The use of Landsat derived vegetation metrics in Generalised Linear Mixed Modelling of River Red Gum (Eucalyptus camaldulensis) canopy condition dynamics in Murray Valley National Park, NSW, between 2008 and 2016

Evan Curtis

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Abstract
Water is a primary determinant of the condition of wetland and riparian vegetation in semi-arid Australia. The species that inhabit these ecosystems, such as River Red Gum (Eucalyptus camaldulensis) (RRG), are well adapted to variability in water supplies intrinsic throughout the Australia climate cycle. Despite climatic variability, many of inland Australia's wetlands and riparian ecosystems function under a depleted state as a partial consequence of logging and river regulation. Murray Valley National Park, NSW (MVNP) is one such example. It is thought that high levels of intra-stand competition for water resources in MVNP are a primary driver of RRG Forest canopy condition. RRG is well known to respond to water availability through the generation and reduction of its canopy, however little is known about the role of stand density on RRG Forest canopy condition.

This study investigated canopy condition of RRG between 2008 and 2016, a period characterised by high levels of hydro-climatic variability in south-eastern Australia. This study aims to determine how water demand and availability drive canopy condition dynamics of RRG in Murray Valley National Park, NSW during this period. Stem density and site quality were used respectively as surrogate measures of water demand and availability in conjunction with hydro-climatic variables, Landsat derived Normalised Difference Vegetation Index (NDVI) and Foliage Projective Cover (FPC) were used to create a strictly empirical data series. Due to the high degree of temporal fragmentation inherent in Landsat data, analyses were undertaken using Generalised Linear Mixed Effects Modelling (GLMM) to determine statistically significant drivers of RRG canopy condition, while allowing trend, periodic and random noise components to be accounted for.

Models found site quality to be a statistically significant driver of canopy condition in both anomalously dry and wet hydro-climatic periods. Site quality was found to exhibit increasingly different canopy conditions following recovery from drought. Conversely, surrogate measures of water demand were not found to be statistically significant, suggesting that despite high stand densities, water supplies across the eight year period have been sufficient to maintain homogeneous canopy condition dynamics throughout MVNP. In concurrence with other studies throughout the Murray-Darling Basin, drivers of RRG canopy condition were modelled as being primarily climatic, and in particular the Southern Oscillation Index (SOI) was a primary driver throughout the eight years. While drivers were primarily climatic, river discharge influenced canopy condition during anomalously wet and dry phases. Periodicity modelling showed a dampened response during the drought phase, and became more pronounced following drought recovery. In many cases, a sub-hectare spatio-temporal investigation such as that presented here would rely on data interpolation to model trend, periodic and random noise components of a data series. This study has been able to model the same components while relating them to the drivers of canopy condition dynamics using an entirely empirical dataset. The research presented here provides scientists at OEH with an empirically derived baseline understanding of RRG canopy condition dynamics in MVNP over a highly variable hydro-climatic multi-year period using remotely sensed vegetation metrics. Furthermore, the methods used have the potential enhance ecosystem research globally, by facilitating the investigation of sub-hectare scale phenomena without the need to rely exclusively on time series analyses or sacrificing data integrity.

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GLMM, River red gum, time series analysis, landsat, eucalyptus camaldulensis, Murray Valley National Park, Intra-stand competition

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Faculty of Science, Medicine and Health

School of Earth and Environmental Science

‘The use of Landsat derived vegetation metrics in Generalised Linear Mixed Modelling of River Red Gum (Eucalyptus camaldulensis) canopy condition dynamics in Murray Valley National Park, NSW, between 2008 and 2016’

Evan Curtis
The information in this thesis is entirely the result of investigations conducted by the author, unless otherwise acknowledged, and has not been submitted in part, or otherwise, for any other degree or qualification.

Evan Curtis
26th October 2016
Abstract

Water is a primary determinant of the condition of wetland and riparian vegetation in semi-arid Australia. The species that inhabit these ecosystems, such as River Red Gum (*Eucalyptus camaldulensis*) (RRG), are well adapted to variability in water supplies intrinsic throughout the Australia climate cycle. Despite climatic variability, many of inland Australia’s wetlands and riparian ecosystems function under a depleted state as a partial consequence of logging and river regulation. Murray Valley National Park, NSW (MVNP) is one such example. It is thought that high levels of intra-stand competition for water resources in MVNP are a primary driver of RRG Forest canopy condition. RRG is well known to respond to water availability through the generation and reduction of its canopy, however little is known about the role of stand density on RRG Forest canopy condition.

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## Contents

Abstract ........................................................................................................................................... 3
Acknowledgements ............................................................................................................................. 9
List of Acronyms ................................................................................................................................ 10
List of Figures .................................................................................................................................... 12
List of Tables ...................................................................................................................................... 14

1. Introduction .................................................................................................................................... 15
   1.1. Murray Valley National Park and its ongoing challenges ......................................................... 15
   1.2. Implementation of an ecological thinning trial ........................................................................... 16
   1.3. Aims and objectives .................................................................................................................... 16

2. Literature Review ............................................................................................................................ 19
   2.1. Conservation concerns and a change in management: The gazettal of Murray Valley National Park ..................................................................................................................... 19
   2.1.2. A description of the adaptive management framework ............................................................ 20
   2.2. The changing nature of River Red Gum ecology in Millewa Forest ......................................... 22
   2.2.1. Natural changes in MVNP: the RRG lifecycle ......................................................................... 22
   2.2.2. Human impacts in Millewa forest: 19th century logging practices ........................................... 24
   2.2.3. Human influence: early 20th century river regulation ............................................................... 24
   2.2.4. Human influence: 20th century logging practices .................................................................... 25
   2.2.1. Factors influencing the relationship between stem density and canopy condition ............ 28
   2.3.1. Water availability: flood and drought ...................................................................................... 29
   2.3.2. Intra-stand competition .......................................................................................................... 30
   2.4. 21st century management, the concept of sustainability and objective measures .................. 31
   2.4.1. The distinction between condition and health ......................................................................... 31
   2.4.2. Ecological Thinning as a potential management technique ...................................................... 32
   2.4.3. Conditional indicators of biodiversity in Inland Riverine Forests ......................................... 33
   2.4.4. The need for a long-term baseline ......................................................................................... 35
   2.4.5. Before & After Control Impact ............................................................................................... 35
   2.4.6. Time Series Analysis ............................................................................................................... 36
   2.4.7. The role of remote sensing in monitoring canopy condition .................................................... 38
   2.4.8. Limitations of Landsat data in time series analysis ................................................................ 42
   2.5. Gaps in the Literature ............................................................................................................... 44

3. Regional Setting .............................................................................................................................. 45
   3.1. Location ...................................................................................................................................... 45
3.2. Geomorphology

3.3. Soils

3.4. Hydro-Climatic Features

3.5. Land Use

4. Methods

4.1. Study area and plot stratification

4.2. Data Acquisition

4.2.1. Stem Density

4.2.2. Live basal area

4.2.3. Water and Climate Variables

4.2.4. Satellite derived vegetation metrics

4.2.5. Useable image selection

4.3. Image Sub-Setting and Raster Value Extraction

4.3.1. Creating 2ha study site layer

4.3.2. Creating MVNP 'fishnet' layer

4.3.3. Extracting vegetation metric values from within 2ha study sites

4.4. Statistical Analyses

4.4.1. The use of median as a statistical parameter

4.4.2. Justification for modelling

4.4.3. Model Selection

4.4.4. Modelling the Data

5. Results

5.1. Relationship between NDVI and FPC

5.2. Visual exploration of general trends and periodicity

5.3. Visual exploration of stratified variables: site quality and stem density

5.4. Investigating drivers of change: Generalised Linear Mixed Effects Modelling

5.4.1. Modelling the entire eight year period

5.4.2. Modelling distinct periods

5.4.3. RRG canopy condition dynamics in the drought period (2008 – 2010)

5.4.4. RRG canopy condition dynamics in the wet period (2010 – 2011)

5.4.5. RRG canopy condition dynamics in the recent period (2013 – 2016)

5.4.6. Periodicity in the models

6. Discussion

6.1. Trends in RRG canopy condition
6.1. Reports of decline in condition ................................................................. 95
  6.1.1. Period of recovery .................................................................................. 97
  6.1.2. Recent conditions and the innate variability of condition in inland freshwater ecosystems ........................................................................................................ 97
  6.1.3. Period of recovery .................................................................................. 97
  6.2. Intra-stand competition ........................................................................... 99
  6.2.1. Stem density .......................................................................................... 99
  6.2.2. Live Basal Area ...................................................................................... 100
  6.2.3. Site quality ........................................................................................... 101
  6.3. Drivers of periodicity .............................................................................. 102
  6.3.1. Modelled NDVI periodicity .................................................................... 102
  6.3.2. Modelled FPC periodicity ...................................................................... 103
  6.4. Recommendations on reducing random noise ........................................ 104
  6.5 The global context of this study .............................................................. 105
  7. Conclusion ................................................................................................. 107
References ........................................................................................................ 110
APPENDIX 1: Exploratory Analyses Script ...................................................... 126
APPENDIX 2: NDVI full period Model .............................................................. 128
APPENDIX 3: Logit FPC full period model script ........................................... 129
APPENDIX 4: NDVI periods script & model output ......................................... 130
APPENDIX 5: Logit FPC periods script and output .......................................... 136
APPENDIX 6: Normal Quantile-Quantile Plots and Residual v Fitted scatterplots for NDVI GLMMS – all periods .................................................................................. 141
APPENDIX 7: Normal Quantile-Quantile Plots and Residual v Fitted scatterplots for Logit FPC GLMMS – all periods .................................................................. 142
APPENDIX 8: El Niño Southern Oscillation conditions for the study period. ........ 143
APPENDIX 9: Daily River Discharge at Yarrawonga Weir for the study period. .......... 143
APPENDIX 10: Mean monthly temperature for the period recorded at Deniliquin Airport .......... 144
APPENDIX 11: Monthly precipitation for the period recorded at Mathoura for the study period. ............................................................................................................. 144
APPENDIX 12: Contrast between ephemeral summer and winter ground cover .......... 145
APPENDIX 13: Skewness testing ........................................................................ 145
For Peggy
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I could not have done this without you all, and I am truly grateful!
List of Acronyms

