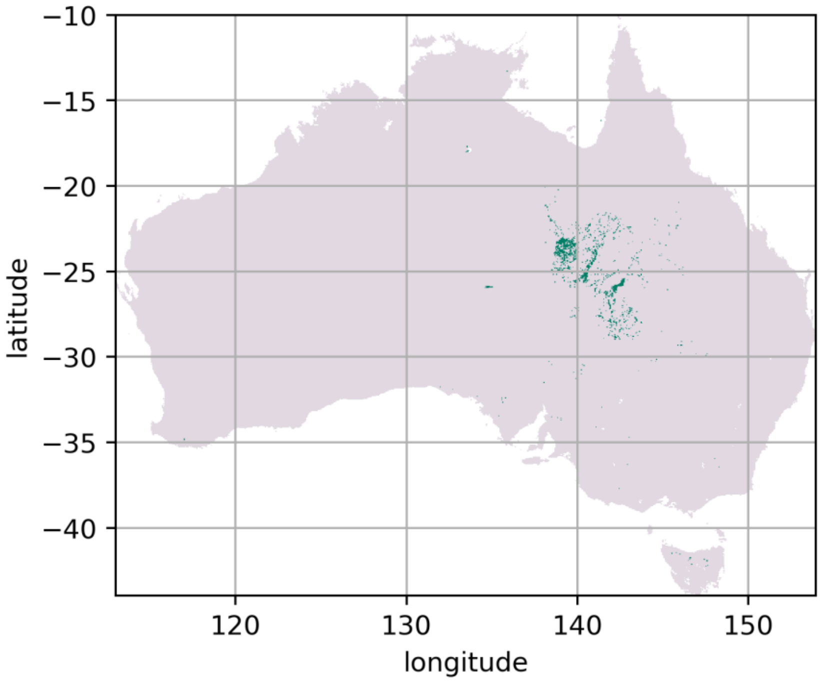


Figure 4.20 Distribution of wet tussock grasslands with herbs, sedges or rushes, herblands or ferns (green areas) in Australia.

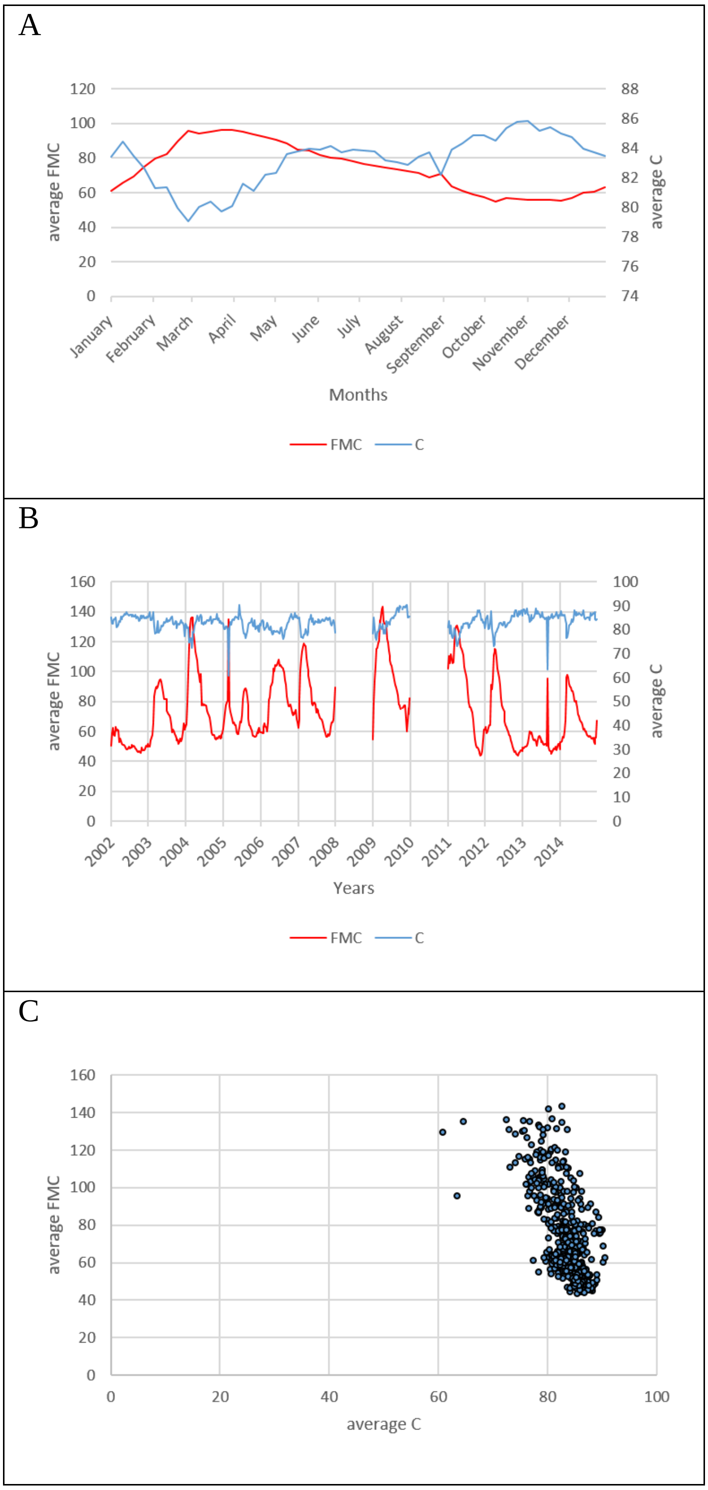


Figure 4.21 Plots of the relationship between average C and FMC in wet tussock grasslands with herbs, sedges or rushes, herblands or ferns in Australia.

(A) Time series plot of average C and FMC over 12 months. Average C and FMC were calculated from the data obtained from 2002 to 2014, except 2008 and 2010. The X-axis represents different months and the average C (blue line) and FMC (red line)

values are plotted on the Y-axis. (B) Time series plot of average C and FMC over 11 years (from 2002 to 2014 except 2008 and 2010). The X-axis represents years and the average C (blue line) and FMC (red line) values are plotted on the Y-axis. (C) Scatter plot of average C and corresponding average FMC in temperate tussock grasslands in Australia on different dates over 11 years (from 2002 to 2014 except 2008 and 2010). Average C is shown on the X-axis and average FMC is shown on the Y-axis. Blue dots represent average C and FCM on different dates.

4.5.7 Mixed chenopod, samphire, or forbs

Mixed chenopod, samphire, or forbs were widely distributed in Australia (Figure 4.22). The monthly change in average C and FMC were plotted for mixed chenopod, samphire, or forbs (Figure 4.23 A) and the average FMC and C during the study period are shown in a time series plot and scatter plot (Figure 4.23 B and Figure 4.23 C, respectively).

In mixed chenopod, samphire, or forbs, the average FMC and C changed constantly in a year, with several peaks and valleys (Figure 4.23 A). Average C reached a valley around March and then increased gradually until June. After that, average C decreased to its lowest value in August and then increased gradually until November, reaching its highest value. Afterwards, average C value decreased until March in the next year. The change in average C corresponded with an opposite change in average FMC. The average C and FMC changes over the 11 years studied were slightly different in amplitude (Figure 4.23 B). The scatter plot showed a negative correlation between C and FMC in mixed chenopod, samphire, or forbs in Australia (Figure 4.23 C). The results of Pearson's and Spearman's correlation analyses illustrated that there was a significantly strong correlation between average C and FMC of mixed chenopod, samphire, or forbs during the study period (Pearson's: $r = -0.75318$, Spearman's: $r = -0.70005$) ($p < 0.0001$).

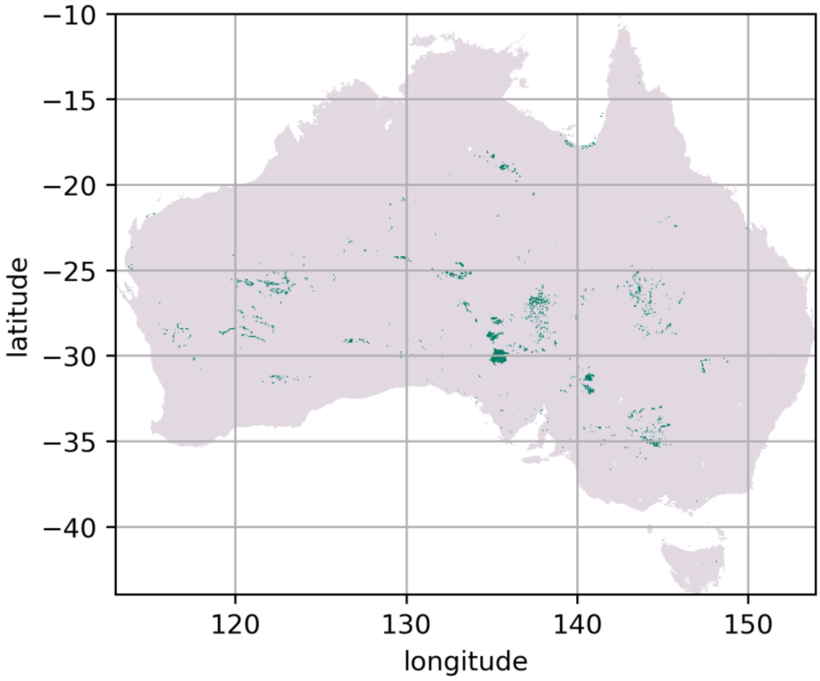


Figure 4.22 Distribution of mixed chenopod, samphire, or forbs (green areas) in Australia.

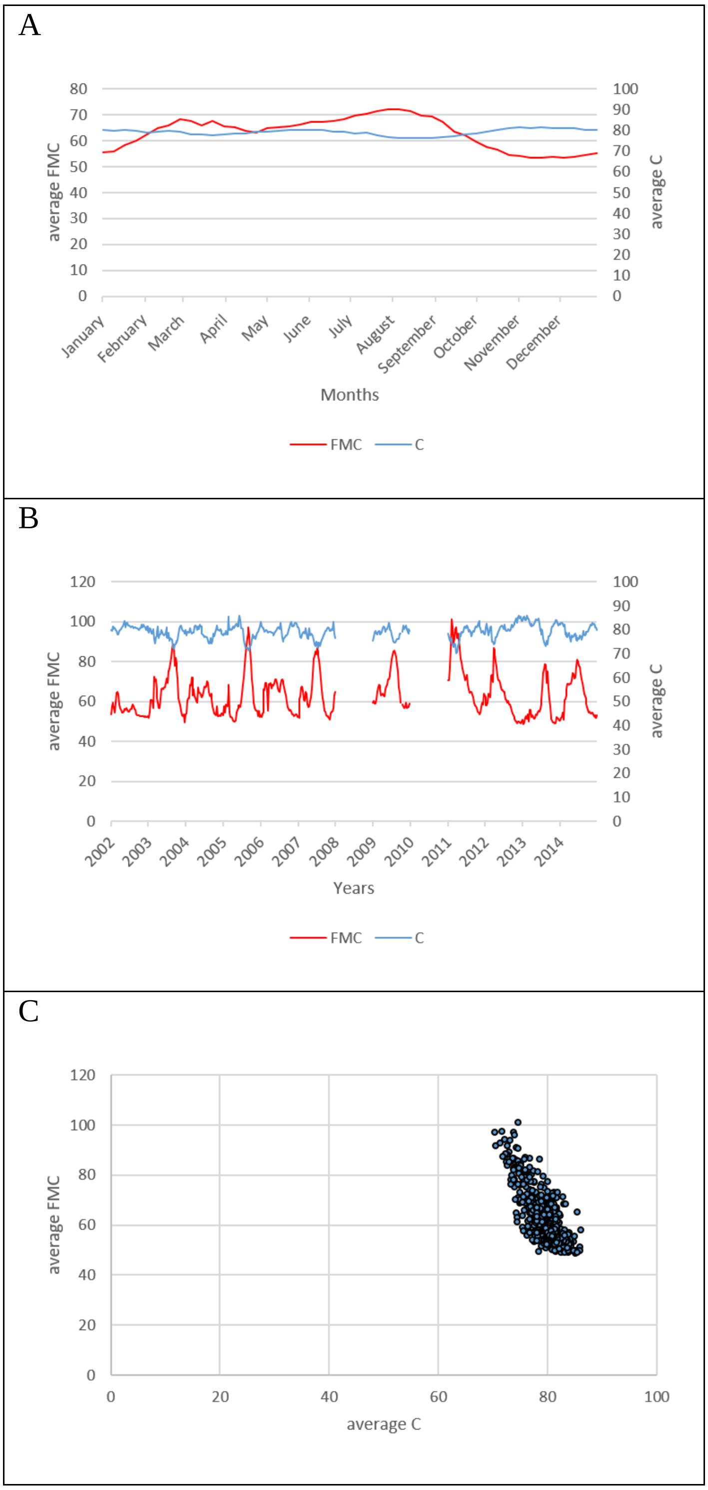


Figure 4.23 Plots of the relationship between average C and FMC in mixed chenopod, samphire, or forbs in Australia.

(A) Time series plot of average C and FMC over 12 months. Average C and FMC were calculated from the data obtained from 2002 to 2014, except 2008 and 2010. The X-axis represents different months and the average C (blue line) and FMC (red line) values are plotted on the Y-axis. (B) Time series plot of average C and FMC over 11 years (from 2002 to 2014 except 2008 and 2010). The X-axis represents years and the average C (blue line) and FMC (red line) values are plotted on the Y-axis. (C) Scatter plot of average C and corresponding average FMC in temperate tussock grasslands in Australia on different dates over 11 years (from 2002 to 2014 except 2008 and 2010). Average C is shown on the X-axis and average FMC is shown on the Y-axis. Blue dots represent average C and FCM on different dates.

4.5.8 Sedgelands, rushes, or reeds

Sedgelands, rushes, or reeds are mainly distributed in south-eastern Australia or Tasmania (Figure 4.24). The yearly average C and FMC of this type of grasslands periods were plotted in time series plots (Figure 4.25 A) and the average FMC and C during the study period are shown in a time series plot and scatter plot (Figure 4.25 B and Figure 4.25 C, respectively).

In sedgelands, rushes, or reeds, both average FMC and C changed constantly in a single year (Figure 4.25 A). These values fluctuated several times in a single year and there was no clear seasonal change and they also varied yearly (Figure 4.25 B). Extreme average C and FMC data were reached on different days; therefore, the yearly average C and FMC of Australian sedgelands, rushes, or reeds could not reflect seasonal change. The scatter plot did not show a clear negative linear or monotonic correlation between C and FMC in sedgelands, rushes, or reeds (Figure 4.25 C). The correlation coefficients (Pearson's: $r = -0.60992$, Spearman's: $r = -0.56163$) illustrate that there was a moderate correlation between average C and FMC for sedgelands, rushes, or reeds during the study period ($p < 0.0001$).

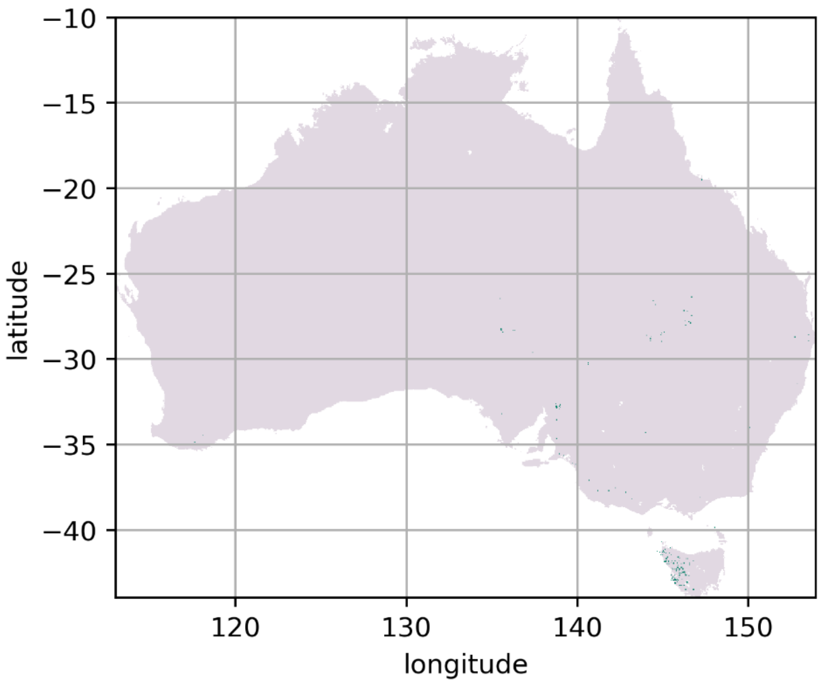


Figure 4.24 Distribution of sedgelands, rushes, or reeds (green areas) in Australia.

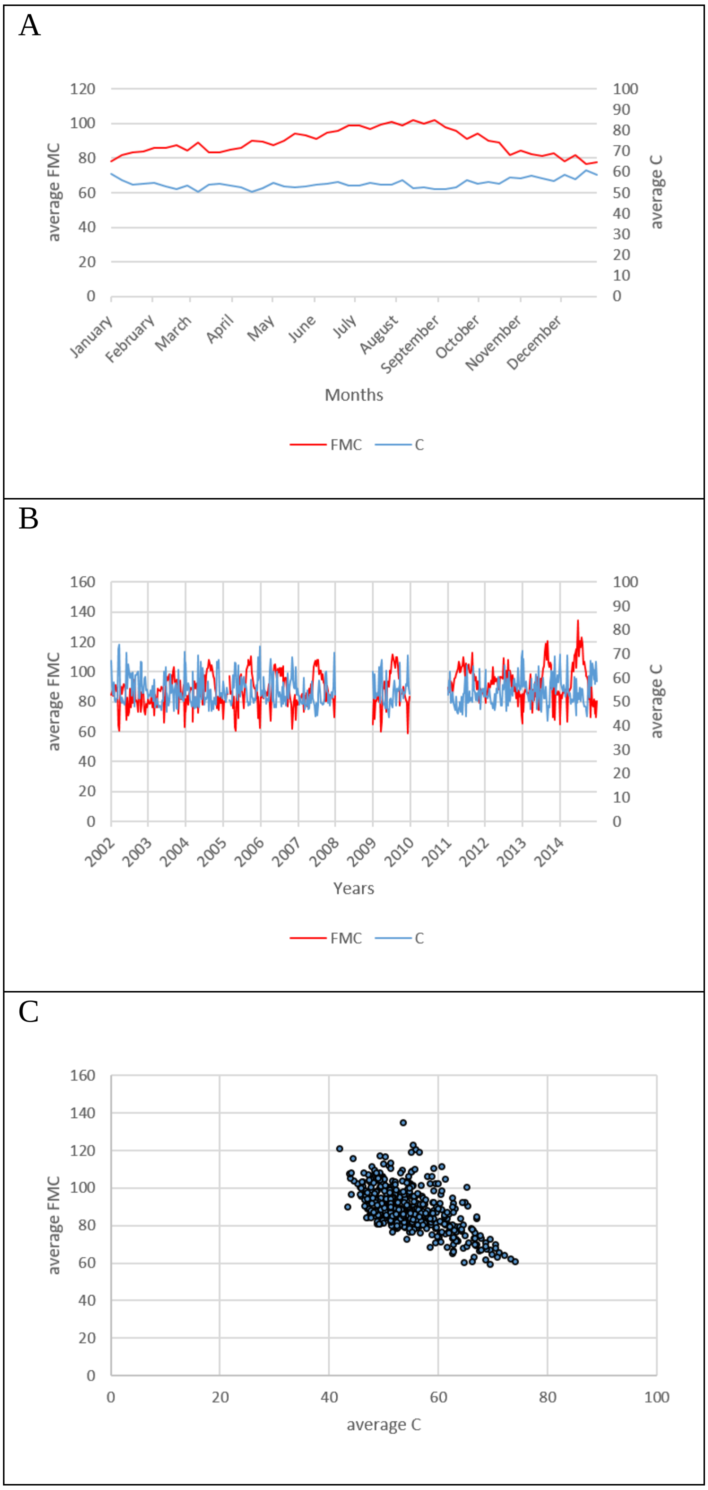


Figure 4.25 Plots of the relationship between average C and FMC in sedgelands, rushes, or reeds in Australia.

(A) Time series plot of average C and FMC over 12 months. Average C and FMC were calculated from the data obtained from 2002 to 2014, except 2008 and 2010. The X-axis represents different months and the average C (blue line) and FMC (red line)

values are plotted on the Y-axis. (B) Time series plot of average C and FMC over 11 years (from 2002 to 2014 except 2008 and 2010). The X-axis represents years and the average C (blue line) and FMC (red line) values are plotted on the Y-axis. (C) Scatter plot of average C and corresponding average FMC in temperate tussock grasslands in Australia on different dates over 11 years (from 2002 to 2014 except 2008 and 2010). Average C is shown on the X-axis and average FMC is shown on the Y-axis. Blue dots represent average C and FCM on different dates.

4.5.9 Non-native grasslands

Non-native grasslands are mainly distributed in modified pasture or irrigated pasture in eastern Australia or south-western Australia (Figure 4.26). The monthly average C and FMC of this type of grasslands are plotted in a time series plot (Figure 4.27 A) and the average FMC and C of Australia non-native grasslands during the study period are shown in a time series plot and scatter plot (Figure 4.27 B and Figure 4.27 C, respectively).

The results indicated that average C and FMC of Australia non-native grasslands had significant seasonal change (Figure 4.27 A). Average FMC reached a minimum of 50.25% in February and it reached a peak of 142.35% around September. Average C performed in the opposite direction. Average FMC changed dramatically from approximately 50.55% to 142.35% in one year (Figure 4.27 A). The change in average C and FMC was similar in different years, although slight differences existed (Figure 4.27 B). Some extreme values in the time series plot were possibly caused by pixels being missed due to atmospheric conditions or poor data quality over several days. The scatter plot showed a clear negative linear correlation between C and FMC in non-native grasslands in Australia (Figure 4.27 C). Results of the correlation analyses (Pearson's: r = -0.91793, Spearman's: r = -0.92085) confirmed that there was a very strong correlation between average C and FMC in non-native grasslands during the study period ($p < 0.0001$). A linear function explains the relation between C and FMC better in non-native grasslands than an exponential function, which is shown in Equation 4.4.

$$\boldsymbol{FMC = -3.8331C + 338.16}$$ **(Equation 4.4)**

$$R^2 = 0.8426$$

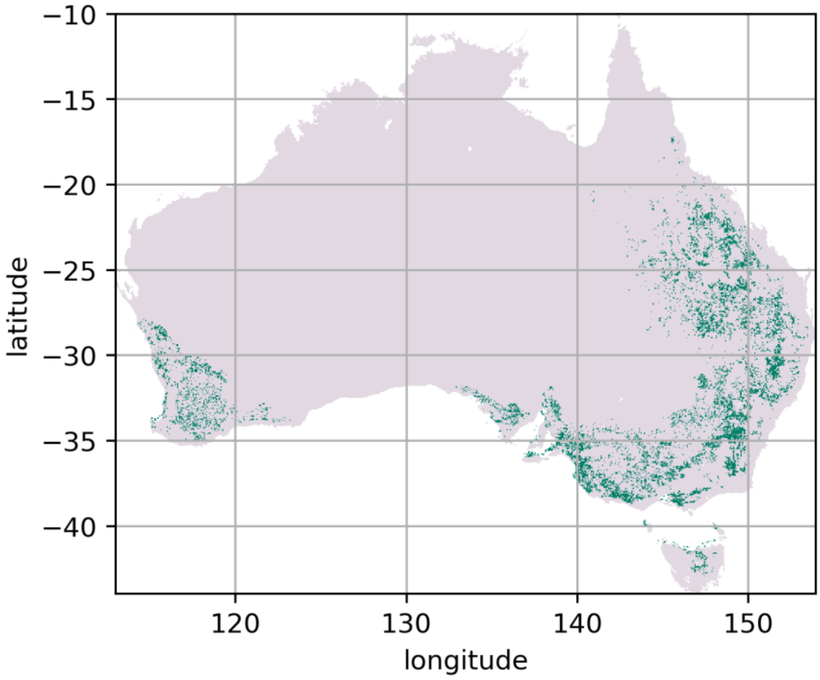


Figure 4.26 Distribution of non-native grasslands (green areas) in Australia.

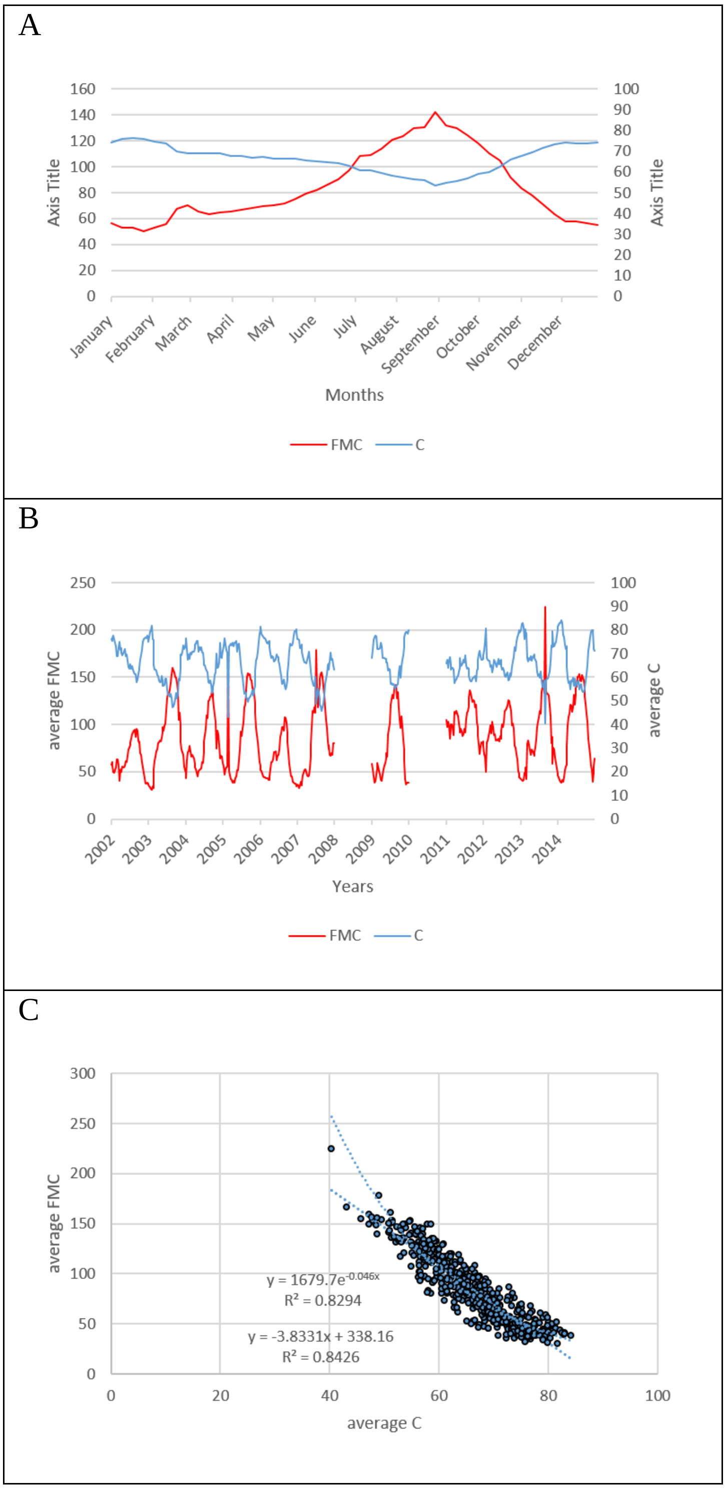
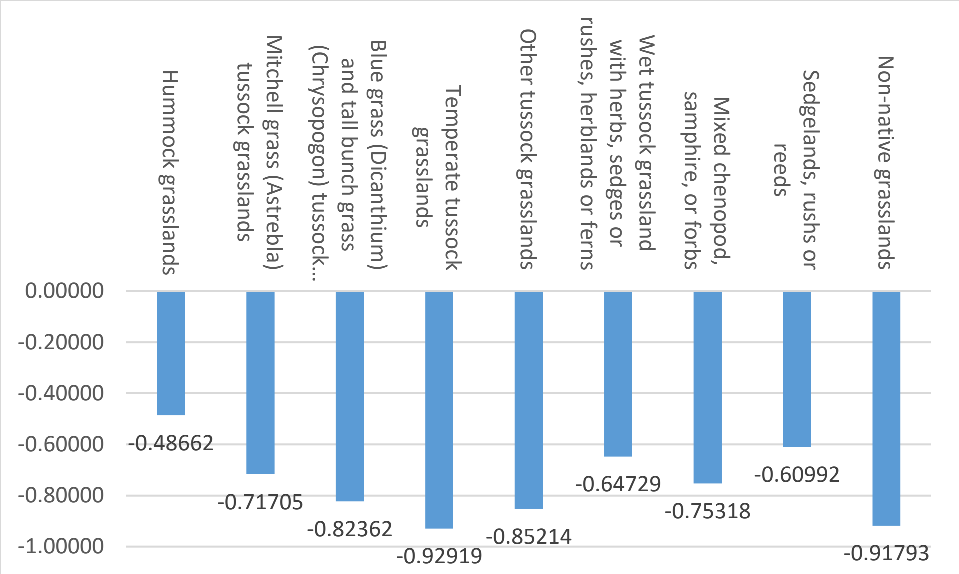


Figure 4.27 Plots of the relationship between average C and FMC in non-native grasslands in Australia.

(A) Time series plot of average C and FMC over 12 months. Average C and FMC were calculated from the data obtained from 2002 to 2014, except 2008 and 2010. The X-axis represents different months and the average C (blue line) and FMC (red line) values are plotted on the Y-axis. (B) Time series plot of average C and FMC over 11 years (from 2002 to 2014 except 2008 and 2010). The X-axis represents years and the average C (blue line) and FMC (red line) values are plotted on the Y-axis. (C) Scatter plot of average C and corresponding average FMC in temperate tussock grasslands in Australia on different dates over 11 years (from 2002 to 2014 except 2008 and 2010). Average C is shown on the X-axis and average FMC is shown on the Y-axis. Blue dots represent average C and FCM on different dates.

Grasslands dominated by different grass species had different degrees of correlation between C and FMC (Figure 4.28). Annual changes in C and FMC values were significant in different types of grasslands. There was a moderate relationship between C and FMC in hummock grasslands. C and FMC were strongly negatively correlated in Mitchell grass (*Astrebla*) tussock grasslands; wet tussock grasslands with herbs, sedges or rushes, herblands or ferns; mixed chenopod, samphire, or forbs; and sedgelands, rushes, or reeds. In blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands, temperate tussock grasslands, other tussock grasslands, and non-native grasslands, there was a strong negative linear correlation between C and FMC.

A



B

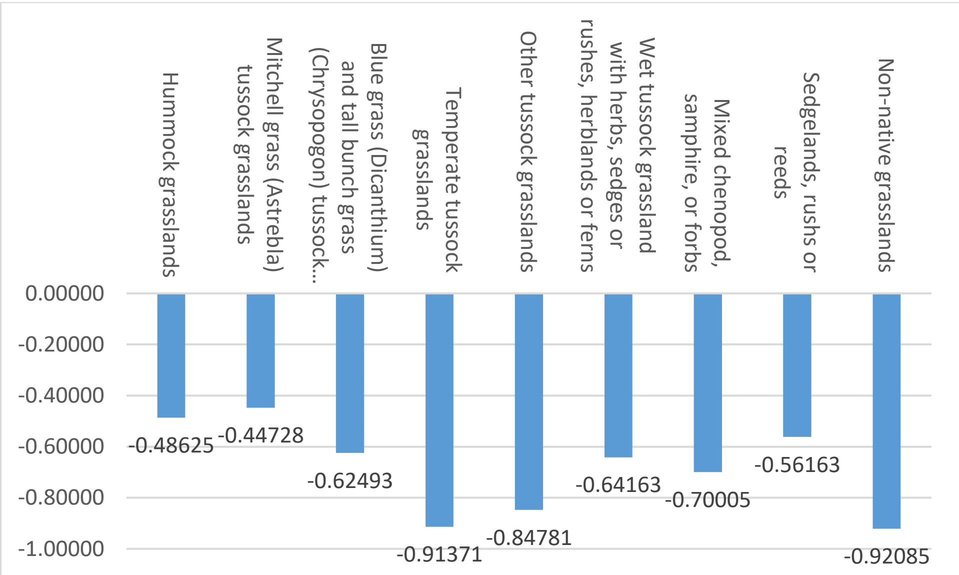


Figure 4.28 Results of Pearson's correlation analysis and Spearman's correlation analysis

Results of Pearson's correlation analysis (A) and Spearman's correlation analysis (B) for the relationship between C and FMC in different types of grasslands ($p < 0.0001$).