ABARES: Australian Bureau of Agricultural Resource Economics and Sciences
ABS: Australian Bureau of Statistics
ACF: Auto-Correlation Function
ADS-40: Airborne Digital Sensor
AGS: Australian Group Selection
AIC: Akaike’s Information Criterion
ANN: Artificial Neural Network
ANOVA: Analysis Of Variance
API: Aerial Photographic Interpretation
ARIMA: Autoregressive Integrated Moving Average
BACI: Before and After Control Impact
BoM: Bureau of Meteorology
CSIRO: Commonwealth Scientific and Industrial Research Organisation
DBH: Diameter at Breast Height
DN: Digital Number
DWT: Depth to Water Table
ENSO: El Nino Southern Oscillation
ESTARFM: Enhanced Spatial and Temporal Adaptive Reflectance Fusion Model
ETM+: Enhanced Thematic Mapper Plus
EVI: Enhanced Vegetation Index
FPC: Foliage Projective Cover
GAMM: Generalised Additive Mixed Effects Modelling
GDA: Geocentric Datum of Australia
GIS: Geographic Information System
GL: Giga Litres
GLMM: Generalised Linear Mixed Effects Modelling
GPS: Global Positioning System
Ha: Hectare
IOD: Indian Ocean Dipole
IPO: Inter-decadal Pacific Oscillation
Ka: Kilo-annum
km: Kilometres
LBA: % Live Basal Area
m: Metres
Ma: Mega-annum
MDBA: Murray-Darling Basin Authority
MJO: Madden-Julian Oscillation
ML: Mega Litres
MODIS: Moderate Resolution Imaging Spectroradiometer
MVNP: Murray Valley National Park
NDVI: Normalised Differenced Vegetation Index
NIR: Near-Infra Red
NPWS: National Parks and Wildlife Service
NRC: Natural Resource Commission
NSW: New South Wales
OEH: Office of Environment & Heritage
OLI: Operational Land Imager
QLD: Queensland
R: Red
RRG: River Red Gum
SA: South Australia
SAM: Southern Annular Mode
SAVI: Soil Adjusted Vegetation Index
SD: Stem Density
SE: South eastern
SOI: Southern Oscillation Index
SQ: Site Quality
STARFM: Spatial and Temporal Adaptive Reflectance Fusion Model
STR: Sub-Tropical Ridge
TM: Thematic Mapper
TSA: Time Series Analysis
Vic: Victoria
WA: Western Australia
List of Figures

Figure 2.1: Schematic diagram of adaptive management process
Figure 2.2: River Red Gum Lifecycle (Colloff, 2014)
Figure 2.3: MVNP API derived stem density mapping (adapted from Bowen et al. (2012))
Figure 2.4: Photograph of dense River Red Gum stand in MVNP
Figure 2.5: Photograph of structurally complex River Red Gum, MVNP
Figure 2.6: Example of Before and After Control Impact design
Figure 2.7: NDVI map of MVNP
Figure 2.8: FPC map of MVNP
Figure 3.1: Map showing location of MVNP
Figure 3.2: Schematic diagram of Cadell Fault and Barmah Fan (Stone, 2006)
Figure 3.3: Soil classification map of MVNP
Figure 3.4: Cracking clay profile (Gibbons & Rowan, 1993)
Figure 3.5: Australian climate classification map (BoM, 2005)
Figure 3.6: Graph showing average precipitation and temperatures for Mathoura (adapted from BoM data)
Figure 3.7: Land use map for the Murray-Darling Basin (ABARES, 2010)
Figure 4.1: Locations of 66 OEH study plots in MVNP (OEH, 2015)
Figure 4.2: Stem Density assessment method
Figure 4.3: Bar chart of observed stem densities throughout MVNP
Figure 4.4: Input specifications for creating ‘fishnet’ in ArcMap 10.2
Figure 4.5: ArcMap 10.2 model for vegetation metric value extraction
Figure 4.6: ArcMap 10.2 ArcMap fishnet overlay and value extraction points
Figure 4.7: ArcMap model for automated value extraction
Figure 5.1: Scatterplot comparing NDVI and FPC values throughout the 8-year period
Figure 5.2: Boxplots showing annual summaries of FPC and NDVI values
Figure 5.3: Scatterplots showing relationship between SQ-1 and SQ-2 plots for both NDVI and FPC
Figure 5.4: Scatterplots showing relationship between SD classes for both NDVI and FPC
Figure 5.5: GLMM models of vegetation metrics over time for entire 8-year period
Figure 5.6: Map of rainfall deficiencies during Millennium Drought (BoM, 2016)
Figure 5.7: Graph of monthly SOI values for the 8-year study period
Figure 5.8: Graph identifying three distinct response periods within the 8-year time frame
Figure 5.9: GLMM output after modelling NDVI for three periods separately
Figure 5.10: GLMM output after modelling FPC for three periods separately
Figure 5.11a: Map of SQ-1 and SQ-2 NDVI values during drought period
Figure 5.11b: Map of SQ-1 and SQ-2 NDVI values during drought period
Figure 5.12a: Map of SQ-1 and SQ-2 NDVI values during wet period
Figure 5.12b: Map of SQ-1 and SQ-2 NDVI values during wet period
Figure 5.13a: Map of SQ-1 and SQ-2 NDVI values during most recent period
Figure 5.13b: Map of SQ-1 and SQ-2 NDVI values during most recent period
Figure 5.14: Modelled NDVI periodicity
Figure 5.15: Modelled FPC periodicity
Figure 5.16: SQ-1 and SQ-2 residuals for each Landsat overpass for the entire 8-year study period
Figure 6.1: Southern Oscillation Index from 2007 – 2016
Figure 6.2: Daily discharge rate recorded at Yarrawonga Weir 2008 – 2016
Figure 6.3: Mean monthly maximum and minimum temperature at Deniliquin Airport, NSW, 2008 – 2016
Figure 6.4: Monthly total precipitation recorded at Mathoura 2008 – 2016
Figure 6.5: Modelled NDVI periodicity for each period
Figure 6.6: Pre-winter average monthly precipitation per period
Figure 6.7a: Summer ground cover, MVNP
Figure 6.7b: Winter ground cover, MVNP
Figure 6.8: Modelled FPC periodicity for each period
**List of Tables**

**Table 2.1:** Summary of site features and corresponding conservation concerns outlines in OEH public environment report (OEH, 2015)

**Table 2.2:** Summary of impacts of river regulation (Di Stefano, 2002)

**Table 2.3:** Description of eight condition indicators assessed for reliability and objectivity in Cunningham et al. (2007)

**Table 3.1:** Summary and description of MVNP soil groups

**Table 3.2:** Summary of hydro-climatic variables affecting MVNP

**Table 4.1:** Frequency and distribution of initial stratified plot variables

**Table 4.2:** Summary of SD classification used in this study

**Table 4.3:** Summary of useable Landsat imagery for entire 8-year study period

**Table 5.1:** Image distribution per year for 54 sites analysed

**Table 5.2:** Summary of variables tested and fitted in initial GLMM

**Table 5.3:** Summary of distinct period features

**Table 5.4:** Summary of variables tested and fitted in NDVI periodic GLMMs

**Table 5.5:** Summary of variables tested and fitted in FPC periodic GLMMs

**Table 5.6a:** Summary of model output for NDVI period 1 (Drought)

**Table 5.6b:** Summary of model output for FPC period 1 (Drought)

**Table 5.7a:** Summary of model output for NDVI period 2 (Wet)

**Table 5.7b:** Summary of model output for FPC period 2 (Wet)

**Table 5.8a:** Summary of model output for NDVI period 3 (Recent)

**Table 5.8b:** Summary of model output for FPC period 3 (Recent)
1. Introduction

1.1. Murray Valley National Park and its ongoing challenges

Freshwater wetland ecosystems provide a variety of fundamental ecosystem services and support biodiversity globally, through the provision of food, habitat and other resources (Finlayson et al. 2005, p. 553). In landscapes otherwise dominated by agricultural activity, freshwater wetland ecosystems are islands of biodiversity scattered throughout inland Australia (Lunt & Spooner, 2005). Murray Valley National Park (MVNP) is a freshwater wetland ecosystem, containing forests and woodlands that support a variety of native and endangered flora and fauna (Figure 1.1). Water is a fundamental component in maintaining biological diversity of forested areas in MVNP, and no tree is more prevalent than River Red Gum (Eucalyptus camaldulensis) (RRG). The ability of RRG to exist in this location is primarily due to the abundance of water brought by the Murray River to the flood prone forest. Flood dependent RRG Forests in semi-arid Australia have been modelled to require inundation for at least 59 days in every three years (Wen et al. 2009), an amount which is expected to become increasingly difficult to ensure.

Water availability is determined by a number of sources in MVNP. Upstream, the average annual rainfall received by the catchment ranges from about 2000 mm in the Snowy Mountains to approximately 360 mm locally. This water is a precious commodity along the Murray River and there are a number of dams and weirs that contain large amounts of it. Stored water is used primarily for agricultural and domestic provision during the summer months. This limits the amount of water MVNP receives by reducing the extent, and altering the timing of flooding (Di Stefano, 2002). As a result, RRG Forests are placed under stress, which land managers attempt to alleviate by allocating environmental river flows to the forest (Murray Darling Basin Authority, 2012). During droughts, many stakeholders compete for their share of dwindling water supplies, and consequently the condition of RRG Forests along the length of the Murray becomes increasingly depleted (Cunningham et al. 2009a).

MVNP is characterised by large areas of dense, even aged stands of RRG (Bowen et al. 2012). These stands are largely bereft of habitat features and foraging resources (Horner et al. 2010), and can subsequently limit the population growth of threatened hollow dependent fauna such as the Superb Parrot (Polytelis swainsonii) (Baker-Gabb, 2011, pp. 6-7). During the Millennium Drought, reports of reduced crown density and extent, and stand dieback were frequent (Cunningham et al. 2007; Cunningham et al. 2009b; NRC 2009a). It is thought that reductions in crown density and extent in RRG may be exacerbated by levels of intra-stand resource
competition, particularly in dense, even aged RRG stands. Intra-stand competition for water resources in MVNP are expected to become amplified with the effects of human induced climate change in the region. Temperatures in the Murray Basin are projected to rise by 0.6 – 1.3°C by 2030. Subsequently, rainfall is expected to become increasingly variable, and by 2090, winter rain in the Murray Basin is predicted to lie between +5% and -40% of its current average (CSIRO & BoM, 2015, p. 91). Surface water availability in the Murray Basin is also predicted to undergo a decrease of up to 13% by 2030 (CSIRO, 2008, as cited in Rogers & Ralph, 2011, p. 315).