4.6 Relationship between C and FMC in areas with different previous fire events

4.6.1 Hummock grasslands

The distribution of hummock grasslands with different fire history classes are shown in Figure 4.29. To study the seasonal changes, the monthly changes of average C and FMC were plotted in a time series plot (Figure 4.30). Average FMC and C values of hammock grasslands with different fire histories over 11 years were plotted as a time series plot and a scatter plot (Figure 4.31 and Figure 4.32, respectively). Pearson's and Spearman's correlation analyses were performed to investigate the relationship between average C and FMC values of areas with different fire histories in hummock grasslands over 11 years (Figure 4.33)

In hummock grasslands, areas with middle fire frequency (class 2, class 5, and class 8) were mainly distributed in northern Australia (Figure 4.29). There was no obvious change in average C and FMC in hummock grasslands except for areas with fire history class 2 and class 5. In these areas, average FMC value reached a peak around March and kept decreasing afterwards until November. After that, average FMC values continuously increased until March in the next year (Figure 4.30). Conversely, C changed in the opposite direction to that of FMC. The changes in average C and FMC in different years were distinct in amplitude and date of change (Figure 4.31). Scatter plots indicated that the change of average C and FMC was minimal in areas with low fire frequency (class 1, class 4, and class 7), whereas the change was relatively obvious in areas with middle fire frequency (class 2, class 3, and class 4) (Figure 4.32). Scatter plots also indicated that average C and FMC of class 2 and class 5 areas were negatively correlated (Figure 4.32). However, in hummock grasslands with other history fire classes, the relationship between C and FMC was not clear. Results of Pearson's and Spearman's correlation analyses between average C and FMC in areas with distinct fire history illustrated that C and FMC were significantly very strongly negatively correlated in hummock grasslands with fire history class 2 ($p < 0.0001$) and were significantly strongly negatively correlated in hummock grasslands with a fire history class 5 ($p < 0.0001$) (Figure 4.33). In hummock grasslands that have never been burned before and with other fire history classes, the negative correlation between C and FMC was moderate or weak ($p < 0.0001$).

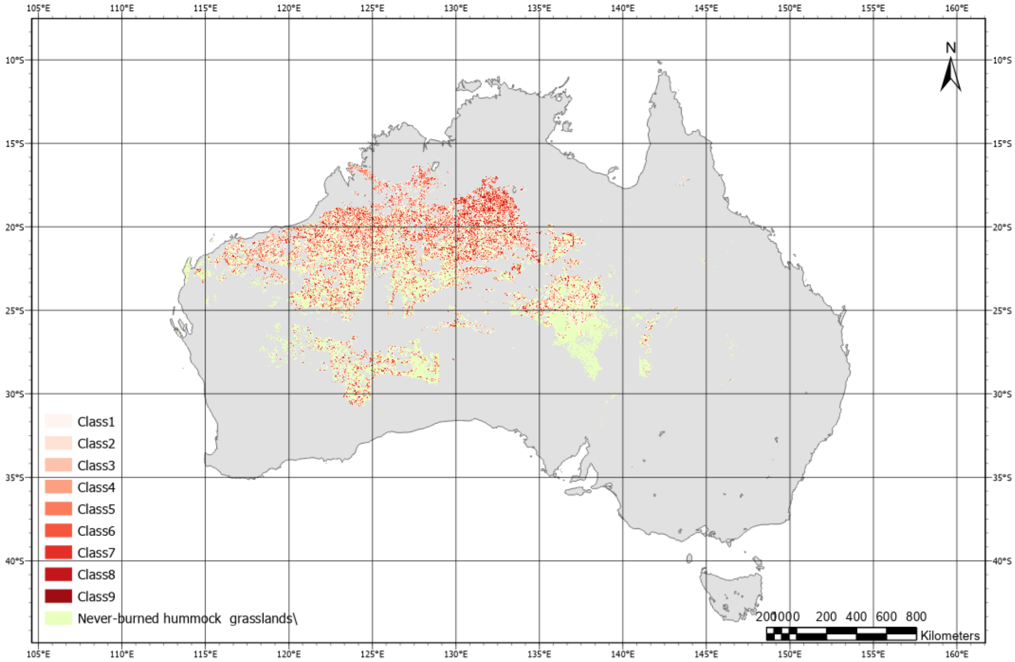
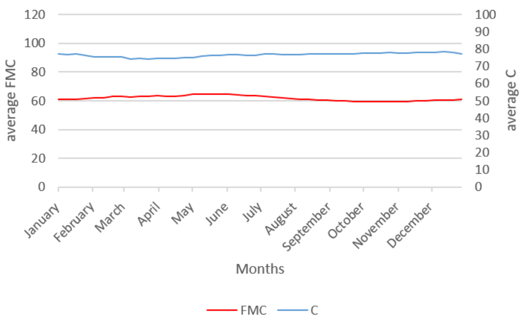


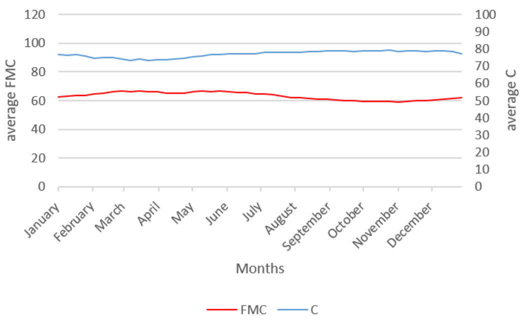
Figure 4.29 Distribution of hummock grasslands with different fire history classes in Australia.

Various colours represent different historical fire events, with the colour scheme listed in the legend.

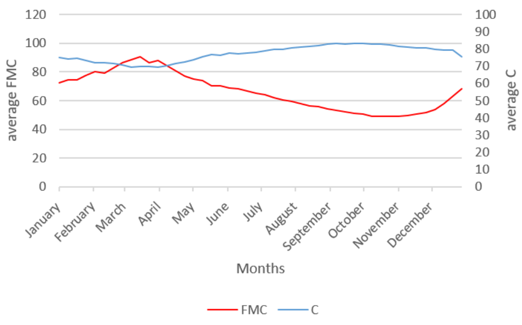
Unburned hummock grasslands



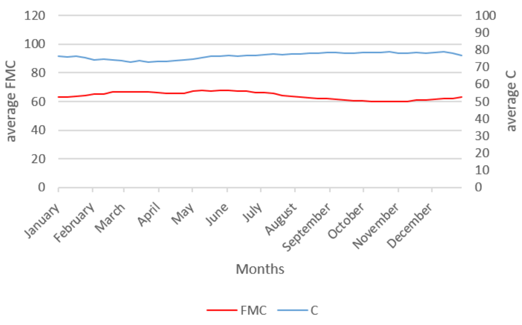
Hummock grasslands with fire history class 1



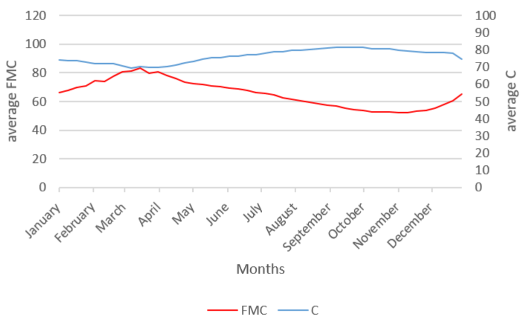
Hummock grasslands with fire history class 2



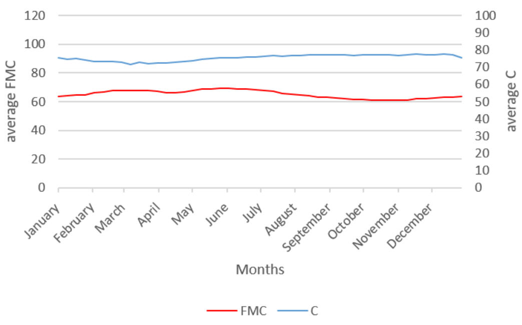
Hummock grasslands with fire history class 4



Hummock grasslands with fire history class 5



Hummock grasslands with fire history class 7



Hummock grasslands with fire history class 8

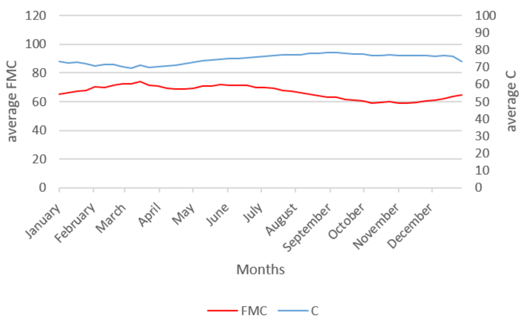


Figure 4.30 Time series plots showing average C and FMC in areas with different fire history classes for Australia hummock grasslands over 12 months.

Red lines represent FMC and blue lines represent C.

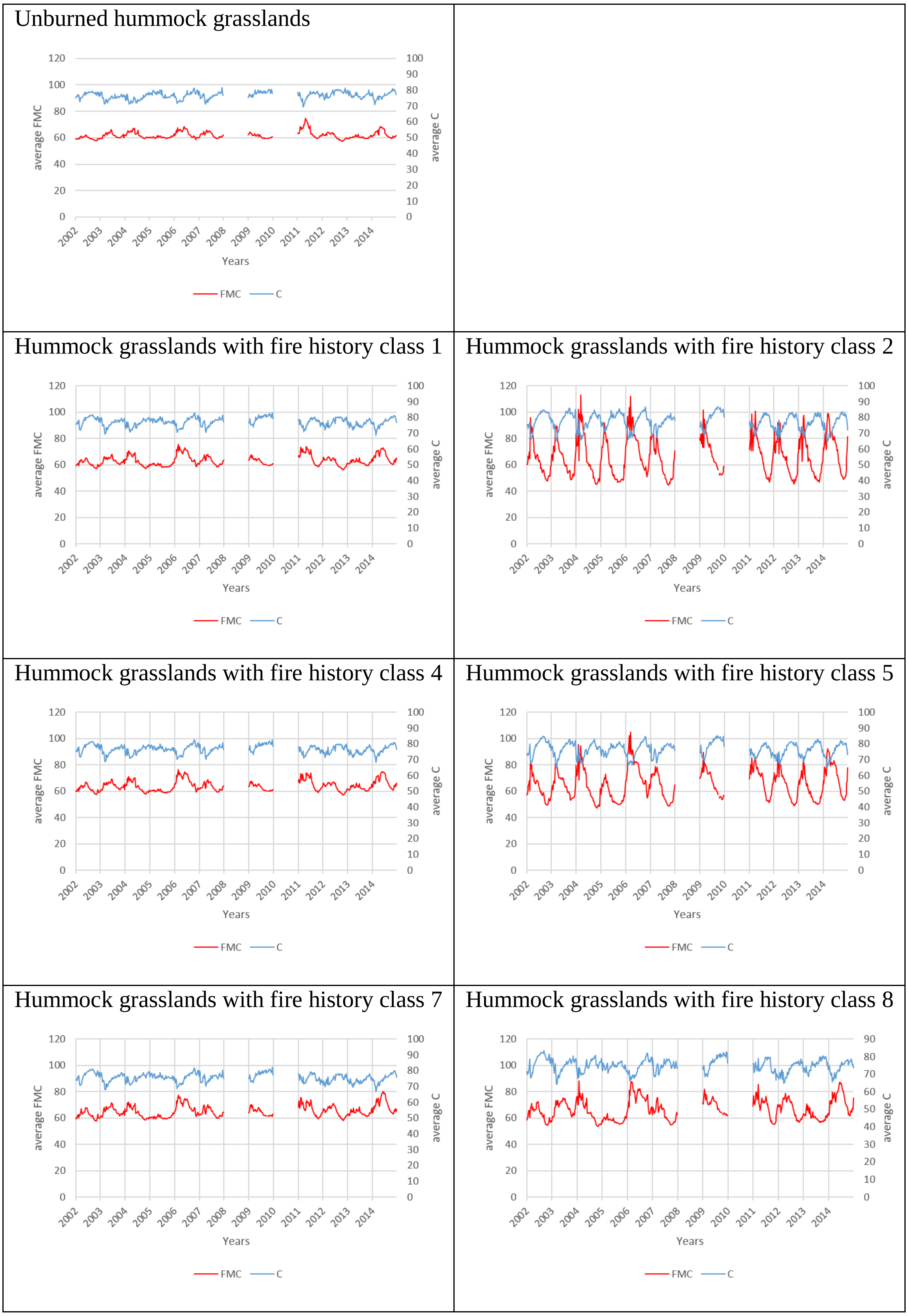


Figure 4.31 Time series plots showing average C and FMC of areas with different fire history classes within Australian hummock

grasslands during the entire study period (from 2002 to 2014 except 2008 and 2010).

The X-axis represents years and the Y-axis is the average C (blue line) and FMC (red line).

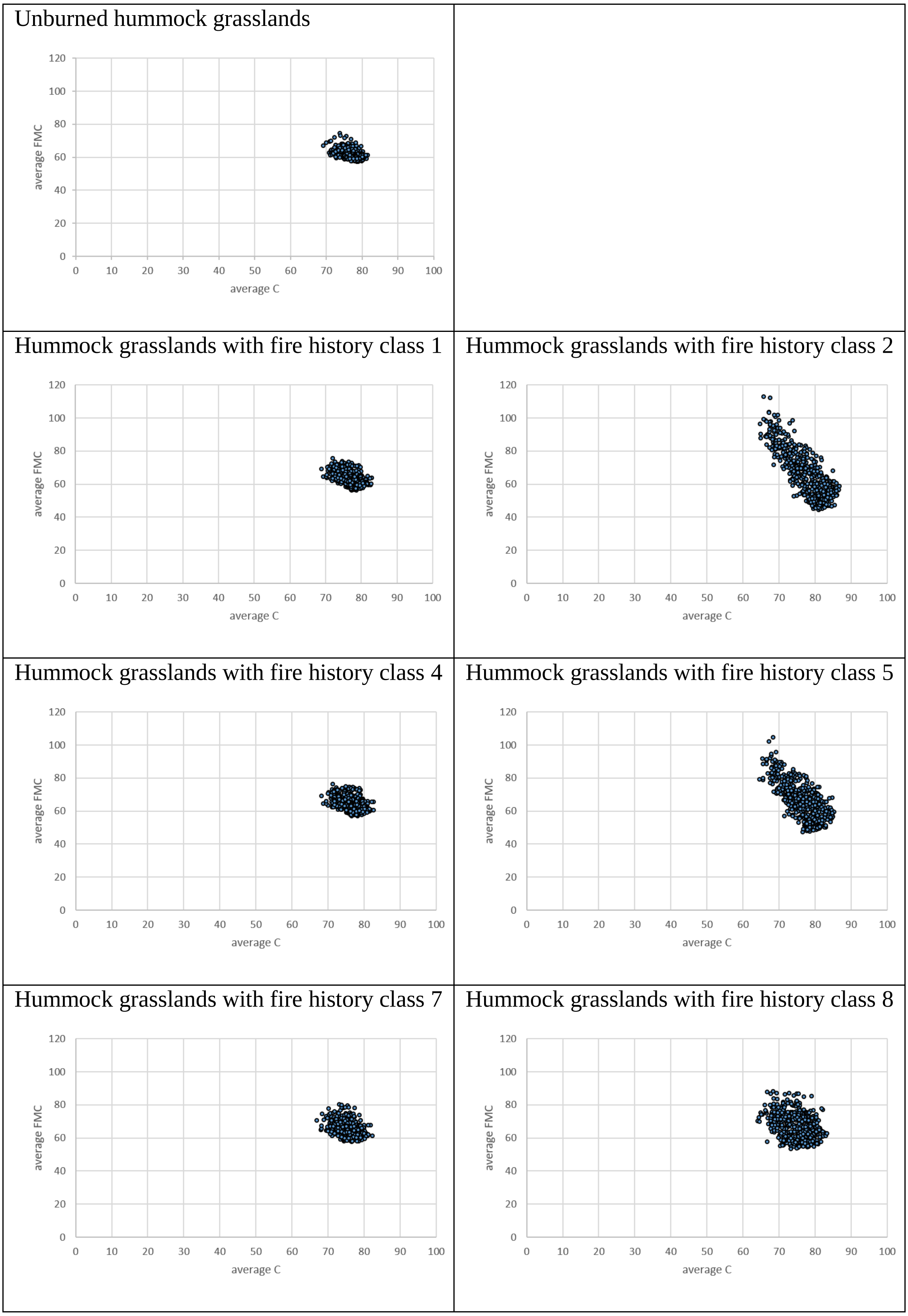
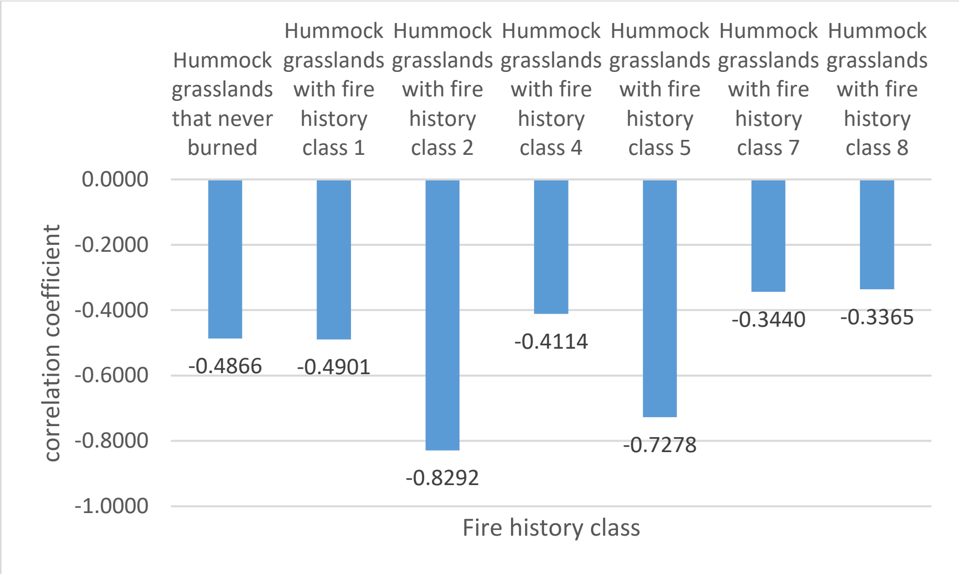


Figure 4.32 Scatter plot showing average C and corresponding average FMC of areas with different fire history classes within

Australia hummock grasslands on different dates over the study period (from 2002 to 2014 except 2008 and 2010).

Each dot represents average C and FMC on different dates.

A



B

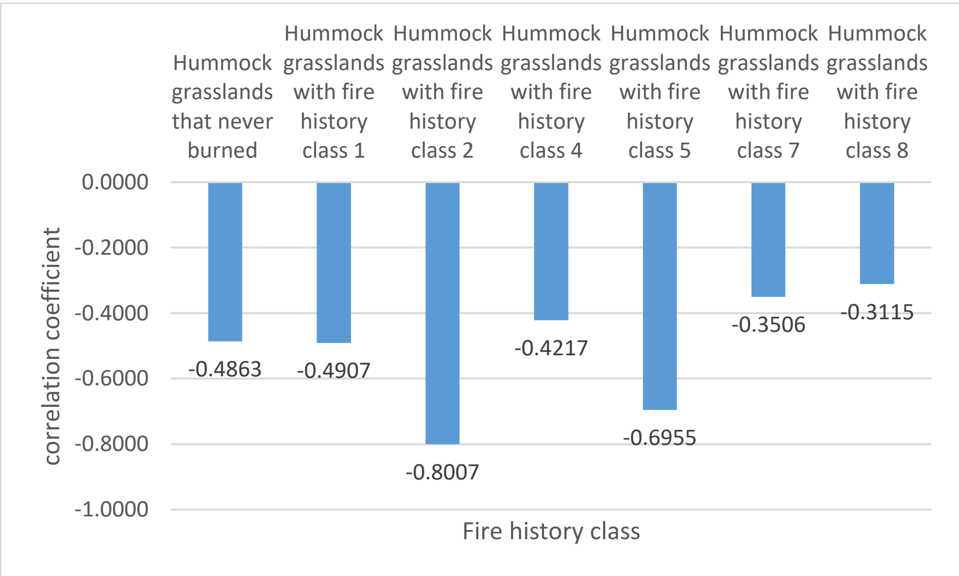


Figure 4.33 Results of Pearson's correlation analysis and Spearman's correlation analysis

Results of Pearson's correlation analysis (A) and Spearman's correlation analysis (B) for the relationship between C and FMC in areas with different fire history classes for hummock grasslands ($p < 0.0001$).

4.6.2 Non-native grasslands

A map of non-native grasslands with different fire history classes in Australia is shown in Figure 4.34. Monthly changes in average C and FMC over 11 years are shown in Figure 4.35. The average FMC and C of areas with different fire history classes in non-native grasslands on different dates throughout the study period were plotted in time series plots and scatter plots (Figure 4.36 and Figure 4.37, respectively). Figure 4.38 shows Pearson's and Spearman's correlation coefficients between average C and FMC.

In non-native grasslands, areas with high fire frequency or intensity were mostly located in north-eastern Australia (Figure 4.34). There were clear seasonal changes in the average C and FMC values, although the degree of changes varied in areas with different fire history classes (Figure 4.35). In areas that had never been burned, class 1 and class 4 areas, average C and FMC changed in opposite directions. Average FMC values reached a maximum around September. In class 2 areas, there were two peaks in average FMC in March and September. In class 5, class 7, and class 8 areas, average C and FMC also changed in opposite directions, but the average FMC value reached a peak around March. Non-native grasslands with distinct fire history classes were distributed in different areas in Australia; therefore, the differences in the seasonal change of the average C and FMC in these grasslands might be attributed to the differences in seasonal precipitation change or distinct climate change in different regions of Australia.

Changes in average C and FMC were slightly different in different years (Figure 4.36). The scatter plots indicate that C and FMC were negatively correlated in non-native grasslands with different fire history classes (Figure 4.37). A comparison was made between plots presenting areas with low fire frequency and corresponding plots representing grasslands with middle fire frequency but the same previous fire intensity. The change in average C was similar, but the areas with middle fire frequency had a smaller average FMC change. Results of Pearson's and Spearman's correlation analyses between average C and FMC of areas with distinct fire histories over 11 years confirmed that C and FMC had a very strong negative correlation in unburned or fire class 1 areas ($p < 0.0001$) (Figure 4.38). In areas with other fire history classes, there were significantly strong negative correlations between C and FMC ($p < 0.0001$).

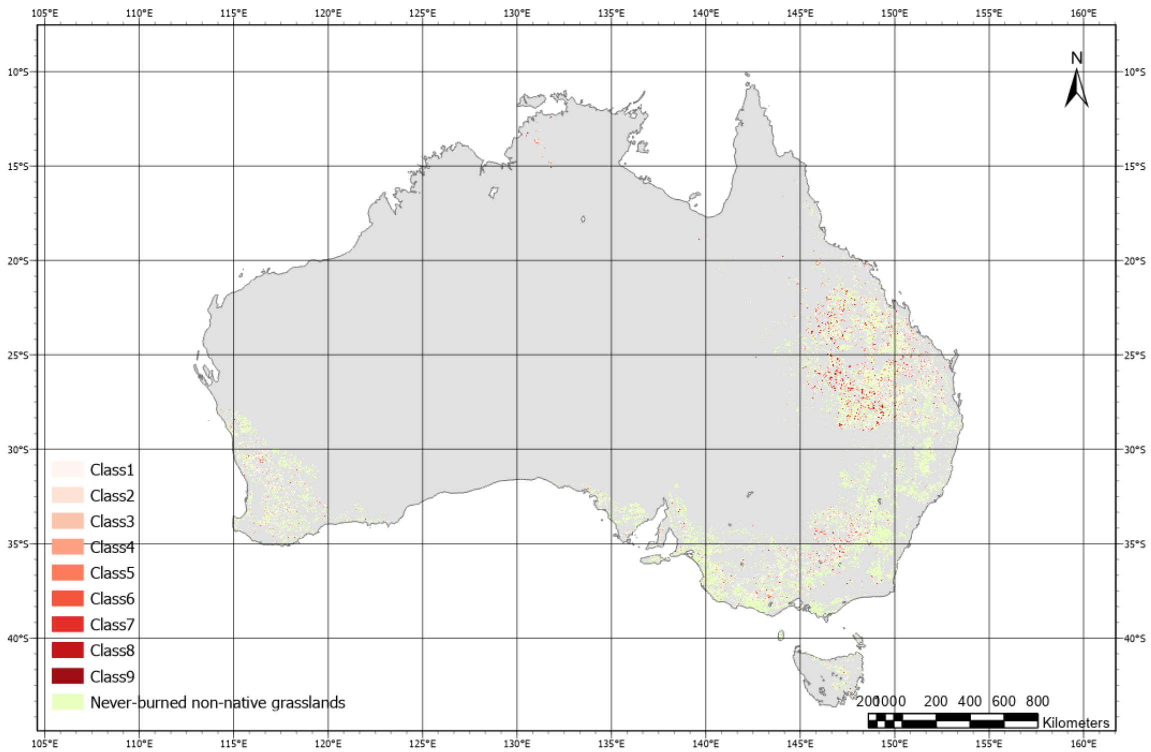
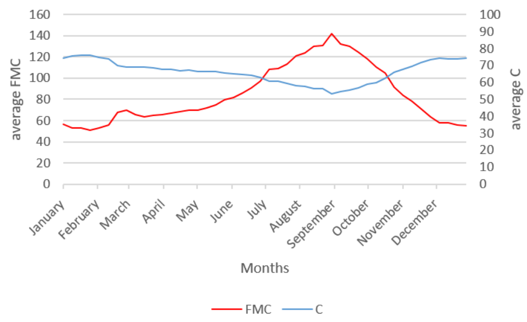


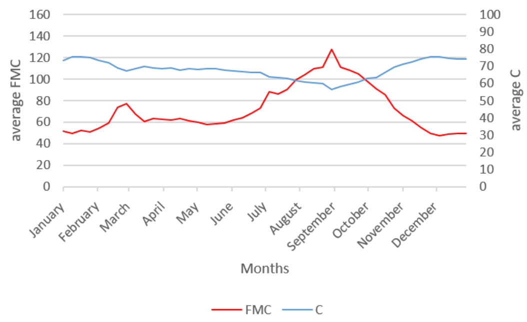
Figure 4.34 Distribution of non-native grasslands with different fire history classes in Australia.

Various colours represent different historical fire events, with the colour scheme listed in the legend.

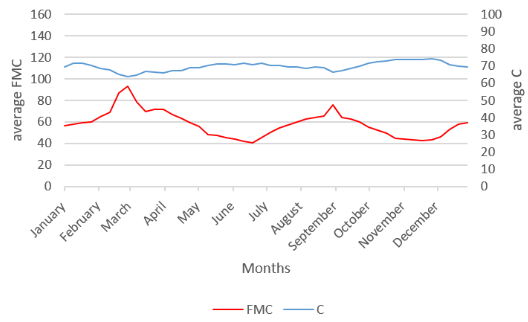
Unburned non-native grasslands



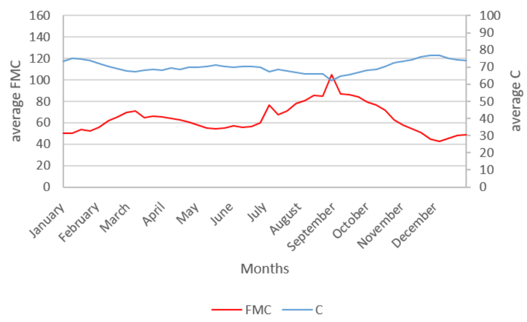
Non-native grasslands with fire history class 1



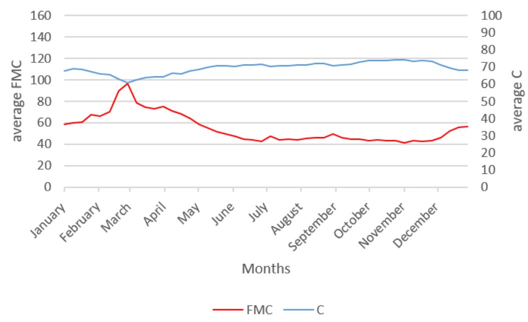
Non-native grasslands with fire history class 2



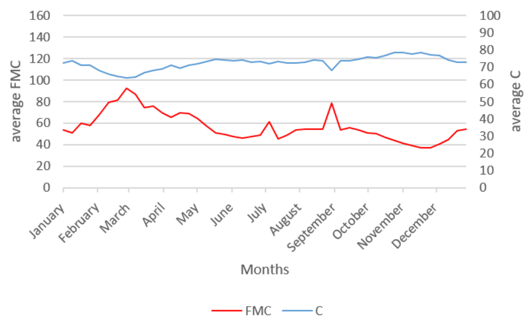
Non-native grasslands with fire history class 4



Non-native grasslands with fire history class 5



Non-native grasslands with fire history class 7



Non-native grasslands with fire history class 8

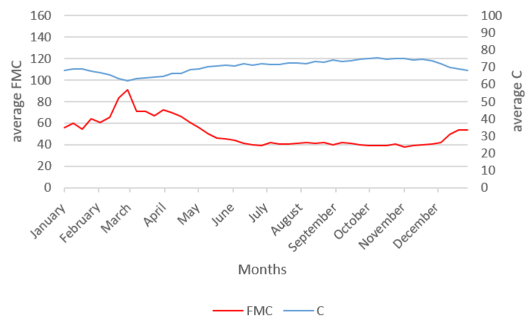
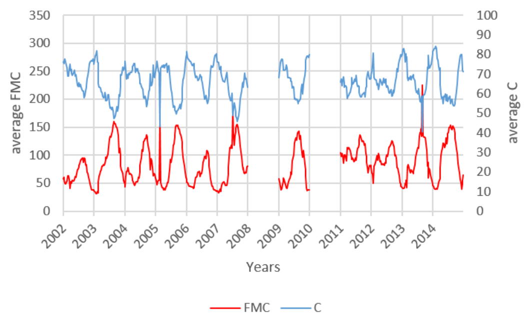


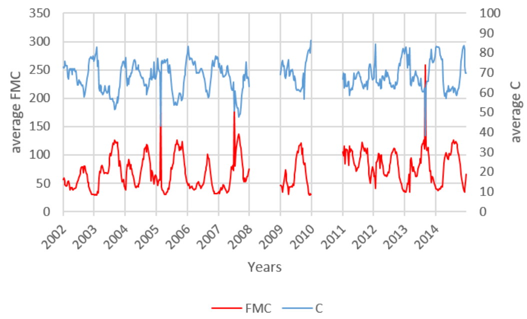
Figure 4.35 Time series plot showing the average C and FMC of areas with different fire history classes in Australia non-native grasslands over 12 months.

Red lines represent FMC and blue lines represent C.