1.2. Implementation of an ecological thinning trial

Ecological thinning involves ‘the reduction of stem density to improve the ecological health of a forest, with adequate fallen timber retained to improve habitat and structure for animals and plants’, (Cunningham et al. 2009c, as cited in OEH, 2014, p. xv). In April 2016 the NSW Office of Environment & Heritage (OEH) commenced an ecological thinning trial in an attempt to address a number of conservation concerns in MVNP and to understand the usefulness of the technique in alleviating drought stress. It is predicted that these actions will promote an increase in habitat and structural diversity of RRG, while enabling structurally complex, hollow-bearing RRG to remain resilient in times of water scarcity (OEH, 2014, p. xv). For scientists and land managers to implement this trial, it is essential to have a detailed understanding of canopy condition under a range of hydro-climatic conditions and stand densities. However, there is little available research on how stand density affects RRG canopy response to water availability in MVNP throughout different climatic periods.

1.3. Aims and objectives

This study aims to use remotely sensed vegetation indices to determine whether intra-stand competition and/or water availability have an impact on RRG canopy condition dynamics in MVNP. The study also seeks to determine how hydrolo-climatic variability impacts RRG canopy condition in MVNP. To achieve this, the following objectives were used:

1. Derive values from suitable vegetation metrics using remotely sensed satellite data obtained between 2008 and 2016.
2. Develop an appropriate methodology based on the available satellite data and vegetation metrics to describe RRG canopy condition.

3. Investigate differences in canopy condition and their causes.

4. Determine how canopy condition dynamics across intra-stand competition levels and/or water availability respond to hydrologic and climatic variables such as Southern Oscillation Index (SOI), precipitation, or river discharge.

Traditionally, a Time Series Analysis (TSA) would be used to investigate trend, periodic and random noise components present in canopy dynamics over a given time period (Ahl et al. 2006; Martinez & Amparo Gilabert, 2009; Wen & Saintilan, 2015). However, due to the temporal fragmentation and data gaps inherent in Landsat derived datasets this study did not permit the use of TSA, and alternative methods were required. Generalised Linear Mixed Effects Modelling (GLMM) was applied to a data series spanning 2008 and 2016, covering highly variable hydro-climatic periods to explore how differences in intra-stand competition levels respond to hydro-climatic drivers of RRG canopy condition. By using GLMM, trend and seasonal components of the modelling can be derived and used to develop a baseline understanding of RRG canopy condition dynamics in MVNP, against which the impacts of ecological thinning can be compared.
Figure 1.1 An interspersion of wetlands, MVNP is located in the Murray-Riverina Basin of the Central Murray Catchment area, NSW, Australia.
2. Literature Review

2.1.1. Conservation concerns and a change in management: The gazettal of Murray Valley National Park

In 2009, following persistent reports of declining condition over a period of twenty years (Margules & Partners, 1990; Cunningham et al. 2007; Cunningham et al. 2009; NRC 2009a) the Australian Government requested the Natural Resources Commission (NRC) carry out a ‘Regional Forest Assessment’ of the River Red Gum (RRG) forests and woodlands of the 9.7 million hectare Riverina Bioregion (NRC, 2009a, p. 8). The NRC highlighted the impacts of Millewa State Forests’ management, and the exacerbating effects that river regulation and climate change were having on the condition of RRG in Millewa State Forest. Subsequent reports found that 79% of Murray RRG forests and woodlands were under stress (Cunningham et al. 2011) and 33% of stands in Millewa Forest had a density >400 stems.ha\(^{-1}\) (Bowen et al. 2012). The NRC recommended a number of active interventions be implemented to encourage and support the resilience of the RRG ecosystems based on ongoing water scarcity. These included the implementation of water delivery infrastructure to divert flows into selected parts of the forest, and an ecological thinning trial within an adaptive management context, both of which were intended to alleviate some of the water demands of the forest resulting from high stem density stands (NRC, 2009b, p. 4, 26, and 29). Following the mounting evidence of declining canopy condition and the NRC’s investigation, Millewa State Forest was gazetted as the Murray Valley National Park (MVNP) in July 2010. The gazettal meant that the 48,894 ha park was now to be managed to conserve biodiversity, maintain ecosystem functions and adhere to a number of other conservation principals outlined in the National Parks and Wildlife Act 1974.

In response to the substantial evidence of canopy decline in the forest, the NSW Office of Environment & Heritage (OEH) are currently attempting to address a number of concerns regarding the impacts of declining canopy condition through the implementation of an ecological thinning trial. This large-scale study stratifies stands of RRG based on surrogate measures of water availability and intra-stand competition, based on the hypothesis that levels of intra-stand competition are highest when stem density (SD) is high and water availability is low, and vice versa. Reductions in canopy density and extent may be indicative of: a) reduced foraging resources for indigenous fauna; b) tree mortality; and c) diminished resilience to climate change.
In order to manage canopy condition into the future, it is important to learn more about its key drivers. A number of MVNP site features and conservation concerns are summarised below in Table 2.1.

**Table 2.1 Summary of site features and corresponding conservation concerns outlined in the OEH PER (2015)**

<table>
<thead>
<tr>
<th>MVNP Site Feature</th>
<th>Conservation Concern</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skewed Tree Size-Class Distribution</td>
<td>Reduced diversity of habitat</td>
</tr>
<tr>
<td></td>
<td>Reduced recruitment of hollow bearing trees</td>
</tr>
<tr>
<td>Paucity of hollow bearing trees</td>
<td>Reduced habitat for hollow dependent species</td>
</tr>
<tr>
<td>Reduced load and heterogeneity of CWD</td>
<td>Reduced habitat for ground dwelling vertebrates and invertebrates</td>
</tr>
<tr>
<td>Reduced understorey structural diversity</td>
<td></td>
</tr>
<tr>
<td>Reduced understorey flora species diversity</td>
<td>Reduced diversity of mid- &amp; under-storey habitats</td>
</tr>
<tr>
<td>Lack of recruitment</td>
<td>Reduced age range diversity</td>
</tr>
<tr>
<td>Reduced canopy density and extent</td>
<td>Reduced foraging resources for fauna</td>
</tr>
<tr>
<td></td>
<td>Reduced resilience to climate change</td>
</tr>
<tr>
<td></td>
<td>Increased likelihood of tree mortality</td>
</tr>
</tbody>
</table>

2.1.2. A description of the adaptive management framework

The OEH ecological thinning trial is being implemented within an adaptive management framework. Adaptive management is a scientifically informed natural resource management framework, where natural resources are managed through an iterative decision making process based either on cycles of time or space. The adaptive management framework provides a link between science and management, where the focus is on ‘learning-by-doing’ rather than just attempting to predict uncertainties and outcomes through modelling (Walters & Hilborn, 1978; Holling, 1986; Walters & Holling 1990). Adaptive management is a useful tool in managing natural resources where there is a degree of uncertainty or competing hypotheses surrounding the fundamental issue, such as how best to alleviate conservation concerns despite limited water resources. Ongoing monitoring and evaluation of the natural resource system enables the minimization of uncertainty over time. While modelling remains an important tool in adaptive management, there is an additional emphasis on the optimization of experimental and
management techniques, and ongoing monitoring and evaluation is used to inform this process of ‘fine-tuning’ (Lyons et al. 2008) (Figure 2.1).

![Adaptive Management Process Diagram](image)

**Figure 2.1** Schematic diagram of an adaptive management process.

In adaptive management, monitoring must be able to fulfil three important roles:

1. Provide information on the current state of a dynamic system on which decision-making depends;
2. Facilitate the evaluation of performance and determine whether management decisions are achieving stated objectives;
3. Enable managers to discriminate between competing hypotheses about the system.

Therefore monitoring should focus on the *uncertainties* in a system that may impede management objectives being reached (Lyons *et al.* 2008; Lindenmayer & Likens, 2009,).
2.2. The changing nature of River Red Gum ecology in Millewa Forest

There is debate as to the cause of high density forest stands in Australia and the cessation of Aboriginal burning regimes is one of the hypotheses put forward (Gammage, 2011). While this theory may apply to a number of environments, there is disagreement surrounding its relevance to resource abundant forested wetlands (Colloff, 2014, p. 101). Wide spread high stem density stands in MVNP are a product of the interactions between a diverse range of natural and human processes and impacts (McGregor et al. 2016). An exploration of the lifecycle of RRG is needed to support analysis and distinction of natural drivers of canopy condition from human-induced drivers.

2.2.1. Natural changes in MVNP: the RRG lifecycle

RRG is a medium to tall woodland and forest tree that is found along watercourses throughout Australia, west of the Great Divide (Brooker & Kleinig, 2006, p.124). River floods and flows are a primary dispersion mechanism (Bren, 1992), and as a result, this tree is known to have the widest distribution of any Eucalypt species. The success of RRG in inhabiting and dominating riparian vegetation zones throughout Australia has been attributed to its ability to withstand both flood and drought (Bacon et al. 1993). The tree has evolved with a number of adaptations that make it well equipped for survival in a variable Australian climate. These include deep tap-roots, allelopathic leaves, litter and branch fall as water-scarcity coping mechanisms (del Moral & Muller, 1970; Briggs & Maher, 1983; Bacon et al. 1993), as well as the ability to shoot adventitious roots and produce aerenchyma tissue during times of flood (Blake & Reid, 1981).