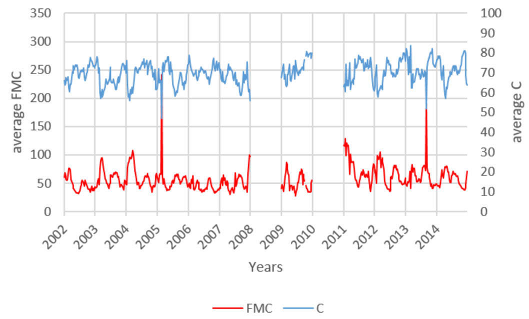
Unburned non-native grasslands



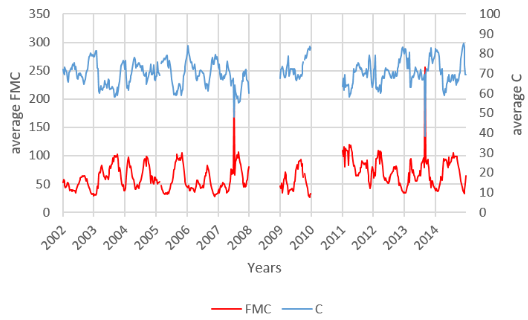
Non-native grasslands with fire history class 1



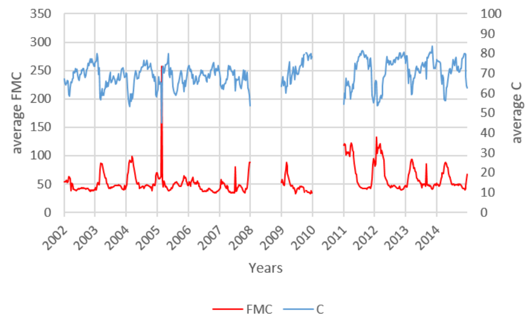
Non-native grasslands with fire history class 2



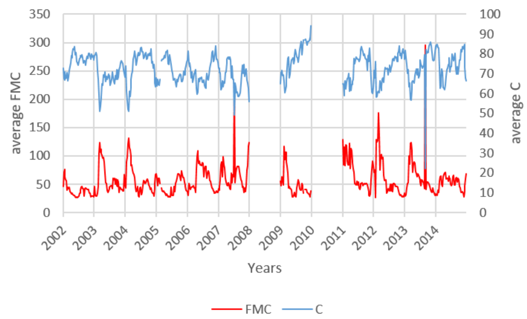
Non-native grasslands with fire history class 4



Non-native grasslands with fire history class 5



Non-native grasslands with fire history class 7



Non-native grasslands with fire history class 8

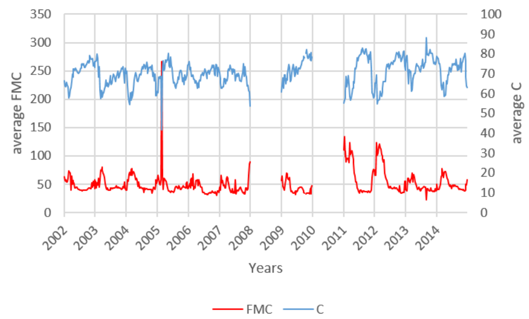


Figure 4.36 Time series plots showing the average C and FMC of areas with different fire history classes in Australia non-native grasslands over 11 years (from 2002 to 2014 except 2008 and 2010)

The X-axis represents the years and the Y-axis is the average C (blue line) and FMC (red line).

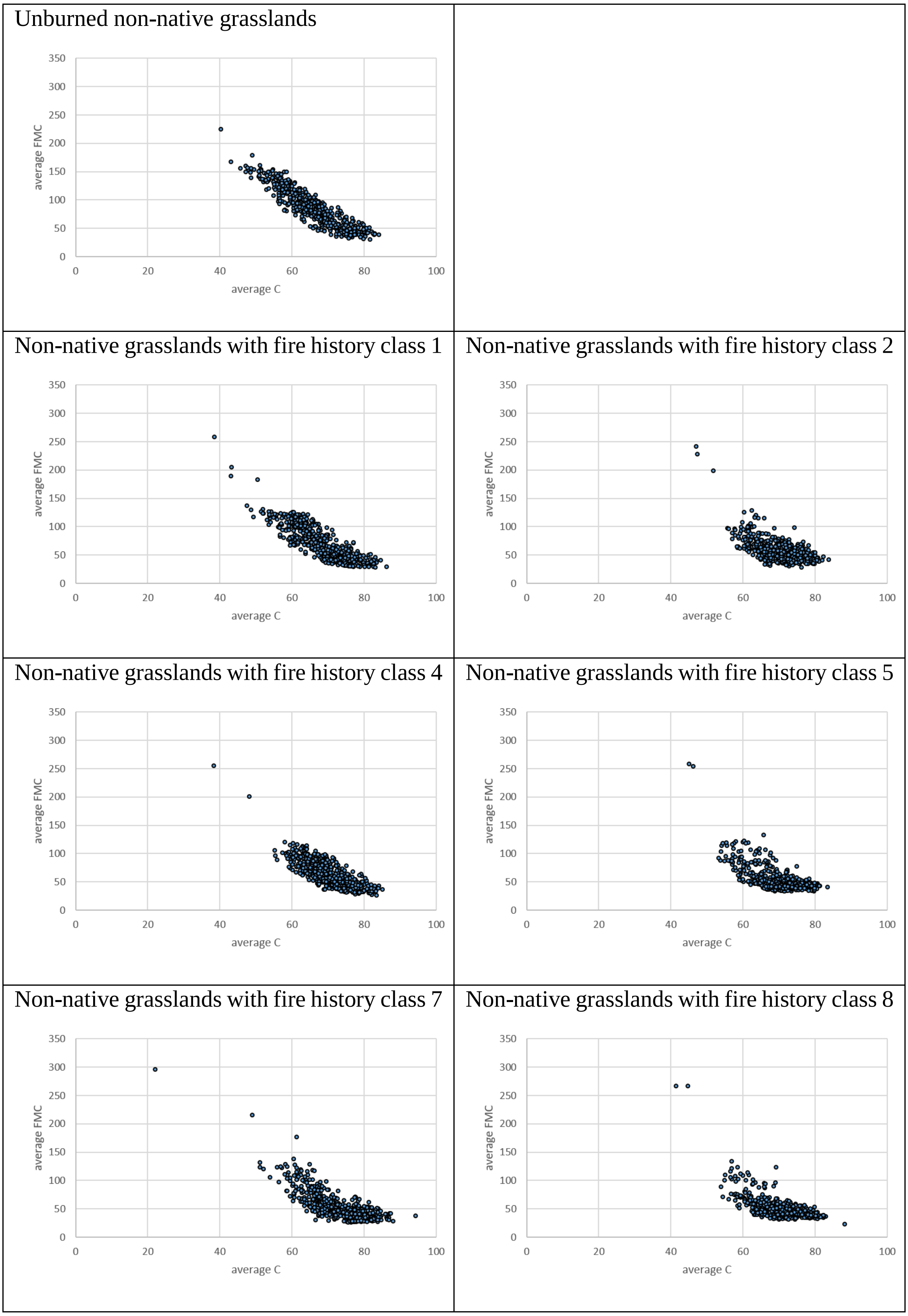
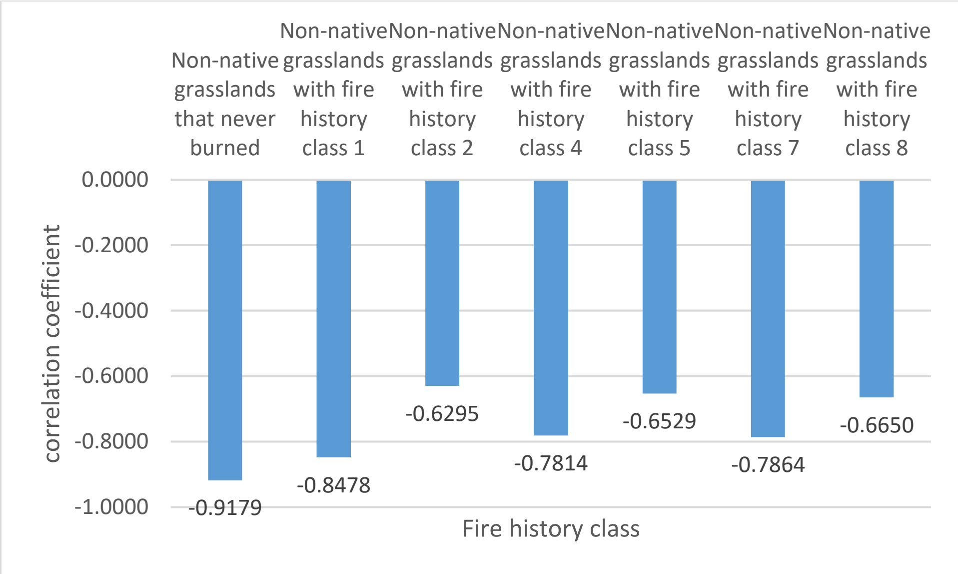


Figure 4.37 Scatter plots showing the average C and corresponding average FMC of areas with different fire history classes in non-

native grasslands on different dates over the study period (from 2002 to 2014 except 2008 and 2010).

Each dot represents C and FMC on different dates

A



B

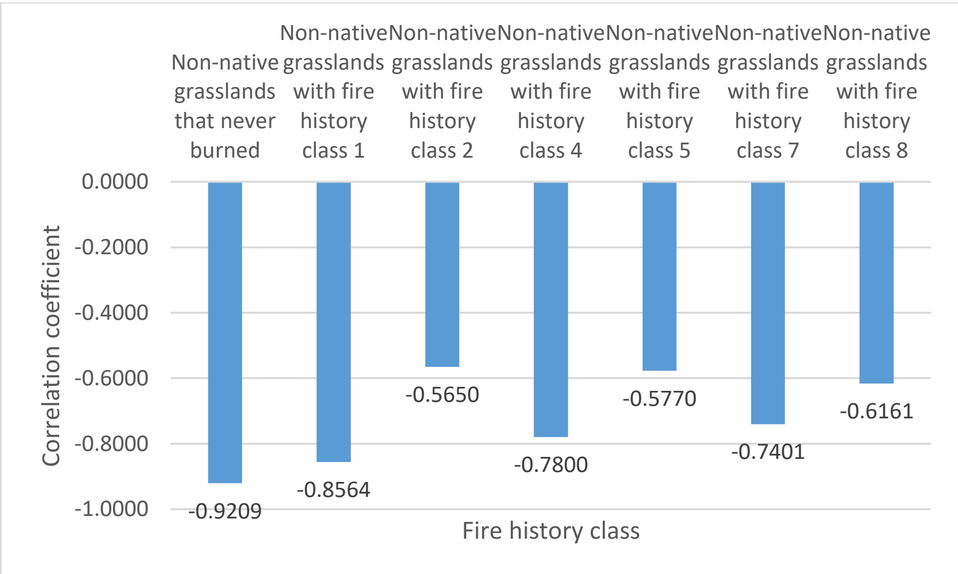


Figure 4.38 Results of Pearson's correlation analysis and Spearman's correlation analysis

Results of Pearson's correlation analysis (A) and Spearman's correlation analysis (B) for the relationship between C and FMC in areas with different fire history classes for non-native grasslands.

4.7 Relationship between C and FMC in different seasons

The average FMC and C of non-native grasslands in different months throughout the study period are plotted in Figure 4.39. The shape indicates a negative correlation between C and FMC in non-native grasslands. In January, average C was high and average FMC was low while it was the opposite in August. Pearson's and Spearman's correlation coefficient were then calculated between average C and FMC (Figure 4.40). The correlation analysis was consistent with the trend shown in the scatter plot and there was always a very strong negative linear correlation between C and FMC in non-native grasslands in different months except January and August ($p < 0.0001$). In January and August, there were strong negative linear correlations between C and FMC in non-native grasslands ($p < 0.0001$). Correlation between C and FMC was weaker in January and August than during the other months.

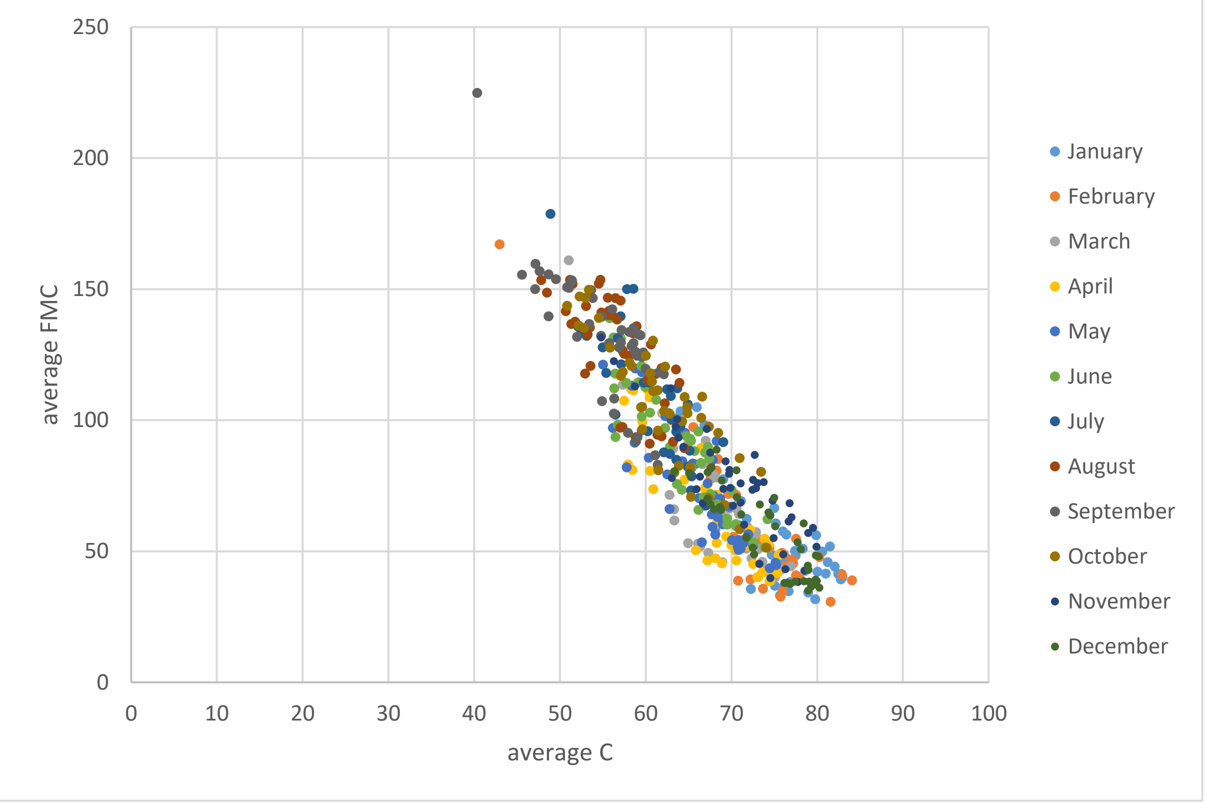
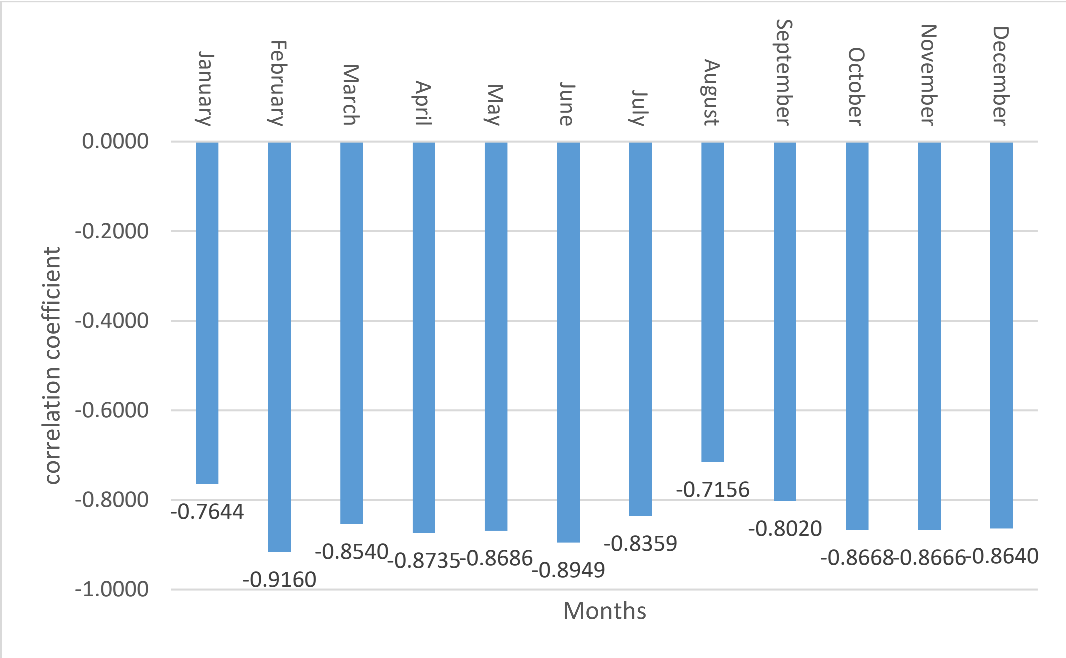


Figure 4.39 Scatter plot showing the average C and corresponding average FMC of Australia non-native grasslands in different months over 11 years.

Various coloured dots represent FMC and C in different months.