The lifecycle of RRG is highly intertwined with a number of important hydrological processes such as precipitation, stream flows, groundwater and flooding (Rogers, 2011, p. 21) (Figure 2.2). The most favourable conditions for the establishment of RRG seedlings occur in years where winter-spring flooding is followed by average precipitation in the summer (Dexter, 1970 & 1978, as cited in Colloff, 2014, p. 55). Under these conditions, a relatively humid forest occurs in the summer, with sufficient water available for seedling establishment. Additionally, this humidity encourages growth of Aspergillus parasitic fungi that regulate numbers of Eucalypt Leaf Skeletonizer Moth (Uraba lugens) (Harris, 1974, as cited in Bren, 1988).
In the flood prone areas of the Murray-Darling Basin, RRG forms large, mono-specific over stores, classified as Inland Riverine Forests (Keith, 2004, p. 223). These RRG forests support a myriad of fauna that make use of coarse woody debris and hollows provided by large, mature RRG trees (Keith, 2004, p. 230). Hollow development in RRG has been related to diameter at breast height (DBH) and age (Bennett et al. 1994). It is also a function of stem density and moisture availability. DBH has been observed increasing at a rate of around 0-6mm per year in remnant stands around central NSW, however, this rate is variable as RRG can efficiently take up water whenever it is available (Rayner et al. 2014; Taylor et al. 2014). In addition to providing habitat features, RRG forests also support a wide range of understorey flora, including grasses, sedges, rushes, shrubs and aquatic macrophytes (Rogers & Ralph, 2011, p. 18). The Inland Riverine forests are of great value to biodiversity, particularly in semi-arid south-east Australia, where they provide some of the few remaining refuges for a large number of flora and fauna species against a backdrop of widespread human impacts like logging, river regulation and land clearance for agriculture (Lunt & Spooner, 2005).
2.2.2. **Human impacts in Millewa forest: 19th century logging practices**

Although the Inland Riverine forests are widely valued and important ecological communities, the conservation issues these forests face today are driven, in part, by the economic value of RRG. RRG is considered a versatile timber suitable for a range of purposes. It has high green and dry densities at 1130kg.m\(^3\) and 900kg.m\(^3\) respectively (Bootle, 1983, p. 283), lending to its utilisation in heavy construction, railway sleepers, flooring, framing and fencing. Due to its size, it became a popular resource in building 19th century infrastructure in Australia and India (Fahey, 1988). The versatility of the wood also gives it a number of other uses including plywood, veneer, turnery, firewood, charcoal production, gums, honey, ornamental, fuel and oils (ANBGCA-NBR, 2004). As a result of its many applications, logging the RRG forests of the Murray Darling Basin has occurred for well over a century. Logging in Millewa forest (MVNP) began in the 1850s to supply sleepers for the Melbourne-Echuca railway, which was completed in 1864. By 1868 entire townships had developed around the industry. A period known as the ‘Reckless Years’ occurred there soon after, where tensions between competing sawmill companies led to the deliberate felling and branding of trees in rival patches in an attempt to control the forest (Fahey, 1988). This resulted in the first of many government interventions into how these forests should be managed.

2.2.3. **Human influence: early 20th century river regulation**

Under natural conditions, Millewa forest would flood after the spring snow-melt made its way down the Murray River. The forest could be inundated for at least five months or until flood water receded in summer (Bren, 1988). Water would exit the forest through evaporation, transpiration, percolation, or via a system of ephemeral streams that divert flood waters to the north through Deniliquin. Regulation of flows impacting Millewa forest occurred after the construction of the Hume Dam in 1935 and Yarrawonga Weir in 1937. This led to a number of changes to the river’s flow regime and the hydrologic cycle of the Millewa forest (Table 2.2).
Table 2.2 Summary of impacts of river regulation (Di Stefano, 2002).

<table>
<thead>
<tr>
<th>Impact of River Regulation</th>
<th>Consequence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flood frequency reduced</td>
<td>The time between floods has increased</td>
</tr>
<tr>
<td>Flood extent reduced</td>
<td>Less forest area is flooded</td>
</tr>
<tr>
<td>Flood timing reduced</td>
<td>Fewer winter/spring floods, more summer floods</td>
</tr>
<tr>
<td>Flood duration reduced</td>
<td>Forests flooded for fewer months of the year</td>
</tr>
</tbody>
</table>

With a channel capacity of 8900ML.day\(^{-1}\), the Barmah Choke just south of Millewa Forest, is the narrowest part of the Murray channel west of the Hume Dam. Flows of a volume greater than 8900ML.day\(^{-1}\) are restricted by the choke and would be forced, under natural conditions, to engage Millewa forest's effluent channel, the Edward River. The Edward River is controlled by a series of regulators and has a channel capacity of 2500ML.day\(^{-1}\). On occasions where flows are higher than 11,000ML.day, measured at Tocumwal, Millewa forest can flood (Bren et al. 1987, 1988). However, forest inundation is controlled by a series of nine regulators dispersed throughout MVNP (MDBA, 2012, p. 29) and flows that are large enough to flood the forest may not be able to.

2.2.4. Human influence: 20\(^{th}\) century logging practices

In addition to ringbarking, popular logging techniques used throughout the 20\(^{th}\) century in Millewa forest were single-tree selection and small group selection (Di Stefano, 2002). Single-tree selection is often used in mixed-age stands to remove merchantable individuals of a prescribed DBH. This method was further developed in the 1950’s to create openings that contained groups of even-aged timber. This method is referred to as ‘Australian Group Selection’ (AGS) and has been used in NSW and QLD (Florence, 2000, pp. 35-46). Squire et al. (1987) compares AGS with ‘clearfelling’, a popular technique in Victoria, NSW, Tasmania and WA, where entire timber stands are cleared, and seedbeds are disturbed mechanically or through burning to encourage even-aged regeneration. These techniques have been subject to scrutiny, particularly in relation to their incompatibility with ecologically sustainable forest management values (Lindenmayer & Possingham, 1995; Florence, 2000, pp. 35-46; Lindenmayer & Franklin, 2002, p. 5). These silvicultural techniques effectively reduce or remove the ‘zone-of-influence’ that RRG trees exert on their immediate surrounds. This zone results from the allelopathic effects of RRG when cineole produced in the leaves leach and adheres to the soil particles within the trees litter-shed (del Moral & Muller, 1970). By removing the zone-of-influence and its water-soluble toxins,
recruitment of seedlings can occur en masse. In conjunction with the changed flow regime of the Murray, large areas of even-aged, high stem density stands have developed in MVNP (McGregor et al. 2016). The effects of AGS can be observed in mapping by Bowen et al. (2012) which highlight large interconnected areas of high stem densities in MVNP (Figure 2.3). This may be attributable to differences in management driven by respective state forestry institutions. Clear-felling had not taken place in Barmah Forest (Vic.) whereas it had been extensively used in Millewa Forest, and throughout the NSW Murray RRG Forests (Childs 2016, pers. comm., 23 June). In conjunction with reduced water availability, these even-aged, high-density stands are believed to contribute to the poor forest condition observed in Millewa and throughout 79% of the Murray Floodplain (Cunningham et al. 2009a; OEH, 2015).
Figure 2.3 Initial API derived stem density mapping of Millewa forest produced by Bowen et al. (2012) sound that large sections of high stem density exist throughout Millewa forest (NSW) on the northern side of the Murray.
2.2.1. Factors influencing the relationship between stem density and canopy condition

Stem density refers to the number of live plants per unit land area (often measured in stems.ha$^{-1}$). Aerial Photographic Interpretation (API) mapping by Bowen et al. (2012) identified large tracts of land in Millewa with stem densities greater than 400 stems.ha$^{-1}$ (Figure 2.3). These areas of high stem density are often dominated by structurally simple, even-aged ‘poles’ with an absence of hollows (Figures 2.4, 2.5). Stem density of this nature has a reduced the diversity of habitat features for many faunal species, and indicates considerable competition for water and nutrient resources (Horner et al. 2009, 2010; Mac Nally et al. 2011). In RRG stands where competition increases with increasing stem density, suppression of growth among individuals is a primary negative effect (Thoranisorn et al. 1990; Bernardo et al. 1998). It is known that denser RRG stands require more water than less dense stands (Paul et al. 2003, as cited in Rogers, 2011, p. 20), and so canopy condition dynamics in high-density stands are likely to be affected in a number of ways; namely the stands’ ability to respond to water availability through foliage production and loss.

Figure 2.4 High stem density stand in Millewa forest characterised by structurally simple trees. Size-class distribution is highly skewed with smaller trees dominating. Photo: E. Curtis
In contrast with Figure 2.3, this RRG, also in Millewa forest, is indicative of the structurally complex trees largely absent in MVNP. These larger gums often provide refuge within the forest for hollow-dependent species. Photo: E. Curtis

2.3.1. Water availability: flood and drought

Literature about the direct influence of stem density on canopy condition dynamics in RRG stands is scarce, however, there are a number of studies that focus on canopy response to different levels of water availability which provide an indication of how canopy condition might respond over a multi-year time scale. During flood periods, RRG develop robust crowns before quickly shedding their leaves as floods recede (Briggs & Maher, 1983). This means that canopy water use reflects water availability, by reducing water use to fewer leaves. Studies into the impacts of a surrogate measure of water stress on RRG found that through an increase in water stress, significant declines in growth and leaf area per branch occurred as well as an increase in insect herbivory rates as a result of smaller leaf sizes (Bacon et al. 1993; Stone & Bacon, 1994).

Several studies have looked at the relationship between RRG canopy condition and water availability. The investigations of Wen et al. (2009, 2010, 2012 & 2015) along the Murrumbidgee River, NSW make a case for water availability being the primary driver of RRG canopy condition and provide a rationale for the inclusion of a variety of measures of water availability in this study.
Using four high resolution images over a 40-year period in conjunction with ‘Classification and Regression Tree’ modelling, Wen et al. (2009, 2010) determined that RRG forest communities of the ‘Lowbidgee’ floodplain require flooding for 59 days in every three years. However, the authors point out that this is a low estimate in comparison to historical estimates of seven month inundation periods in Barmah forest, NSW (Roberts & Marston, 2000). Wen et al. (2012) used MODIS 250m² NDVI imagery to determine that in addition to flooding local rainfall determined the primary productivity in RRG communities in the Macquarie Marshes, NSW. More recently, Wen and Saintilan (2015) used MODIS 250m² imagery to relate thirteen years of RRG canopy response to the Standardised Precipitation Evaporation Index (SPEI). SPEI is a drought index that related closely to El Nino Southern Oscillation (ENSO). While these studies make important observations regarding the relationship between RRG canopy condition and water availability, none of them investigate the impacts of water availability on different levels of stand density in RRG forest. Nor do they provide information regarding RRG canopy condition at a spatial and temporal scale pertinent to OEHs investigation (i.e. a sub-hectare scale).

### 2.3.2. Intra-stand competition

Intra-stand competition is driven by the amount of available resource (i.e. water availability) and the level of demand for that resource (i.e. stem density). Competition can be described as an interaction that occurs among or between species that results in a detrimental impact on all individuals involved (Larocque et al. 2012). While impacts on individuals may be detrimental, over time dieback resulting from competition reduces stem density and hence competition. This is known as ‘self-thinning’. There has been little research into the process of self-thinning at the individual stem level, and based on the observations that do exist, it may be site-specific. Colloff (2014, p. 60) provides a rare insight into the processes at play in a self-thinning stand. He refers to a 40-year old, self-thinning stand of RRG in Barmah forest where stems 10-15cm DBH are less than an arms width from one another. The author suggests that competition for water in the dense stand may lead to cracked sapwood and the production and shedding of foliage at a higher rate, indicated by intense epicormic growth. The heavy accumulation of leaf litter then remains damp and hosts a build-up of fungal hyphae and borer beetles that infect the cracked sapwood, eventually killing the tree.

The rate of self-thinning is relevant to the fundamental problem driving the present study, that is, the absence of habitat features in Millewa forest. Why use an active intervention such as
ecological thinning in an ecosystem that has the capacity to equilibrate and maintain itself through natural self-thinning? Because faunal populations that depend on large, structurally complex RRG for habitat are growth limited because of high density stands, and self-thinning does not occur at a rate sufficient for population existence in the face of climate change and increasing external water demands.

In 2010, Horner et al. carried out a stem density investigation study in RRG forests using three replicate plots of three thinning treatments (270, 560 & 750 stems.ha\(^{-1}\)), compared with an unthinned control plot (4000 stems.ha\(^{-1}\)). They modelled the impacts of thinning on stand size distributions and found that with increasing thinning intensity, median and maximum individual tree and stand DBH increased, mortality rates decreased and presence of hollow-bearing trees increased approximately 20 times that of unthinned plots. Hollows were only found in trees >50cm DBH. The study concluded that early stage stand management through planting, or later stage stand management through thinning can be used effectively to reduce the impacts of water deficit induced stress on semi-arid riparian ecosystems as a result of climate change and river regulation.

2.4. 21st century management, the concept of sustainability and objective measures

The following section emphasises the importance of objective measures in condition assessments.

2.4.1. The distinction between condition and health

As one of the twelve member countries of the Montreal Process Working Group, Australia is committed to conserving and sustainably managing its forest ecosystems according to the seven criteria below, as outlined by the Montreal Process (Montreal Process, 2015, p. 15).

1. For the conservation of biological diversity
2. To maintain the productive capacity of forest ecosystems
3. To maintain forest ecosystem health and vitality
4. For the conservation and maintenance of soil and water resources
5. To maintain forest contribution to global carbon cycles
To maintain and enhance long-term multiple socio-economic benefits to meet the needs of societies

Within a legal, institutional and economic framework for forest conservation and sustainability.

However, the ambiguity of the term, ‘health’ has led to some confusion (Kolb et al. 1994). Tree health refers to physiological or pathological status, whereby measures such as ‘pre-dawn water potential’ are used to provide scientists with an indication of the plants’ potential to internally transport water (Chisholm, 2006) and thus, is an indicator of plant stress or strain. Measures of tree health can be used to monitor an immediate, physiological response to some form of biotic or abiotic disturbance. Alternatively, ‘condition’ is a morphological measure that has been commonly mistaken for health in the past, and is used to assess visible signs of strain (Stone, 1999). Condition is a term used to describe a qualitative state or level of fitness, and is often ranked along a continuum. Like health, the inherent subjectivity of the term ‘condition’ means that with each application, its scope, context and meaning must be clearly outlined (Keith & Gorrod, 2006). Condition is a useful indicator as it can be efficiently and inexpensively measured at landscape and regional scales.

2.4.2. Ecological Thinning as a potential management technique

It is thought that reducing competition may be useful in alleviating water stress. A 20-year study on the effects of ecological thinning on Cedrus atlantica trees in the French alpine region found that lower stem densities exhibited a higher resilience in coping with drought periods. Notably, lower density plots recovered faster from drought, and these stands had proportionally larger basal areas over the 20-year time period (Guillemot, et al. 2015). Other studies that focus on competitive interactions exhibit similar findings in relation to canopy response. Forrester et al. (2012) increased the amount of water available for uptake by using thinning to decrease the level of competition in several Eucalypt species. In response, authors observed an increase in crown girth, branch size and canopy leaf area in the largest of the retained trees. Forrester et al. (2012) suggest the freeing up of water and nutrient resources leads to increased leaf production and growth, as well as increased physiological functioning such as transpiration. These findings are supported by Bernardo et al. (1998) who found that a decrease in density enabled RRG to allocate more growth to its root system, thus increasing the trees’ ability to take up more water.
and nutrient resources (Akeroyd et al. 1998), and increasing the need to transpire through an increased leaf area.

Horner et al. (2009) carried out an experiment to investigate the effects of competition on a 44 year-old even-aged stand of RRG at Black Swamp in Barmah Forest. Authors focussed on three replicate plots of five stem density treatments (600, 1000, 2000, 4000, 8000 stems.ha\(^{-1}\)). Results showed that at a decadal time scale, trees in stands of lower stem density grew taller and had a larger DBH than those in high-density stands. Findings also agreed with that of Thoranisorn et al. (1990), Stone & Bacon, (1994), Bernardo et al. (1998), Forrester et al. (2012) and Guillemot et al. (2015), indicating that during long periods of water deficit, high density stands showed high levels of mortality whereas the lower density stands did not change mortality rates in response to water availability. In addition, lower water availability led to mortality occurrence at a lower tree biomass.

The literature indicates that different stem densities exhibit a different canopy response to water deficit. Foliage in dense stands regenerates at a slower rate than in less dense stands, which has been attributed to the surface area of the root-stock (Bernardo et al. 1998). In situations of water deficit, canopy can also be impacted by the trees physiological capacity to generate leaf area and cineole content as a defence against insect herbivory (Stone & Bacon, 1994). Water availability may therefore be intertwined with levels of stem density. This is widely perceived in terms of ‘competition’, and often, in the case of RRG, intra-specific competition.

### 2.4.3. Conditional indicators of biodiversity in Inland Riverine Forests

In conservation-based management, ‘health’ is often determined by outcomes relating to biodiversity. However biodiversity is difficult to objectively quantify, and so ecologically sustainable forest management requires ecologists and land managers to monitor indicators of biodiversity to achieve conservation goals. This may involve monitoring a potential indicator species and/or structure-based indicators like stand structural complexity or connectivity (Lindenmayer et al. 2000). Whatever the indicator may be, objectivity must be exercised to minimise ambiguity and to aide in interpretation of research.

In relation to the Inland Riverine Forests of NSW, RRG is an indicator species of biodiversity because these forests have a largely mono-specific over storey. RRG plays a key role in ecosystem function by providing a number of resources and habitat for flora and fauna. As a structure-based
indicator, the canopy condition of RRG can tell ecologists and land managers useful information regarding forest health, as it strongly reflects water availability (Yang et al. 1997; Cunningham et al. 2007; Cunningham et al. 2009; Aguilar et al. 2012; Wen et al. 2012; Fu & Burgher, 2015; Wen & Saintilan, 2015).

The role of quantitative data is important in ensuring objectivity in tree and stand condition assessments. Cunningham et al. (2007) tested a range of stand condition indicators and their relationships with physiological stress on RRG along the Murray River. Testing was carried out at twelve sites dispersed along the upper, middle and lower reaches of the Murray to account for longitudinal gradients in water availability. Of the eight indicators measured in situ (Table 2.3), three of them were deemed reliable. These were ‘Percent Live Basal Area’, ‘Plant Area Index’ and ‘Crown Vigour’, all of which can be used in estimates of canopy dieback.

Table 2.3 Description of the eight condition indicators assessed for reliability and objectivity in Cunningham et al. (2007).

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Live Basal Area</td>
<td>Proportion of a stand's basal area taken up by live trees</td>
</tr>
<tr>
<td>Plant Area Index</td>
<td>Area of leaves and stems per unit ground area</td>
</tr>
<tr>
<td>Crown Vigour</td>
<td>Percentage of potential crown that contains foliage</td>
</tr>
<tr>
<td>Epicormic Growth</td>
<td>Percent of live foliage containing epicormic growth</td>
</tr>
<tr>
<td>Crown Depth</td>
<td>Difference between top and base of tree crowns</td>
</tr>
<tr>
<td>Crown Size</td>
<td>Crown projected area per basal area</td>
</tr>
<tr>
<td>Leaf Condition</td>
<td>Per crown percentage of healthy, chlorotic and damaged leaves</td>
</tr>
<tr>
<td>Foliage Density</td>
<td>Percent canopy cover per crown</td>
</tr>
</tbody>
</table>

Additionally, these three indicators were found to correlate well with the Normalised Difference Vegetation Index (NDVI) (Rouse et al. 1973; Tucker, 1978). Plant Area Index had the strongest correlation with NDVI ($r = 0.86$), and this was later found to perform well when integrated into an Artificial Neural Network (ANN) with NDVI to predict stand condition for the entire Murray River floodplain (Cunningham et al. 2007).

In 2009, Cunningham et al. followed up previous work and used these indicators to investigate the influence of a number of stand structure variables on canopy condition along the Murray River. They found that longitude has a moderately positive relationship with condition, as it is directly related to water availability, with a downstream decrease in precipitation and increase in
irrigation and extraction. Additionally, stand condition models identified 79% of the Murray River forests to be in a moderate to severely degraded condition (Cunningham et al. 2009, 2011).

2.4.4. The need for a long-term baseline

The extent of the monitoring (entire Murray River) by Cunningham et al. (2009) is highly relevant, particularly for basin managers such as the Murray Darling Basin Authority, and when compared with other studies of Inland Riverine forest (Margules & Partners, 1990; Jurskis et al. 2005; Pennay, 2009), condition appears to be declining. However, the temporal resolution of these studies is low. Based on RRGs’ opportunistic use of available water and their subsequent canopy response, fluctuations in canopy condition may not necessarily be detected by a single or even annual snapshot condition assessment. This is because water availability in semi-arid southeastern Australia is influenced by climatic drivers, such as El Nino Southern Oscillation (ENSO), that occur at different intensities irrespective of annual seasonal cycles. For this reason, accurate condition monitoring of RRG stands must occur frequently and over a long period of time.

An adaptive management program, such as the OEH ecological thinning trial, requires ongoing monitoring to inform land managers and ecologists about the impacts of thinning on RRG. Critical to this is an understanding of initial RRG canopy condition prior to implementation of different thinning treatments. Current condition reports relating to RRG are insufficient as a baseline dataset for two reasons: they do not capture the dynamic behaviour of canopy condition in response to water availability and intra stand competition; and a number of them have been captured during the millennium drought period. As a result, canopy condition would likely indicate an improvement irrespective of the impacts of ecological thinning. Instead, multiple measures of RRG canopy condition should be analysed to develop an understanding of condition dynamics over time, and in response to climatic and hydrologic influences.