A



B

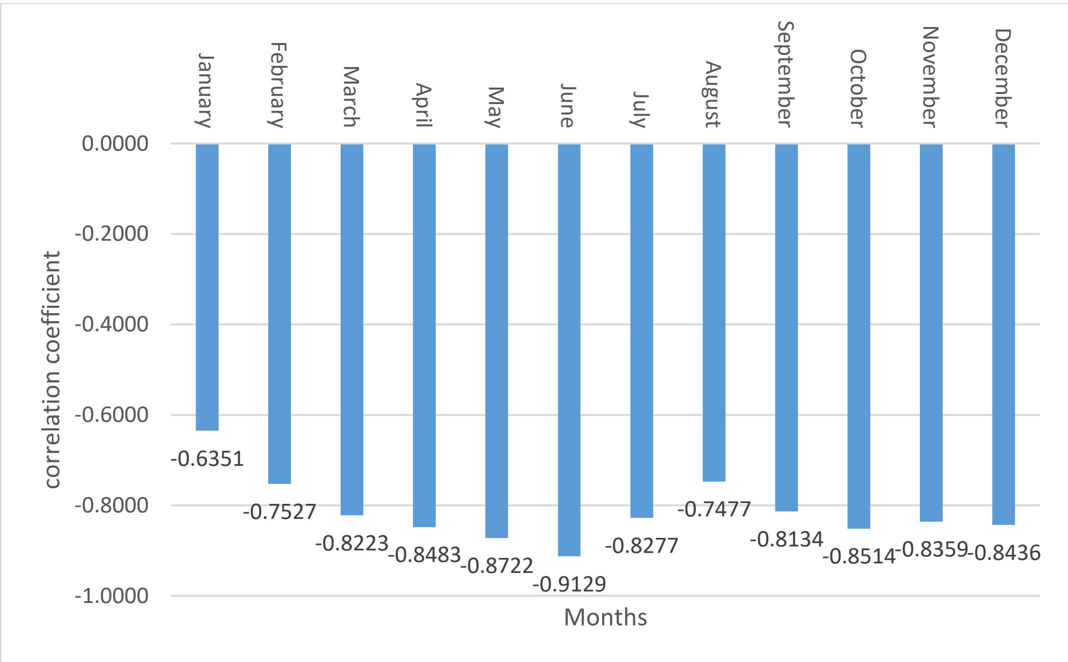


Figure 4.40 Results of Pearson's correlation analysis and Spearman's correlation analysis

Results of Pearson's correlation analysis (A) and Spearman's correlation analysis (B) for the relationship between C and FMC in different months in non-native grasslands ($p < 0.0001$)

Chapter 5: Discussion

The present study confirmed that there was a strong negative linear correlation between C and FMC at the whole Australian grasslands scale, although their correlation was regionally specific or grass species-specific. Further studies regarding C and FMC correlation in different types of grasslands showed that the correlation between C and FMC was moderately negatively linear in hummock grasslands. Moreover, there was a strong negative linear correlation between C and FMC in Mitchell grass (*Astrebla*) tussock grasslands; wet tussock grasslands with herbs, sedges or rushes, herblands or ferns; mixed chenopod, samphire, or forbs; and sedgelands, rushes, or reeds. There was a very strong negative correlation between C and FMC in blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands, temperate tussock grasslands, other tussock grasslands, and non-native grasslands. The results confirmed the statement that the correlation between C and FMC in grasslands is grass species-specific (Gill *et al.*, 2010; Wittich, 2011). Previous fire behaviours modified the correlation between C and FMC. Fire removes dead fuel, whereas FMC in live or senescing fuel is relatively stable. Therefore, frequent fire events lead to a weaker correlation between C and FMC. Moreover, in dry or rainy seasons, the correlation between C and FMC is weaker, which might be caused by uncertainty in the estimation of C or the phonological stage of grasses. Moreover, the correlation between C and FMC might be weak when C is too high or too low.

5.1 C and FMC in different types of grasslands

The results of the correlation analysis between average C and FMC suggested that they are species-specific. In southern temperate zones, except for sedgelands, rushes, or reeds, average C and FMC had a very strong negative significant linear correlation, while in other areas, a very strong significant correlation between C and FMC only existed in blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands.

The seasonal change in C and FMC suggested that grasslands with significant seasonal FMC and C variations had a very strong correlation between C and FMC. This included blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands, temperate tussock grasslands, and non-native grasslands. Seasonal change of FMC was weaker in Mitchell grass (*Astrebla*) tussock grasslands; therefore, the correlation between C and FMC was relatively weaker ($r = -0.71705$). In other grasslands, C and FMC remained constant during different seasons because (i) C and FMC were always constant throughout the study period (in hummock grasslands), or (ii) average FMC and C were obviously changing, but C and FMC changed irregularly on different dates in different years (in mixed chenopod, samphire, or forbs; and in sedgelands, rushes, or reeds). Different seasonal change of C and FMC in grasslands can be attributed to variations in climate or the formation of grasslands. Variations in climate or grasslands might result in a higher correlation between C and FMC. For grasslands with obvious seasonal change, a larger amplitude in FMC change meant a larger amplitude in C change, which resulted in a higher correlation between C and FMC. Other tussock grasslands that contained different species were not discussed because the seasonal change of FMC and C could be different in grasslands dominated by different grass species. The average value of all grasslands under this category may not reflect the real situation in differentiated grasslands.

The results from the present study challenged the idea by Wittich (2011) that C and FMC correlation was distinct in grasslands dominated by annual grasses and perennial grasses because they have different tolerances towards meteorological changes. Both perennial tussock grasslands and annual non-native grasslands had a very strong negative linear correlation between C and FMC, but other perennial grasslands did not show a strong correlation between C and FMC. Therefore, the relationship between C and FMC is not related to whether the grasslands are perennial or annual.

Blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands, temperate tussock grasslands, other tussock grasslands, and non-native grasslands had a very strong correlation between C and FMC and were continuous. The discontinuous hummock grasslands and mixed chenopod, samphire, or forbs grasslands did not show a very strong correlation between C and FMC. C in discontinuous hummock grasslands might be influenced by exposed bare soil. Exposed soils resulted in increases in the Red bands and reduction in the NIR, and red soil in hummock grasslands would have even more influences (Huete *et al.*, 1984). Furthermore, exposed water or woody vegetation also influences C estimation (Newnham *et al.*, 2010). Sedgelands, rushes, or reeds were continuous; however, C and FMC did not have a very strong linear correlation in sedgelands, rushes, or reeds. Therefore, C and FMC relation are not simply determined by continuous or discontinuous of grasslands.

5.2 C and FMC in areas with different fire histories

Fire removes both live and dead fuel in grasslands, but unburned areas preserve all fuel categories. After fire events, grass re-grows and creates new green or senescing fuel. Analysis of the influence of previous fire events on the relationship between C and FMC helped to understand the role of different fuel categories for determining C and FMC.

In hummock grasslands, the relationships between C and FMC in areas with low fire frequency and areas with middle fire frequency were significantly different. Strong or very strong negative linear C and FMC correlations and clear seasonal changes in FMC or C were observed in areas with middle fire frequency (grasslands with fire history class 2 or class 4). Burrows *et al.* (2009) stated in their study that *Spinifex* hummock grasslands were discontinuous and two-thirds of the ground surface was bare. Bare ground influences the accuracy of C estimation based on NDVI (Newnham *et al.*, 2010). Inaccurate C data leads to misinterpretation of C and FMC correlations. Positive correlations between C and FMC in the time series in some grids might be caused by inaccurate C data in hummock grasslands. FMC was the main factor limiting the ignition and sustained fire spread in continuous fuels but in patchy hummock grasslands, fire cannot spread until the flames from the burning hummocks breach the inter-hummock space and ignite the adjacent hummock (Gill *et al.*, 1995). Discontinuous *Spinifex* hummock grasslands do not have the potential to burn within 5–7 years after a fire event because it takes time to recover the fuel load to enable a fire to spread (Burrows *et al.*, 2009). Thus, hummock grasslands with a middle fire frequency, 7–36 fire events during the study period, should be more continuous or include co-occurring species. Thus, in these areas, the proportion of bare ground was smaller than that in other areas in hummock grasslands, which would enhance fire risks and the spread of fires. Different formation of grasslands or grass species results in significantly different C and FMC correlations in these grasslands.

Hummock grasslands with a low fire frequency and high fire frequency can be significantly different; therefore, it is necessary to observe them separately. In hummock grasslands with different previous fire intensities, the correlation between C and FMC was slightly different. In grasslands with low previous fire frequency, previous fire intensity variation did not lead to changes in average C and FMC. Results of the correlation analysis indicated that higher previous fire intensity resulted in weaker correlations between C and FMC. In areas with middle fire frequency, the higher the historical fire intensity, the lower the amplitude of C change. Fire intensity variations were always correlated with a change in correlation between C and FMC. Conversely, in grasslands with higher previous fire intensity, the correlation between C and FMC was weaker. Although higher fire intensity is related to lower C and FMC correlation, the role of fuel dynamics remains unknown. The fire intensity of hummock grasslands is influenced by the fuel load and weather condition (Griffin and Allan, 1984; Burrows *et al.*, 1991; Burrows *et al.*, 2009). There are no direct links between fire intensity and fuel load or fuel structure; therefore, it is difficult to analyse the influences of different fuel categories for grasslands with different previous fire intensities.

In non-native grasslands, varying seasonal C and FMC changes indicated that areas with different fire history classes were located in different regions. Areas with lower fire frequency or intensity were located in southern temperate zones, whereas areas with higher fire frequency and fire intensity were mostly located in north-eastern Australia. Distinct weather conditions in different regions introduce uncertainties when evaluating the influences of previous fire events. The results of the correlation analysis indicated that the correlation between C and FMC was relatively weaker in areas with more intensive previous fire events. Furthermore, frequent previous fire events modified the correlation between C and FMC, as C and FMC correlation is weaker in areas with higher fire frequency. Similar to hummock grasslands, more intensive previous fire events are related to a weaker correlation between C and FMC in grasslands with low fire frequency. Conversely, in areas with middle fire frequency, higher previous fire intensity has a stronger correlation between C and FMC. Therefore, due to a lack of knowledge regarding the influences of previous fire intensity on fuel condition, it is not clear how previous fire intensity modifies the correlation between C and FMC in non-native grasslands. The scatter plots showed that compared to low frequently burned grasslands, C change was similar whereas FMC was relatively more stable in grasslands with middle fire frequency (Figure 6.9). A previous study showed that the FMC of senescing or live fuel was relatively stable, whereas the FMC of dead fuel was highly influenced by weather conditions (Kidnie *et al.*, 2015). Therefore, frequent bushfires result in the removal of fuel in these grasslands. The dead fuel is completely depleted while the remaining live and senescing fuel re-develop and maintain a stable FMC. However, the greenness is changing with metrological changes, resulting in a weaker correlation between C and FMC.

5.3 C and FMC in different seasons

The present study confirmed that there was always a very strong negative linear correlation between C and FMC in non-native grasslands in different months except for January and August. In January, C was high and FMC was relatively low in non-native grasslands. In August, the average FMC of non-native grasslands increased rapidly from approximately 120.86% to 142.35% (Figure 4.27 A). Accumulated water in grasslands from precipitation might result in an overestimation of the C value (Newnham *et al.*, 2010). In January, C might achieve 100% in some grids, thus FMC changed continuously without any corresponding C change. For some species, chlorophyll concentration decreases due to the phenological status of the vegetation, but the water content remains constant (Gond *et al.*, 1999). It is possible that C value changes due to the phenological stage of grasses instead of water stress, so change in C are not related with change in FMC in January or August. The results of the present study validate the statement in the study by Ceccato *et al.* (2001) that FMC is not always directly related to the chlorophyll concentration. Moreover, C and FMC might not be correlated when C is too high or too low.

5.4 Implications for fire management and fire prediction models

The results of the present study suggested that the correlation between C and FMC was grass species-specific. It validated recommendation from CSIRO that three different grass classes fit different fire prediction models based on a different assumption regarding the relation between C and FMC (Cruz *et al.*, 2014). Fire prediction models recommended for southern grasslands were developed based on McArthur's grassland fire danger meter that assumed that C and FMC were related (Cruz *et al.*, 2014). This model can effectively predict fire risks and fuel conditions in southern grasslands except for areas covered by sedgelands, rushes, or reeds due to a significantly very strong negative linear or exponential correlation between C and FMC in grasslands (temperate tussock grasslands, other tussock grasslands, and non-native grasslands) in this region. Models that use C as the input variable can be developed in blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands and non-native grasslands in north-eastern Australia, which show a significant very strong negative linear or exponential correlation between C and FMC. Moisture content data is still important after the C value reaches 100 in summer and linear functions fit better for FMC and C rather than an exponential function.

Relationships between C and FMC are slightly different in grasslands that are dominated by different species; therefore, developing different fire prediction models for different grasslands can help improve accuracy. Models that predict the rate of spread in grasslands with both C and FMC can be simplified using C values lower than 100 as an input coefficient because there is always a very strong negative linear correlation between C and FMC in southern grasslands except for in sedgelands, rushes, or reeds (Cheney *et al.*, 1998). However, previous fire events and observation time may influence the accuracy of these fire prediction models.

The results also support the fact that FMC should be an input variable for models developed to estimate fire behaviour in hummock *Spinifex* grasslands. C cannot infer FMC in hummock grasslands because C and FMC are only moderately negatively correlated. FMC should be used as an input variable in these grasslands for current fire prediction models.

The results illustrated that the very strong correlation between C and FMC is specific to grass species, fire history, and season; therefore, FMC may not directly relate to chlorophyll concentration. Indirect observation of FMC via spectral indices focusing on NIR and red contrast can be inaccurate in some situations. These results support the statements by Yebra *et al.* (2008) and Davidson *et al.* (2006) that compared spectral indices to the contrast between NIR and red to illustrate chlorophyll concentration or greenness, and showed that the models that focused on contrast between NIR and SWIR better reflected FMC change because they have direct links with FMC. Observing FMC with spectral indices focusing on NIR and red was more effective in grasslands with a very strong correlation between C and FMC (e.g. in blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands, in temperate tussock grasslands, in other tussock grasslands, and in non-native grasslands). However, they were not suitable for observing FMC in hummock grasslands or other grasslands for which the correlation between C and FMC is weaker. These spectral indices cannot be used to observe FMC in areas with intensive or frequent fire events and they are inaccurate in drought or rainy seasons because the correlation between C and FMC is weaker in burned areas and during extreme drought or the rainy season.

The proportion of dead fuel influences the correlation between C and FMC in grasslands. Frequent fire events that remove dead fuel in grasslands weaken the correlation between C and FMC.

5.5 Limitations

Although the present study determined the relationship between C and FMC in different regions and seasons, some limitations might cause uncertainties in the results.

There are many irrigated pastures in the areas alongside the Murray River in northern Victoria and southern New South Wales that can significantly change the C and FMC relationship in Australian grasslands (Bethune and Armstrong, 2004). The irrigation season is different between regions (Bethune and Armstrong, 2004). Irrigation water immediately changes the moisture content of dead fuel from the equilibrium moisture content that is determined by meteorological factors and fuel types. While the change in C in grasslands remains relatively slow, irrigation changes the C and FMC correlation.

In addition to irrigation, grazing is another factor that might cause inaccuracy in the present study. Grazing is an important economic activity in Australian grasslands; however, it can influence fire behaviour and the relationship between C and FMC by changing the fuel composition. Davies *et al.* (2016) suggested that winter grazing reduced the herbaceous fuel load and increased FMC. Schmelzer (2009) also agreed that grazing and clipping in pasture reduced the fuel loads in grasslands. The fuel composition in unburned grasslands can be influenced by grazing. Therefore, the grazing intensity differences in different districts interfere with the results of the present study.

FMC and C data, derived from MCD43A4 and MOD09A1, respectively, represent surface reflectance during different periods. Although FMC was paired with C that had the same median date in the present study, they represented different periods. FMC data were derived from MCD43A4, which is a 16-day composite (Schaaf and Wang, 2015), while C data were derived from MOD09A1, which is an 8-day composite (Vermote, 2015). In addition, in RTMs, FMC data in cloudy areas are removed (Yebra *et al.*, 2018); therefore, FMC and C in cloudy pixels are hard to estimate and they are neglected in this study. Furthermore, arid areas that are less likely to be covered by cloud are more influential in this analysis. This research covers the data collected over 11 years, so land use changes, the changes in distribution or population of different grass species (Williams *et al.*, 2007), and the invasion of exotic species (Brown and Carter, 1998; Lenz *et al.*, 2003) could have occurred within this period. This will change the structure, fuel condition, and fire behaviour of grasslands (McGranahan *et al.*, 2013; Setterfield *et al.*, 2013). Thus, differences exist between MVS released in 2018 and the actual distribution of grassland types that change consistently during the study period. Australia's Environment Explorer provided the annual fire occurrence and fire intensity over the study period. Nonetheless, fire events that happened before 2002 or in 2008 and 2010 would still influence fuel dynamics and previous fire events might have long-term impacts on the grasslands because of the change in soil quality (Úbeda *et al.*, 2005). Impacts from fire that occurred outside the study period were not evaluated.