2.4.5. Before & After Control Impact

The requirement for detailed understanding of dynamic behaviour prior to an experimental manipulation is justified in literature on ‘Before and After Control Impact’ experimental design. It has been suggested that singular before and after means sampling is over simplistic, based on poor logic, and does not necessarily indicate whether a change in an environmental variable is
due to human impact or some other influence occurring at a timescale undetectable in before and after sampling (Underwood, 1991). Therefore, determining impacts within a dynamic system requires multi-temporal monitoring before and after impact in both control and treatment sites (Bernstein & Zalinski, 1983; Stewart-Oaten & Murdoch; 1986; Underwood, 1991; Underwood, 1994) (Figure 2.6).

**Figure 2.6** Illustration shows a benefit of multiple before and after impact sampling. Multiple sampling shows that the amplitude of the cycle is affected by the impact, more so than the mean/trend. This is particularly relevant in studies where a cyclical process may be present.

In the interest of developing a robust set of baseline data with which to detect impacts of thinning, monitoring must be able to detect sustained patterns of difference occurring across time-scales that are pertinent to known broader periods of water availability (El Nino, La Nina). For this reason, monitoring of RRG canopy condition must provide a multi-year dataset that is able to detect canopy condition dynamics across dry (2008-2009) and wet (2010-2011) periods (BoM, 2012), prior to the implementation of thinning operations in early 2016.

**2.4.6. Time Series Analysis**

A ‘Time Series Analysis’ (TSA) is a suitable methodological approach for analysing canopy
condition dynamics because it has the ability to account for the entire stochastic process present. A **stochastic process** is a collection of “related random variables, often ordered in time or space” (Upton & Cook, 2014, p. 213). A time series is just one example of a stochastic process, and is primarily made up of three components: **trend**, **periodicity** and **noise** (Legendre & Legendre, 2012, pp. 637-707). There are a number of ways **trend** can be defined, and it varies from application to application however it is generally described as the long term variation of a system. Trend is analysed to gain a better understanding of how a natural system is or has evolved over time (Chandler & Scott, 2011, pp. 1-23; Legendre & Legendre, 2012, p. 647). **Periodicity** is the cyclical component of a time series; it can follow a range of natural rhythms such as lunar, daily or annual cycles. Many natural systems exhibit a seasonal periodicity, whereby the cyclical pattern repeats itself annually (Legendre & Legendre, 2012, p. 653). **Noise** represents the random, natural variation of the time series (Cryer & Chan, 2008, pp. 11-26).

TSA is a frequently used and increasingly important method for quantifying and accounting for components in a time series. Publicly available remotely sensed data collected at regular time intervals and covering moderate to large spatial scales has spurred the popularity of TSA. In natural systems, TSA can be utilised in one of three ways: a) **change-detection**; b) **vegetation monitoring**; or c) **forecasting** (Banskota et al, 2014). TSA for change-detection is a technique whereby the focus is on identifying and characterising the presence or absence of trends over time. Since change-detection focusses on trend, periodicity must be removed from data. This is done by analysing time-points that occur on or near the same location of the periodic cycle (e.g. analysing 10 years of data collected on or near the solstice annually) (Banskota et al. 2014). Vegetation monitoring is often concerned with phenology, and is analysed with the intention of characterising a number of parameters described by both trend and periodicity (such as onset of greenness, senescence or rate of green-up) (Bradley et al. 2007; Hermance et al. 2007). To do this, temporal data collection should be driven by the 'observational window', which describes the time period within which phenomena must occur to permit statistical analyses (Legendre & Legendre, 2012). The observational window used to identify the season when tree canopies begin to senesce would require data be collected at a minimum of four times per year and cover at least two years. Forecasting involves broadly modelling all components of the time series before extrapolating forward in time to give an indication of how a variable might behave in the future. Autoregressive Integrated Moving Average (ARIMA) is an example of a modelling technique used to forecast linear time series, while Artificial Neural Networks (ANN) have been used to forecast non-linear time series (Zhang, 2003). TSA methods for vegetation monitoring were most relevant to this study. Subsequently, methods relied on the concept behind TSA to
describe canopy condition – that is that a time series signal is made up of three additive components: trend; periodicity; and random noise. However, due to the spatial requirements of the study (sub-hectare scale), substantial challenges were faced and unconventional methods were sought.

TSA are based on the assumption that data are sampled at equal time intervals. When this assumption is met, data can be decomposed into various components in a straightforward manner (e.g. by differencing and using the autocorrelation function to determine seasonality). Satellite sensors with high temporal frequency, such as MODIS, are well suited to meeting the temporal requirements of a time series determined by an annual cycle. However, the best spatial resolution afforded by MODIS is 250m², which limits its use in stand-scale monitoring. To analyse canopy condition dynamics at a scale pertinent to the OEH ecological thinning trial, a better spatial resolution is required. The minimum limit of the temporal observational window to analyse RRG canopy condition dynamics means that an image must be recorded at least twice in six months in order to capture seasonal variation. Landsat satellites revisit every 16 days, have a 30m² spatial resolution, and with imagery easily accessible, Landsat imagery meets the requirements for this application.

### 2.4.7. The role of remote sensing in monitoring canopy condition

In 2008, Landsat adopted an open access data policy, enabling spatial scientists to access global images taken at 16-day intervals since 1972 free of charge. This exploitation of the temporal domain at medium spatial and spectral resolution has subsequently led to the popularization of Landsat images, with its use becoming widespread throughout a number of scientific applications, in particular ecological monitoring (Wulder et al. 2012).

The use of satellite-based remote sensing provides a large number of vegetation indices that are useful for measuring biophysical variables. Some of the more popular indices include: ‘Normalised Difference Vegetation Index’ (NDVI) (Rouse et al. 1973), ‘Soil Adjusted Vegetation Index’ (SAVI) (Huete, 1988) and ‘Enhanced Vegetation Index’ (EVI) (Huete et al. 1997). Many of the spectral indices are based on the red/near-infrared inverse relationship between healthy and unhealthy green vegetation (Jensen, 2014, p. 384). Further, there are several other metrics that have been developed in Australia for the purpose of monitoring terrestrial vegetation in semi-arid and arid rangeland environments, such as ‘Foliage Projective Cover’ (FPC) (Scarth et al. 2008).
& ‘Fractional Cover’ (FC) (Scarth et al. 2010). This study has access to an ongoing collection of radiometrically and geometrically processed Landsat TM, ETM+ & OLI data pertaining to the study area (path 93, row 85) beginning from mid-2008 available from OEH.

**Normalised Difference Vegetation Index**

Normalised Difference Vegetation Index (NDVI) is an index used to measure photosynthetic activity in plants, and is commonly used as an indicator of plant condition. It was first used in satellite remote sensing by Rouse et al. (1973) and since then, has been used in a wide range of terrestrial applications including agriculture, silviculture and ecology. It evaluates the proportion of chlorophyll’s absorption capacity in the red wavelength versus reflectance in the near-infrared.

\[
\text{NDVI} = \frac{r_{NIR} - r_R}{r_{NIR} + r_R}
\]

(Eq 2.1)

The difference between near-infrared \(r_{NIR}\) and red \(r_R\) reflectance is divided by their combined values. This is particularly useful in multi temporal studies as it accounts for different levels of brightness between time periods by effectively normalising the ratio. Countless studies have used NDVI in time series applications, with many generating important information regarding woody vegetation phenology in semi-arid and wetland ecosystems (Wen et al. 2012, Petus et al. 2013, Baghzouz et al. 2010, Helman et al. 2015). It should be noted that remotely sensed NDVI imagery does not discriminate between canopy and groundcover, and background signal produced by the groundcover has the potential to come through as ‘noise’ in open canopies. However, studies have used this to their advantage in separating out canopy from groundcover due to differences in their phenological behaviour (Roderick et al. 1999, Lu et al. 2001, 2003). An NDVI map used in this study can be seen in Figure 2.7.
**Figure 2.7** NDVI map of Barmah-Millewa forest, with lighter shades representing higher levels of photosynthetic activity. The black area in the SW corner of Millewa is a standing water body.
**Foliage Projective Cover**

Foliage Projective Cover (FPC) is a measure of canopy density that describes the fraction of ground cover to green canopy for woody vegetation greater than 2m in height. While FPC permits the comparison of canopies within species, comparison between species may not be permitted due to differences in canopy habit (spreading, clumped, sparse, etc.). FPC is an effective indicator of physiological activity at the community level (Specht, 1970). Scarth *et al.* (2008) were able to relate FPC to other canopy condition indicators (namely crown cover) via the following relationship:

\[
CC = \frac{FPC}{1 - (1 - FPC)^{ae^{-b(CC-1)}}}
\]

(Eq 2.2)

where the superscript in the denominator describes the ratio between stand and individual crown clumping. FPC tends to saturate when a crown cover of 75% is reached. Seventy percent of the RRG in the nearby Barmah State Forest was considered open forest (51-80% canopy cover) in 1984 (Chesterfield *et al.* 1984, as cited in Dexter & Macleod, 2010) and the Millewa RRG inland riverine forest is defined partially on its 30-70% canopy cover (Keith, 2004, p. 223). This should be considered if high FPC values are apparent during analysis. An FPC map used in this study can be seen in Figure 2.8.
Figure 2.8 FPC map of NSW, with darker green areas representing higher vertically projected foliage cover. Darker shades of green indicate denser canopy.

2.4.8. Limitations of Landsat data in time series analysis

An issue faced when undertaking a statistical analysis of a time series using Landsat data is the presence of unavoidable data gaps. These gaps occur spatially and temporally, due to a number of reasons. An example of spatial gapping is the Landsat ETM+ scan line corrector failure that
occurred post 2003, resulting in the loss of pixels from 22% of every image (Maxwell et al. 2007). Gaps in the temporal domain are more often due to cloud cover and other atmospheric interactions. Tulbare et al. (2016) highlight the patchiness of Landsat data in the Murray-Darling Basin in the winter from 2008 to 2011, and this was reflected in the image data available for the present study from OEH. Irregularly spaced data in time-series analysis can hinder the computational accuracy of fundamental statistical inferences, including the annual mean and standard deviation, and autocorrelation. As a result, alternative statistical methods must be employed (Chandler & Scott, 2011, pp. 127-170; Ambrosino & Chandler, 2013). Some scientists have used image fusion techniques to avoid data gaps by interpolating missing dates (Hilker et al. 2009; Schmidt et al. 2012; Bhandari et al. 2012; Emelyanova et al. 2013; Jarihani et al. 2014), whereby the ‘Spatial & Temporal Adaptive Reflectance Fusion Model’ (STARFM) algorithm (Gao, et al. 2006) and ‘Enhanced Spatial & Temporal Adaptive Reflectance Fusion Model’ (ESTARFM) (Zhu, et al. 2010) have been widely used. Both algorithms use MODIS derived surface reflectance changes captured at a high temporal/low spatial resolution (daily/500m) to predict surface values at the spatial resolution of Landsat (Hilker et al. 2009; Bhandari et al. 2012).