NVIS's MVS only provides information about the dominant vegetation types in a pixel, although variation exists in the observation scale (Australian Government Department of the Environment and Energy, 2018). Australia's Environment Explorer generates fire behaviours in a pixel; however, fire behaviour can be uneven within a pixel.

Areas with different fire histories are located in different regions; therefore, climate differences or co-occurring vegetation differences can introduce errors into the analysis of the influence of fire history. Moreover, the distributions of fire events and grass species are highly influenced by the local climate, which influences the relationship between C and FMC. When analysing the influence of fire history and grass species, the impact of climate on C and FMC correlation must be considered. For average C and FMC, some pixels in C and FMC data were missing due to atmospheric conditions or poor data quality; therefore, average C and FMC data on different days were collected in slightly different areas.

In the present study, the correlation between C and FMC was discussed within different types of grasslands and areas with different fire classes. The relationship between C and FMC might be different at the research scale and these differences were neglected. In some types of grasslands or areas with a particular fire history, the correlation between C and FMC could have slight variation in different grids, which were not reflected in the present study.

5.6 Future research

In the present study, it was confirmed that fire intensity influenced the correlation between C and FMC. However, the influence of fuel load and fuel composition in areas with different fire intensities remain unclear. Field-based observations in areas before and after fire events with different fire intensities should be conducted for better understandings regarding the linkage between fire intensity and fuel load or fuel composition in different grasslands. This would help explain how previous fire intensity influences the correlation between C and FMC. Furthermore, it would help determine the influence of different fuel composites in grasslands on C and FMC correlation.

Correlation analysis between C and FMC in different pixels in a time series revealed that the correlation changed in different years. This yearly difference can be attributed to long-term climate change, including El Nino or global warming that significantly changes precipitation or temperature. Long-term studies would be useful for identifying the causes of these yearly changes.

Non-native grasslands in Australia include different grass species (Morgan, 1999), which may result in different relationships between C and FMC. Further studies should focus on mapping the distribution of non-native grass species in Australian grasslands and analyse the correlation between C and FMC in grasslands containing different non-native grass species.

As mentioned in Section 5.5, irrigation and grazing have significant influences on the correlation between C and FMC. Future studies should identify the irrigated and grazed areas and these areas should be excluded to reduce their influence on C and FMC. In addition, ground observations of C and FMC should be conducted in pastures to identify the influences of grazing and irrigation on different grass types.

Chapter 6: Conclusion

The present study confirmed that there were strong negative linear correlations between C and FMC at the whole of Australian grasslands scale; however, there were obvious differences in the correlation coefficients in different types of grasslands. The correlation between C and FMC was influenced by grass species, previous fire events, and seasonal change. In blue grass (*Dichanthium*) and tall bunch grass (*Chrysopogon*) tussock grasslands, temperate tussock grasslands, other tussock grasslands, and non-native grasslands, C and FMC were very strongly negatively linearly correlated. In other types of grasslands, the correlation between C and FMC was weaker. Compared with exponential functions, linear functions better represented the relationship between C and FMC. In areas with frequent fire events and during the dry or rainy seasons, the correlations between C and FMC were weaker.

This study supports the assumption of the fire prediction model recommended by CISRO for southern grasslands because C and FMC are very strongly significantly correlated in grasslands in this area except for sedgelands, rushes or reeds. In sedgelands, rushes or reeds, models that directly use FMC as an input should be developed because C is not related to FMC in this area. Moreover, FMC should be used as an input variable in fire prediction models for hummock grasslands. Overall, FMC data should be included in fire prediction models for grasslands that do not have very strong significant correlations between C and FMC.

This study questioned the indirect observations of FMC using spectral indices that focused on the contrast between red and NIR. These were developed based on the assumption that C was always related to FMC. However, C and FMC are not always very strongly negatively correlated in grasslands and their correlation can be affected by grass species, previous fire events, and seasons. Spectral indices focusing on the contrast between C and FMC can be inaccurate in some situations. Spectral indices that focus on the contrast between NIR and SWIR would better reflect FMC.

References

Allan, G., Johnson, A., Cridland, S. and Fitzgerald, N., 2003. Application of NDVI for predicting fuel curing at landscape scales in northern Australia: can remotely sensed data help schedule fire management operations?, *International Journal of Wildland Fire,* **12**(4): 299-308. Available at: https://doi.org/10.1071/WF03016

Anderson, S. and Pearce, H., 2003. *Improved methods for the assessment of grassland curing*, Proceedings: International Wildland Fire Conference,

Andrews, P. L., Anderson, S. A. and Anderson, W. R., 2006. *Evaluation of a dynamic load transfer function using grassland curing data*, In: Andrews, Patricia L.; Butler, Bret W., comps. 2006. Fuels Management-How to Measure Success: Conference Proceedings. 28-30 March 2006; Portland, OR. Proceedings RMRS-P-41. Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station. p. 381-394,

Australian Bureau of Agricultural and Resource Economics and Sciences, 2016.

Australian Government Department of the Environment and Energy, 2018. x, Canberra.

Barber, J., 1990. Monitoring the curing of fire fuels in Victoria Australia with sensors in satelltes and aircraft, *Tech. Rep.*: 58.

Beadle, N. C. W., 1981. *The vegetation of Australia*, Cambridge University Press.,

Beer, T., 1990. The Australian National Bushfire model project, *Mathematical and Computer Modelling,* **13**(12): 49-56. Available at: https://doi.org/10.1016/0895-7177(90)90098-8

Beer, T., 1991. Bushfire rate-of-spread forecasting: Deterministic and statistical approaches to fire modelling, *Journal of Forecasting,* **10**(3): 301-317.

Beer, T. and Williams, A., 1995. Estimating australian forest fire danger under conditions of doubled carbon dioxide concentrations, *Climatic Change,* **29**(2): 169-188. Available at: 10.1007/bf01094015

Bethune, M. and Armstrong, D. P., 2004. Overview of the irrigated dairy industry in Australia, *Australian Journal of Experimental Agriculture,* **44**(2): 127-129. Available at: https://doi.org/10.1071/EA03148

Blanchi, R., Leonard, J., Haynes, K., Opie, K., James, M. and Oliveira, F. D. d., 2014. Environmental circumstances surrounding bushfire fatalities in Australia 1901–2011, *Environmental Science & Policy,* **37**: 192-203. Available at: https://doi.org/10.1016/j.envsci.2013.09.013

Bowman, W. D., 1989. The relationship between leaf water status, gas exchange, and spectral reflectance in cotton leaves, *Remote Sensing of Environment,* **30**(3): 249-255. Available at: https://doi.org/10.1016/0034-4257(89)90066-7

Brown, J. R. and Carter, J., 1998. Spatial and temporal patterns of exotic shrub invasion in an Australian tropical grassland, *Landscape Ecology,* **13**(2): 93-102. Available at: 10.1023/a:1007939203931

Burgan, R. E. and Rothermel, R. C., 1984. BEHAVE: fire behavior prediction and fuel modeling system--FUEL subsystem, *General Technical Report INT-167. Ogden, UT: US Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station. 126 p.,* **167**.

Burrows, N., Ward, B. and Robinson, A., 1991. Fire behaviour in spinifex fuels on the Gibson Desert nature reserve, Western Australia, *Journal of Arid Environments,* **20**(2): 189-204.

Burrows, N., Ward, B. and Robinson, A., 2009. Fuel dynamics and fire spread in spinifex grasslands of the Western Desert, *Proceedings of the Royal Society of Queensland, The,* **115**: 69.

Carter, O., Murphy, A. M. and Cheal, D. C., 2003. *Natural temperate grassland*, Australian Government, Department of the Environment and Heritage,

Ceccato, P., Flasse, S. and Grégoire, J.-M., 2002. Designing a spectral index to estimate vegetation water content from remote sensing data: Part 2. Validation and applications, *Remote Sensing of Environment,* **82**(2): 198-207. Available at: https://doi.org/10.1016/S0034-4257(02)00036-6

Ceccato, P., Flasse, S., Tarantola, S., Jacquemoud, S. and Grégoire, J.-M., 2001. Detecting vegetation leaf water content using reflectance in the optical domain, *Remote Sensing of Environment,* **77**(1): 22-33. Available at: https://doi.org/10.1016/S0034-4257(01)00191-2

Cheney, N., Gould, J. and Catchpole, W., 1993. The Influence of Fuel, Weather and Fire Shape Variables on Fire-Spread in Grasslands, *International Journal of Wildland Fire,* **3**(1): 31-44. Available at: https://doi.org/10.1071/WF9930031

Cheney, N., Gould, J. and Catchpole, W., 1998. Prediction of Fire Spread in Grasslands, *International Journal of Wildland Fire,* **8**(1): 1-13. Available at: https://doi.org/10.1071/WF9980001

Chladil, M. and Nunez, M., 1995. Assessing Grassland Moisture and Biomass in Tasmania - the Application of Remote-Sensing and Empirical-Models for a Cloudy Environment, *International Journal of Wildland Fire,* **5**(3): 165-171. Available at: https://doi.org/10.1071/WF9950165

Chuvieco, E., Aguado, I., Cocero, D. and Riaño, D., 2003. Design of an empirical index to estimate fuel moisture content from NOAA-AVHRR images in forest fire danger studies, *International Journal of Remote Sensing,* **24**(8): 1621-1637.

Chuvieco, E., Aguado, I., Yebra, M., Nieto, H., Salas, J., Martín, M. P., Vilar, L., Martínez, J., Martín, S., Ibarra, P., de la Riva, J., Baeza, J., Rodríguez, F., Molina, J. R., Herrera, M. A. and Zamora, R., 2010. Development of a framework for fire risk assessment using remote sensing and geographic information system technologies, *Ecological Modelling,* **221**(1): 46-58. Available at: https://doi.org/10.1016/j.ecolmodel.2008.11.017

Chuvieco, E., Cocero, D., Aguado, I., Palacios, A. and Prado, E., 2004. Improving burning efficiency estimates through satellite assessment of fuel moisture content, *Journal of Geophysical Research: Atmospheres,* **109**(D14). Available at: 10.1029/2003jd003467

Coleman, P., 1998. Changes in a mangrove/samphire community, North Arm Creek, South Australia, *Transactions of the Royal Society of South Australia,* **122**: 173-178.

Cruz, M. G., Gould, J. S., Kidnie, S., Bessell, R., Nichols, D. and Slijepcevic, A., 2015. Effects of curing on grassfires: II. Effect of grass senescence on the rate of fire spread, *International Journal of Wildland Fire,* **24**(6): 838-848. Available at: https://doi.org/10.1071/WF14146

Cruz, M. G., Sullivan, A. L., Leonard, R., Malkin, S., Matthews, S., Gould, J. S. and Alexander, M., 2014. Fire behaviour knowledge in Australia: a synthesis of disciplinary and stakeholder knowledge on fire spread prediction capability and application, *Melbourne, Victoria: Bushfire Cooperative Research Centre*.

Davidson, A., Wang, S. and Wilmshurst, J., 2006. Remote sensing of grassland–shrubland vegetation water content in the shortwave domain, *International Journal of Applied Earth Observation and Geoinformation,* **8**(4): 225-236. Available at: https://doi.org/10.1016/j.jag.2005.10.002

Davies, K. W., Boyd, C. S., Bates, J. D. and Hulet, A., 2016. Winter grazing can reduce wildfire size, intensity and behaviour in a shrub-grassland, *International Journal of Wildland Fire,* **25**(2): 191-199. Available at: https://doi.org/10.1071/WF15055

Department of the Environment and Energy, *NVIS Fact sheet series,*

Dilley, A. C., Millie, S., O'Brien, D. M. and Edwards, M., 2004. The relation between Normalized Difference Vegetation Index and vegetation moisture content at three grassland locations in Victoria, Australia, *International Journal of Remote Sensing,* **25**(19): 3913-3930. Available at: 10.1080/01431160410001698889

Dyer, R. and Smith, M. S., 2003. Ecological and economic assessment of prescribed burning impacts in semi-arid pastoral lands of northern Australia, *International Journal of Wildland Fire,* **12**(4): 403-413. Available at: https://doi.org/10.1071/WF03026

Evans, J. D., 1996. *Straightforward statistics for the behavioral sciences,* Thomson Brooks/Cole Publishing Co,

Feng, G., Yufang, J., Schaaf, C. B. and Strahler, A. H., 2002. Bidirectional NDVI and atmospherically resistant BRDF inversion for vegetation canopy, *IEEE Transactions on Geoscience and Remote Sensing,* **40**(6): 1269-1278. Available at: 10.1109/TGRS.2002.800241

Gao, B.-C., 1996. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space, *Remote Sensing of Environment*, **58**(3): 257-266.

Gill, A., Burrows, N. and Bradstock, R., 1995. Fire modelling and fire weather in an Australian desert.

Gill, A. M., 2006. *Grass Curing: A Fire-Oriented Review – 'Curing' and the moisture content of grasses*.

Gill, A. M., King, K. J. and Moore, A. D., 2010. Australian grassland fire danger using inputs from the GRAZPLAN grassland simulation model, *International Journal of Wildland Fire*, **19**(3): 338-345. Available at: https://doi.org/10.1071/WF09023

Gitelson, A. A., Kaufman, Y. J., Stark, R. and Rundquist, D., 2002. Novel algorithms for remote estimation of vegetation fraction, *Remote Sensing of Environment*, **80**(1): 76-87.

Gond, V., de Pury, D. G. G., Veroustraete, F. and Ceulemans, R., 1999. Seasonal variations in leaf area index, leaf chlorophyll, and water content; scaling-up to estimate fAPAR and carbon balance in a multilayer, multispecies temperate forest, *Tree Physiology*, **19**(10): 673-679. Available at: 10.1093/treephys/19.10.673 (accessed 10/29/2019).

Griffin, G. and Allan, G., 1984. Fire behaviour, *Anticipating the Inevitable: a Patch Burn Strategy for Fire Management at Uluru (Ayers Rock-Mt Olga) National Park. Edited by Saxon, E. CSIRO Australia, Melbourne*: 55-68.

Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X. and Ferreira, L. G., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices, *Remote Sensing of Environment*, **83**(1): 195-213. Available at: https://doi.org/10.1016/S0034-4257(02)00096-2

Huete, A. R., 1988. A soil-adjusted vegetation index (SAVI), *Remote Sensing of Environment*, **25**(3): 295-309. Available at: https://doi.org/10.1016/0034-4257(88)90106-X

Huete, A. R., Post, D. F. and Jackson, R. D., 1984. Soil spectral effects on 4-space vegetation discrimination, *Remote Sensing of Environment*, **15**(2): 155-165. Available at: https://doi.org/10.1016/0034-4257(84)90043-9

Hunt Jr, E. R. and Rock, B. N., 1989. Detection of changes in leaf water content using near-and middle-infrared reflectances, *Remote Sensing of Environment*, **30**(1): 43-54.

Jordan, C. F., 1969. Derivation of leaf-area index from quality of light on the forest floor, *Ecology*, **50**(4): 663-666.

Jurdao, S., Yebra, M., Guerschman, J. P. and Chuvieco, E., 2013. Regional estimation of woodland moisture content by inverting Radiative Transfer Models, *Remote Sensing of Environment*, **132**: 59-70. Available at: https://doi.org/10.1016/j.rse.2013.01.004

Kidnie, S., Cruz, M. G., Gould, J., Nichols, D., Anderson, W. and Bessell, R., 2015. Effects of curing on grassfires: I. Fuel dynamics in a senescing grassland, *International Journal of Wildland Fire*, **24**(6): 828-837. Available at: https://doi.org/10.1071/WF14145

Larcher, W., 2003. *Physiological plant ecology: ecophysiology and stress physiology of functional groups*, Springer Science & Business Media,

Lenz, T. I., Moyle-Croft, J. L. and Facelli, J. M., 2003. Direct and indirect effects of exotic annual grasses on species composition of a South Australian grassland, *Austral Ecology*, **28**(1): 23-32. Available at: 10.1046/j.1442-9993.2003.01238.x

Martin, D., Chen, T., Nichols, D., Bessell, R., Kidnie, S. and Alexander, J., 2015. Integrating ground and satellite-based observations to determine the degree of grassland curing, *International Journal of Wildland Fire*, **24**(3): 329-339. Available at: https://doi.org/10.1071/WF14029

McArthur, A., 1967. Fire behaviour in eucalypt forests. Commonwealth of Australia Forest and Timber Bureau, Leaflet Number 107.