Interpolation is not a perfect solution (Zhu et al. 2010). Eckner (2012) showed that interpolation of missing temporal data introduces bias into the analyses and tends to underestimate seasonality. This is an important point as seasonality is an expected component in RRG canopy condition dynamics data. Rehfeld et al. (2011) showed that interpolation and Fast Fourier Transform tend to greatly increase RMSE with increasing sample spacing. This study has avoided relying on interpolation of large numbers of missing dates to ensure a simple time series analysis could be carried out. Instead, the study has used only measured values of canopy condition and a creative methodological approach to meet objectives.
2.5. Gaps in the Literature

The NRC report, referred to in section 2.1.1 (2009b, pp. 5-6) highlights the scarcity of research into the ecological impacts of different thinning treatments, and states the value of carrying out studies in the area. This is due to its potential to be an effective technique in managing conservation concerns that environmental flows and self-thinning cannot alleviate. By studying ecological thinning within an adaptive management framework, robust and prudent guidelines can be developed to help inform the management of RRG forests against ongoing uncertainties of water availability and climate change in semi-arid Australia. In regards to ecosystem response modelling in the Murray-Darling Basin, a number of knowledge gaps have been identified pertaining to our ability to optimally manage riverine ecosystems. One such area is the absence of long-term monitoring programs (Saintilan & Overton, 2010, p. 411). More of an emphasis needs to be placed on long-term monitoring at multiple spatial and temporal scales across all ecosystems, in order to provide robust, empirical data in support of ecosystem science (Magurran et al. 2010; Saintilan & Overton, 2010, p. 411; Thackway et al. 2013). A number of studies exist that consider the role of water availability on RRG canopy condition for extended periods of time (Wen et al. 2009, 2010, 2011, 2012 & 2015; Fu & Burgher, 2015), and others consider the impacts of high density stands of RRG (Thoranisorn et al. 1990; Bernardo et al. 1998; Horner et al. 2009, 2010). Overall, there is no available information directly regarding the influence of stem density and water availability on canopy condition dynamics over time at the spatial and temporal scale presented in this study. An investigation into these relationships will provide land managers and ecologists with a valuable baseline dataset, against which the effects of ecological thinning on RRG stands can be evaluated. There is little information regarding undertaking a time series analysis on data series with large numbers of missing dates without interpolating to fill the gaps. This study strives to tackle this issue by accounting for the same components (trend, periodicity and noise) described in a TSA without relying on interpolation of missing dates. This means that results are based on an empirical foundation that will ensure a true baseline of RRG canopy condition dynamics.
3. **Regional Setting**

3.1. **Location**

The 2844 km Murray River is a low gradient river that forms the border between NSW and Victoria, and flows west from Mount Kosciusko, NSW to Wentworth, SA. It is a key drainage component of the 1,042,730 km² Murray-Darling basin, which is made up of 22 individual catchments. The Central Murray catchment spans from the Hume Dam in the east to the Murray Darling confluence at Wentworth NSW in the west. This catchment covers approximately 1200 km of the Murray River. The 38,631 ha Murray Valley National Park (MVNP) is situated on the northern bank of the central Murray catchment, directly east of the town of Mathoura, NSW (35°48'55.7"S, 144°54'02.1"E). The Murray River carries water from five upstream basins to the forest (Figure 3.1). Along with the adjacent Barmah forest (Vic), MVNP is part of Australia’s largest RRG forest, and is made up of an interspersion of wetland, forest and woodland environments. The size of this forest is due to the interaction between river hydrology and the unique geology of the area, namely the Cadell Fault.

3.2. **Geomorphology**

The Cadell fault is a defining geologic feature of the region. This fault has undergone multiple uplift events over the past 5-10 Ma, with the resultant 12-15 m scarp face stretching 55 km in a north-south direction between Echuca and Deniliquin (McPherson et al. 2012). The scarp face of the Cadell fault provides a natural barrier along the western flank of MVNP, where the Murray swings southward, and the Edward River diverts flows to the north. Thermoluminescence dating of riverine plain sediments suggests uplift diverted the Murray northward approximately 60 Ka (Page et al. 1991). Since then, several channel avulsions have occurred prior to the Murray following its current southerly passage (Rutherford & Kenyon, 2005) around the Cadell fault around 550 years ago (Stone, 2006). The current flow is through the ‘Barmah Choke’, a narrow stretch of the river channel with a capacity of 10,600ML.day⁻¹ (Ladson & Chong, 2005). This causes flows to back up into the surrounding Moira lake wetland system, and on occasions where flows exceed capacity, the forest floods (Colloff, 2014, p. 19). River flow following uplift of the Cadell fault produced a large, triangular, low-angle alluvial fan, known as the Barmah Fan which
provides the canvas upon which the vegetation communities of MVNP sit (Rutherford & Kenyon, 2005). The Barmah Choke provides enough channel restriction to cause flooding across the fan and subsequently, RRG forests have been able to expand throughout the area (Figure 3.2).

![Image of the Cadell Fault and Barmah Fan, showing the location of MVNP](image: Stone, 2006)

**Figure 3.2** Schematic diagram of the Cadell Fault, showing the Barmah Fan upon which MVNP sits, immediately east of the fault (image: Stone, 2006).

### 3.3. Soils

Cracking clay soils are common along much of the Murray River floodplain. Because of their tendency to dry out and crack, these soils exert physical limitations on the vegetation that inhabits them, and as a result, grassland is a common understorey (Gibbons & Rowan, 1993, p. 184) (Figure 4.3). In MVNP, surface soil groups consist of *Grey, Brown & Red Clays* and *Red Brown Earths* (Table 3.1, Figure 3.3) are made up of layers of sediment ranging from fine clays to coarse sands. Sandy lenses represent water infiltration pathways that facilitate lateral percolation (Bacon et al. 1993). There are also a number of large Aeolian sand dunes scattered throughout the region. These ancient lunettes are the result of the deflation of the drying Plio-Pleistocene, Lake Bungunnia by south-westerly winds, during glacial-maximas (Stephenson, 1986; Colloff, 2014, p. 7). In MVNP, these dunes are characterised by well drained soils, and are inhabited by less flood tolerant species such as *Callitris glaucocephala* (White Cypress Pine) and *Allocasuarina luehamannii* (Buloke).
<table>
<thead>
<tr>
<th>Soil Group</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grey, Brown and Red Clays</td>
<td><em>Ancestral streams and floodplain complex</em></td>
</tr>
<tr>
<td>Red Brown Earths 1</td>
<td><em>Hard, pedal, alkaline, red, duplex soils with sporadically bleached A2 horizons (DR2.33)</em> with grey &amp; brown clays</td>
</tr>
<tr>
<td>Red Brown Earths 2</td>
<td><em>Hard, pedal, alkaline, red, duplex soils with sporadically bleached A2 horizons (DR2.33)</em> with other duplex soils</td>
</tr>
</tbody>
</table>

**Figure 3.4** Cracking clay soil profile (Image: Gibbons & Rowan, 1993)
3.4. **Hydro-Climatic Features**

MVNP lies within a warm, persistently dry grassland climate (Stern & de Hoedt, 2000), which has a hot dry summer and cold winter and an annual mean temperature range of $9.1 - 22.0 \, ^\circ\text{C}$ (Figures 3.5, 3.6). Average annual precipitation is approximately 360 mm.year$^{-1}$ and can be attributed to frontal systems sweeping southern Australia from the west (BoM, 2016). The region
also experiences high potential evapotranspiration and low rates of annual runoff, subsequently much of MVNP relies heavily on river discharge in addition to groundwater and local precipitation (BoM, 2016) (Table 3.1). Historically, river flows would peak during spring as a result of snow melt (Bren, 1988) however, since regulation MVNP often experiences unseasonal flooding in summer as a result of ‘rain rejected’ water allocations (MDBA, 2012, p. 28).

Figure 3.5 Australian climate classification. MVNP sits just within the grassland climate region (Image: BoM, 2005).
Figure 3.6 Graph showing average monthly rain (recorded at Mathoura), maximum and minimum temperatures (recorded at nearby Deniliquin, NSW). Source: BoM.

Table 3.2 Summary of hydro-climatic averages affecting MVNP (Source: BoM, 2016).

<table>
<thead>
<tr>
<th>MVNP Hydro-Climatic Features</th>
<th>Average Annual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climate Class</td>
<td>Grassland</td>
</tr>
<tr>
<td>Minimum Temperature</td>
<td>$9.1,^\circ C$</td>
</tr>
<tr>
<td>Maximum Temperature</td>
<td>$22.0,^\circ C$</td>
</tr>
<tr>
<td>Precipitation</td>
<td>361.9 mm</td>
</tr>
<tr>
<td>Runoff</td>
<td>1 - 50 mm</td>
</tr>
<tr>
<td>Potential Evapotranspiration</td>
<td>1251 - 1400 mm</td>
</tr>
</tbody>
</table>

3.5. Land Use

Rain rejected water allocations are common due to surrounding industries in the central Murray Catchment. In times of water scarcity, surface water is contained in upstream dams and weirs, before being released in summer to maintain the regions agricultural industry, whose gross value sits at $647,000,000 (ABS, 2011). If an industrial water allocation is released, and the recipient
irrigator receives sufficient rainfall at the same time, that irrigator has the option to call a ‘rain rejection’, and if the allocation exceeds channel capacity at the Barmah choke, MVNP receives unseasonal flooding (MDBA, 2012, p. 28). Both dryland and irrigated agriculture are predominant industries and in combination with urban areas, use over 36% of available surface water in the region (CSIRO, 2008) (Figure 3.7). MVNP was managed as a timber reserve for 150 years, which had a significant effect on the forests structure (McGregor et al. 2016). In 2010 it was gazetted as a national park, which meant that it was to be managed for conservation.

Figure 3.7 Barmah-Millewa forest in the Southern Basin is surrounded by dryland and irrigated agriculture (Source: ABARES, 2010).
4. Methods

To undertake this study at a landscape scale, remotely sensed imagery was used to construct a retrospective data series for plots stratified by water availability and intra-stand competition. With the inclusion of hydro-climatic variables, the data series was then analysed statistically to determine which variables impact canopy condition dynamics across water availability and intra-stand competition classifications.