McArthur, A., 1973. Forest fire danger meter mk. 5, *Forest Research Institute, Forestry and Timber Bureau, Canberra*.

McArthur, A. G., 1966. *Weather and grassland fire behaviour*, Forestry and Timber Bureau, Department of national Development, Commonwealth of Australia,

McGranahan, D. A., Engle, D. M., Miller, J. R. and Debinski, D. M., 2013. An Invasive Grass Increases Live Fuel Proportion and Reduces Fire Spread in a Simulated Grassland, *Ecosystems*, **16**(1): 158-169. Available at: 10.1007/s10021-012-9605-4

Moore, R. M., 1970. Australian grasslands, *Australian grasslands.*

Morgan, J. W., 1999. Defining grassland fire events and the response of perennial plants to annual fire in temperate grasslands of south-eastern Australia, *Plant Ecology,* **144**(1): 127-144. Available at: 10.1023/a:1009731815511

Newnham, G. J., Grant, I. F., Martin, D. N. and Anderson, S. A., 2010. Improved methods for assessment and prediction of grassland curing, *Bushfire Cooperative Research Centre, Melbourne, VIC*.

Newnham, G. J., Verbesselt, J., Grant, I. F. and Anderson, S. A. J., 2011. Relative Greenness Index for assessing curing of grassland fuel, *Remote Sensing of Environment*, **115**(6): 1456-1463. Available at: https://doi.org/10.1016/j.rse.2011.02.005

Noble, I. R., Gill, A. M. and Bary, G. A. V., 1980. McArthur's fire-danger meters expressed as equations, *Australian Journal of Ecology,* **5**(2): 201-203. Available at: 10.1111/j.1442-9993.1980.tb01243.x

NVIS Technical Working Group, 2017. Department of the Environment and Energy, Canberra. Prep by Bolton, MP ….

Paltridge, G. W. and Barber, J., 1988. Monitoring grassland dryness and fire potential in australia with NOAA/AVHRR data, *Remote Sensing of Environment,* **25**(3): 381-394. Available at: https://doi.org/10.1016/0034-4257(88)90110-1

Peñuelas, J. and Inoue, Y., 1999. Reflectance indices indicative of changes in water and pigment contents of peanut and wheat leaves, *Photosynthetica,* **36**(3): 355-360.

Pinty, B. and Verstraete, M. M., 1992. GEMI: a non-linear index to monitor global vegetation from satellites, *Vegetatio,* **101**(1): 15-20. Available at: 10.1007/bf00031911

Pitman, A. J., Narisma, G. T. and McAneney, J., 2007. The impact of climate change on the risk of forest and grassland fires in Australia, *Climatic Change,* **84**(3): 383-401. Available at: 10.1007/s10584-007-9243-6

Pittock, B., Arthington, A., Booth, T., Cowell, P., Hennessy, K., Howden, M., Hughes, L., Jones, R., Lake, S. and Lyne, V., 2003. *Climate change: an Australian guide to the science and potential impacts,* Australian Greenhouse Office,

Plucinski, M. P., Sullivan, A. L., Rucinski, C. J. and Prakash, M., 2017. Improving the reliability and utility of operational bushfire behaviour predictions in Australian vegetation, *Environmental Modelling & Software,* **91**: 1-12. Available at: https://doi.org/10.1016/j.envsoft.2017.01.019

Prober, S. and Thiele, K. R., 2004. Floristic patterns along an east-west gradient in grassy box woodlands of Central New South Wales, *Cunninghamia,* **8**(3): 306-325.

Prober, S. M. and Thiele, K. R., 2005. Restoring Australia's temperate grasslands and grassy woodlands: integrating function and diversity, *Ecological Management & Restoration,* **6**(1): 16-27. Available at: 10.1111/j.1442-8903.2005.00215.x

Rouse Jr, J. W., Haas, R., Schell, J. and Deering, D., 1974. Monitoring vegetation systems in the Great Plains with ERTS.

Ruprecht, E., Fenesi, A., Fodor, E. I. and Kuhn, T., 2013. Prescribed burning as an alternative management in grasslands of temperate Europe: The impact on seeds, *Basic and Applied Ecology,* **14**(8): 642-650. Available at: https://doi.org/10.1016/j.baae.2013.09.006

Schaaf, C. and Wang, Z., 2015. NASA EOSDIS Land Processes DAAC.

Schmelzer, L., 2009. *Reducing fuel load of key cheatgrass (Bromus tectorum L.) dominated range sites by the use of fall cattle grazing*, University of Nevada, Reno,

Setterfield, S. A., Rossiter-Rachor, N. A., Douglas, M. M., Wainger, L., Petty, A. M., Barrow, P., Shepherd, I. J. and Ferdinands, K. B., 2013. Adding fuel to the fire: the impacts of non-native grass invasion on fire management at a regional scale, *PLoS One,* **8**(5): e59144.

Stephenson, C., Handmer, J. and Betts, R., 2013. Estimating the economic, social and environmental impacts of wildfires in Australia, *Environmental Hazards,* **12**(2): 93-111. Available at: 10.1080/17477891.2012.703490

Tucker, C. J., 1980. Remote sensing of leaf water content in the near infrared, *Remote Sensing of Environment,* **10**(1): 23-32. Available at: https://doi.org/10.1016/0034-4257(80)90096-6

Úbeda, X., Lorca, M., Outeiro, L. R., Bernia, S. and Castellnou, M., 2005. Effects of prescribed fire on soil quality in Mediterranean grassland (Prades Mountains, north-east Spain), *International Journal of Wildland Fire,* **14**(4): 379-384. Available at: https://doi.org/10.1071/WF05040

Underwood, E. C. and Christian, C. E., 2009. Consequences of Prescribed Fire and Grazing on Grassland Ant Communities, *Environmental Entomology,* **38**(2): 325-332. Available at: 10.1603/022.038.0204 (accessed 10/29/2019).

Van Dijk, A. I. J. M. and Summers, D., 2016. The Australian National University

Vermote, E., 2015. MOD09A1 MODIS/terra surface reflectance 8-day L3 global 500m SIN grid V006, *NASA EOSDIS Land Processes DAAC,* **10**.

White, A., Orr, D., Novelly, P. and Bastin, G., 2014. '12 Tussock grasslands',in Burns, E., Lindenmayer, D., Lowe, A. and Thurgate, N. (eds), *Biodiversity and environmental change: monitoring, challenges and direction,* pp. 479.

Williams, A. L., Wills, K. E., Janes, J. K., Vander Schoor, J. K., Newton, P. C. D. and Hovenden, M. J., 2007. Warming and free-air CO2 enrichment alter demographics in four co-occurring grassland species, *New Phytologist,* **176**(2): 365-374. Available at: 10.1111/j.1469-8137.2007.02170.x

Wittich, K.-P., 2011. Phenological observations of grass curing in Germany, *International Journal of Biometeorology,* **55**(3): 313-318. Available at: 10.1007/s00484-010-0338-9

Worthy, M. and Wasson, R., 2004. *Fire as an agent of geomorphic change in southeastern Australia: implications for water quality in the Australian Capital Territory*, Regolith, CRC LEME, Belconnen, ACT.

Yebra, M., Chuvieco, E. and Riaño, D., 2008. Estimation of live fuel moisture content from MODIS images for fire risk assessment, *Agricultural and Forest Meteorology,* **148**(4): 523-536. Available at: https://doi.org/10.1016/j.agrformet.2007.12.005

Yebra, M., Quan, X., Riaño, D., Rozas Larraondo, P., van Dijk, A. I. J. M. and Cary, G. J., 2018. A fuel moisture content and flammability monitoring methodology for continental Australia based on optical remote sensing, *Remote Sensing of Environment,* **212**: 260-272. Available at: https://doi.org/10.1016/j.rse.2018.04.053

Appendix 1: Python Script Developed For Data Analysis

```
import netCDF4 as nc
import time,os
import pandas as pd
import numpy as np
from osgeo import gdal,ogr
import matplotlib.pyplot as plt
import scipy.stats as stat

fmc_file=r"C:\UserData\xuans\Downloads\fmc\fmc_c6_****.nc"
#This is the netCDF document for FMC of **** year
dirr="C:\\UserData\\xuans\\Downloads\\c\\****\\"
#This is the folder that contains netCDF document for C of **** year
curing = nc.Dataset(r"C:\UserData\xuans\Downloads\c\****\curing_modis-method-
b_8day_500m_aust_********_********.nc").variables
#This is one of the netCDF document for curing
shapefile =r"X:\shpfile\***.shp"
#This is the shpfile that represents the study area
aus = r"X:\GIS\aus.nc"
aus1 = nc.Dataset(aus).variables
land =aus1["land"][:]

def makeMask(lon,lat,res):
    source_ds = ogr.Open(shapefile)
    source_layer = source_ds.GetLayer()
    mem_ds = gdal.GetDriverByName('MEM').Create('', lon.size, lat.size,
gdal.GDT_Byte)
    mem_ds.SetGeoTransform((lon.min(), res, 0, lat.max(), 0, -res))
    band = mem_ds.GetRasterBand(1)
    gdal.RasterizeLayer(mem_ds, [1], source_layer, burn_values=[1])
    array = band.ReadAsArray()

    mem_ds = None
    band = None
    return array
```

```
fmc = nc.Dataset(fmc_file).variables
lat = np.arange(-10, -44, -0.05)
lon = np.arange(113, 154, 0.05)
lat_fmc = fmc["latitude"][:]
lon_fmc = fmc["longitude"][:]

y_fmc = [list(abs(i - lat_fmc)).index(np.min(list(abs(i - lat_fmc)))) for i in lat]
x_fmc = [list(abs(i - lon_fmc)).index(np.min(list(abs(i - lon_fmc)))) for i in lon]
lat_curing = curing["latitude"][:]
lon_curing = curing["longitude"][:]

cellsize_curing = lon_curing[:][1] - lon_curing[:][0]

y_curing = [list(abs(i - lat_curing)).index(np.min(list(abs(i - lat_curing)))) for i in lat]
x_curing = [list(abs(i - lon_curing)).index(np.min(list(abs(i - lon_curing)))) for i in lon]

for r,w in zip(os.listdir(dirr),np.arange(1,92,2)):
    curing1=nc.Dataset(dirr+r).variables
    curing_DDD = curing1["curing"][:]
    fmc_DD=fmc["fmc_mean"][w]
    maskshp_curing = makeMask(lon_curing,lat_curing,cellsize_curing)
    curing_DD = np.ma.masked_where(maskshp_curing==0,curing_DDD)
    curing_data,fmc_data=[],[]
    for i in y_curing:
        for k in x_curing:
            b=curing_DD[i][k]
            curing_data.append(b)

    for i in y_fmc:
        for k in x_fmc:
            b=fmc_DD[i][k]
            fmc_data.append(b)

    curing_data=np.ma.array(curing_data, mask=False)
    fmc_data=np.ma.array(fmc_data, mask=False)
    bad=~np.logical_or(np.isnan(curing_data),np.isnan(fmc_data))
    curing_in=np.compress(bad,curing_data)
    fmc_in=np.compress(bad,fmc_data)
    T=time.localtime(fmc["time"][w])
    t=str(T[0])+"-"+str(T[1])+"-"+str(T[2])
```

```
    C=np.mean(curing_in)
    F=np.mean(fmc_in)
    print("zen-kuaon",t, "curing",C, "seh-du",F)  # There will output date, average C and average FMC

curing_data=np.ma.array(curing_data, mask=False)
ran=~np.isnan(curing_data)
curing_data[ran]= 0
R=np.reshape(curing_data,(len(lat),len(lon)))
extent=[min(lon),max(lon),min(lat),max(lat)]
plt.imshow(land,extent=extent,cmap="twilight")
plt.imshow(R,extent=extent,cmap="summer")
plt.grid()
plt.xlabel('longitude',fontsize=10)
plt.ylabel('latitude', fontsize=10)
plt.tick_params(labelsize=10)
plt.savefig("***.png", dpi=350, bbox_inches='tight')
#This is the image that represent the distribution of research area
plt.show()


import netCDF4 as nc
import time,os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from osgeo import gdal,ogr

t1 = time.time()
fmc_file=r"C:\UserData\xuans\Downloads\fmc\fmc_c6_****.nc"
#This is the netCDF document for FMC of **** year
dirr="C:\\UserData\\xuans\\Downloads\\c\\****\\"
#This is the folder that contains netCDF document for C of **** year
curing = nc.Dataset(r"C:\UserData\xuans\Downloads\c\****\curing_modis-method-b_8day_500m_aust_********_********.nc").variables
#This is one of the netCDF document for curing
shapefile =r"X:\shpfile\***.shp"
#This is the shpfile that represents the study area
aus = r"X:\GIS\aus.nc"
aus1 = nc.Dataset(aus).variables
```

```
land =aus1["land"][:]

def makeMask(lon,lat,res):
    source_ds = ogr.Open(shapefile)
    source_layer = source_ds.GetLayer()
    mem_ds = gdal.GetDriverByName('MEM').Create('', lon.size, lat.size,
gdal.GDT_Byte)
    mem_ds.SetGeoTransform((lon.min(), res, 0, lat.max(), 0, -res))
    band = mem_ds.GetRasterBand(1)
    gdal.RasterizeLayer(mem_ds, [1], source_layer, burn_values=[1])
    array = band.ReadAsArray()
     mem_ds = None
    band = None
    return array
fmc = nc.Dataset(fmc_file).variables
lat = np.arange(-10, -44, -0.025)
lon = np.arange(113, 154, 0.025)
lat_fmc = fmc["latitude"][:]
lon_fmc = fmc["longitude"][:]
cellsize_fmc = lon_fmc[:][1] - lon_fmc[:][0]
y_fmc = [list(abs(i - lat_fmc)).index(np.min(list(abs(i - lat_fmc)))) for i in lat]
x_fmc = [list(abs(i - lon_fmc)).index(np.min(list(abs(i - lon_fmc)))) for i in lon]
lat_curing = curing["latitude"][:]
lon_curing = curing["longitude"][:]
y_curing = [list(abs(i - lat_curing)).index(np.min(list(abs(i - lat_curing)))) for i in lat]
x_curing = [list(abs(i - lon_curing)).index(np.min(list(abs(i - lon_curing)))) for i in lon]
TT=np.ones((1,len(lat)*len(lon)))
RR=np.ones((1,len(lat)*len(lon)))
for r,w in zip(os.listdir(dirr),np.arange(1,92,2)):
    print("leh-soe di%stsah ven-jie"%w)
    curing1=nc.Dataset(dirr+r).variables
    curing_DD=curing1["curing"][:]
    fmc_DDD=fmc["fmc_mean"][w]
    maskshp_fmc = makeMask(lon_fmc,lat_fmc,cellsize_fmc)
    fmc_DD = np.ma.masked_where(maskshp_fmc==0,fmc_DDD)
    curing_data,fmc_data=[],[]
    for i in y_curing:
        for k in x_curing:
            b=curing_DD[i][k]
            curing_data.append(b)
```

```
    for i in y_fmc:
        for k in x_fmc:
            b=fmc_DD[i][k]
            fmc_data.append(b)

    curing_data=np.ma.array(curing_data, mask=False)
    fmc_data=np.ma.array(fmc_data, mask=False)
    TT=np.vstack((TT,curing_data))
    RR = np.vstack((RR, fmc_data))
t2=time.time()
np.delete(TT,0,axis=0)
np.delete(RR,0,axis=0)
print(TT)
RRR=[]
for u in range(np.shape(TT)[1]):
    a=[TT[x,u] for x in range(np.shape(TT)[0]) ]
    b = [RR[x, u] for x in range(np.shape(TT)[0])]
    rrr=pd.Series(a).corr(pd.Series(b),min_periods=10)
    RRR.append(rrr)
RRR=np.reshape(RRR,(len(lat),len(lon)))
print(RRR)
extent=[min(lon),max(lon),min(lat),max(lat)]
plt.imshow(land,extent=extent,cmap="twilight")
plt.imshow(RRR,extent=extent,cmap="rainbow")
plt.xlabel('longitude',fontsize=10)
plt.ylabel('latitude', fontsize=10)
plt.tick_params(labelsize=10)
plt.colorbar()
plt.grid()
plt.savefig("****.png", dpi=350, bbox_inches='tight')
#This is the map of correlation between C and FMC for year ****
plt.show()
```