4.1. Study area and plot stratification

The study focussed on mono-specific RRG stands in MVNP in the NSW Riverina. Sixty-six pre-established 2ha plots were set up during initial stages of the OEH Adaptive Management Project between 2012 and 2015. Initial mapping facilitated the landscape scale study design by allowing stands of RRG to be stratified based on surrogate measures of water availability and intra-stand competition (Figure 4.1). This is based on the hypothesis that levels of intra-stand competition are highest when stem density (SD) is high and water availability is low, and vice versa. Site quality (SQ) is an indicator of water availability, based on mature canopy height. This relationship is supported by studies in the Central Murray RRG forests that have identified correlation between dominant tree height at maturity and depth to groundwater, whereby taller mature trees with a height >32 m had a depth to water Table (DWT) = <6 m; at height 21 m-32 m DWT = 3-9 m; and at height <21 m DWT = >9 m, and so the tallest mature trees are found in places with the best access to ground water (Baur, 1984) (Table 4.1). SD is an indicator of intra-species competition level. SD was classified as high (>400 stems.ha\(^{-1}\)), medium (200-400 stems.ha\(^{-1}\)) or low (<200 stems.ha\(^{-1}\)) based on mapping carried out by Bowen et al. (2011) using aerial photographic interpretation (API) of 50cm\(^2\) spatial resolution ADS-40 imagery obtained by NSW Land & Property Information in 2010. SD and SQ are surrogates for intra-stand competition and were used as ‘blocking’ factors in the initial randomised block design. No study plot has been affected by fire or logging since 2001 (OEH, 2014). Table 4.2 summarises the study design.
Table 4.1 Summary of Forestry NSW Site Quality Classification for NSW RRG forests (Baur, 1984).

<table>
<thead>
<tr>
<th>Site Quality</th>
<th>Mature Canopy Height</th>
<th>Depth to Water Table</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1</td>
<td>&gt;34m</td>
<td>&lt;6m</td>
</tr>
<tr>
<td>Q2</td>
<td>21-34m</td>
<td>3-9m</td>
</tr>
<tr>
<td>Q3</td>
<td>&lt;21m</td>
<td>&gt;6m</td>
</tr>
</tbody>
</table>

Table 4.2 Frequency and distribution of initial stratified plot variables.

<table>
<thead>
<tr>
<th>Site Quality</th>
<th>Site Quality 1 (≥32m height)</th>
<th>Site Quality 2 (&lt;32m height)</th>
<th>Total plots</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>&lt; 200 stems. ha⁻¹</td>
<td>6</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>200 – 400 stems. ha⁻¹</td>
<td>12</td>
<td>24</td>
</tr>
<tr>
<td></td>
<td>&gt; 400 stems. ha⁻¹</td>
<td>15</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>Total plots</td>
<td>33</td>
<td>66</td>
</tr>
</tbody>
</table>

The study was designed to determine the impacts of ecological thinning on high density stands, thus, replication was skewed towards high density stands as this is where many of the conservation concerns lay. Ecological thinning will be carried out in 9 ha plots in April 2016, and edge effects will be reduced by focussing monitoring efforts on a 2 ha plot contained within each of the 9ha plots. All plots are stratified as either site quality 1 (SQ-1) or site quality 2 (SQ-2), and each plot has been assigned to stem density (SD) classification based on the number of stems in that particular plot (Figure 4.1).
Figure 4.1 Locations of the 66 plots in the MVNP set up by OEH. They are stratified based on ‘Site Quality’ (FC NSW 1984) which is measure of water availability and stem density (stems per hectare (sph) mapped by Bowen et al. 2010) (OEH, 2015).
4.2. Data Acquisition

4.2.1. Stem Density

Previously mapped classes of SD (Bowen et al. 2011) were deemed unreliable for the purpose of this study because field observations indicated that they may have underestimated dense stands of smaller trees that presumably contribute to intra-stand competition levels. SD can be thought of as live tree density, however, many cases of ‘mallee’ growth habit exist, mostly due to coppicing after logging, whereby trees appear to be individuals but are joined to the same lignotuber. Consequently for stem density assessment, each stem that connected to the main trunk below 1.37 m was counted. In-situ assessments were undertaken to provide an empirical estimate of stem density on 53 of the 66 original plots with the assistance of NPWS staff in June 2016. This ensured accurate and precise information regarding stem size and quantity could be used in this study.

Southern corners of the pre-established plots were located within a 4 m accuracy using a handheld Garmin GPSmap 62 device. True-north was determined using a Suunto-Tandem compass/clinometer by subtracting the given magnetic declination for the date and location (+10.74 deg.) (GeoScience Australia, 2015). Plus/minus 90 degrees was then used to determine east/west flanks and 50 m boundary strings were set up in a north-south direction, demarcating an area 10 m either side of the southern corners and 50 m in length (1000 m²) (Figure 4.2). All stems >1.37 m in height were counted and diameter at breast height (DBH) measured in 8 x 20 m x 50 m transects. This data was then collated with stem density counts and measures taken in late 2015 covering a central area of 200 m². Total area assessed for each plot was 1 ha.
Figure 4.2 Graphical depiction of stem density assessment method, whereby each of the numbered 20x50 m plots had all stems >1.37 m height counted and DBH measured.

Based on the empirical measures of SD that had been obtained, SD was split into three classes; ‘Low’, ‘Medium’ and ‘High’ of which are summarised below (Table 4.3, Figure 4.3). Each class was roughly equal in size.

Table 4.3 Summary of SD classification used in the study.

<table>
<thead>
<tr>
<th>SD Class Summary</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SD Class</strong></td>
</tr>
<tr>
<td>Low</td>
</tr>
<tr>
<td>Med</td>
</tr>
<tr>
<td>High</td>
</tr>
<tr>
<td><strong>Total</strong></td>
</tr>
</tbody>
</table>
Figure 4.3 Bar chart shows number of stems observed in each plot for SQ-1 and SQ-2. Plots with ≤ 449 stems were classed as ‘low SD’, plots with 350-749 stems were classed as ‘med SD’, and plots with ≥ 750 stems were classified as ‘high SD’.

4.2.2. Live basal area

Percent Live Basal Area (LBA) for each plot was calculated using the following method:

1. Determine the DBH (cm) of each live stem on a plot (n)

2. Convert DBH (cm) to LBA (m²) using: 
   \[ LBA = \frac{\pi DBH^2}{40000} \]

3. Sum all individual LBA values for the plot: 
   \[ \sum_{i=1}^{n} LBA_i \]

4. Convert LBA to % using: 
   \[ \% LBA = \frac{LBA}{10000} \times 100 \]

Live Basal Area provided an additional dimension to intra-species competition that could be investigated in concert with stem density.
4.2.3. Water and Climate Variables

Hydrologic and climatic variables previously identified as important drivers of canopy condition (Bren, 1988; Wen et al. 2009; Wen & Saintilan, 2011; Wen et al. 2010, p.231; Fu & Burgher, 2015) were collated for the period 2008 – 2016. These included rainfall and temperature data for Mathoura obtained from the Australian Bureau of Meteorology (2016), River Discharge measured at Yarrawonga Weir, directly upstream from MVNP, obtained from the NSW Office of Water (2016) and Southern Oscillation Index (SOI) data downloaded from the National Oceanic and Atmospheric Administration (2016). Doody et al. (2014) found there to be a lag in RRG response to increased flows as a result slow lateral percolation, so once a suitable set of predictor variables had been determined, lagged values were applied to see if there was a temporal lag present in the time it took for RRG canopy condition to respond to hydrologic variables as a result of either vertical or horizontal percolation.

SOI describes the difference in standardised air pressure at mean sea level between Tahiti and Darwin. SOI values that >7 indicate La Nina conditions, whereas values < -7 indicate El Nino conditions in south-eastern Australia. La Nina events are known to result in wetter conditions throughout southeastern Australia as well as increased snowfall in the Australian alps, while El Nino events tend to bring dryer conditions to southeastern Australia (Stone & Auliciems, 1992; Pepler et al. 2015). The effects of SOI tend to develop during Autumn months, and have their strongest impact during Winter and Spring before dissipating during late Summer (noaa.gov, 2016; bom.gov.au, 2016). SOI closely relates to drought indices such as the Standardized Precipitation Evapotranspiration Index, used by Wen and Saintilan (2015).

4.2.4. Satellite derived vegetation metrics

Satellite derived vegetation metrics encompassing the years 2008 – 2016 were acquired from OEH. This period was chosen as the study aims to investigate canopy condition during climate anomalies that occurred in recent years such as the end of the Millennium Drought and the La Nina period that followed, but also ‘standard’ climatic conditions. In addition to capturing long term climatic variability, capturing the phenological variability was also necessary, as it may change in response to climate phase. For this reason, remotely sensed data captured on board Landsat satellites were deemed the best available option. Level-1 data products derived from Landsat missions 5 & 8 both have a 30 m² spatial resolution for data in the visible spectrum and a
revisit time of 16-days (2016). Landsat imagery was deemed suitable for investigating RRG canopy condition in this study, as the 30 m² pixel size is able to detect RRG response to minor topographical features, such as flood runners, that may influence canopy condition at a relative spatio-temporal scale. All images were geometrically and radiometrically calibrated by OEH.

OEH provided vegetation metrics derived from Landsat 5 TM data for the years 2008-2011, and Landsat 8 OLI data for the years 2013-2016 for path 93, row 98. Landsat 7 ETM+ imagery is available for 2012, but was excluded from the analysis due to a scan-line corrector failure, which resulted in the loss of pixels from 22% of every image (Maxwell et al. 2007). Consequently, the year 2012 is devoid of any remotely sensed imagery and therefore represents a ‘data gap’ in the analyses.

Vegetation metrics used in this study are the Normalised Difference Vegetation Index (NDVI) and Foliage Projective Cover (FPC). NDVI provides a reliable measure of photosynthetic activity in green vegetation, whereas FPC is a measure of the proportional vertically projected foliage cover in woody vegetation >2 m in height. By investigating canopy condition dynamics using these metrics, this study can provide insight as to where differences may occur between the two. NDVI has been calculated using surface reflectance imagery and scaled to 8-bit range allowing it to be converted from pixel value (DN) back to NDVI using equation 4.1.

\[
NDVI = 0.005 \times DN - 0.3
\]

(eq. 4.1)

FPC was converted using top of atmosphere reflectance and BRDF corrected using techniques described in Danaher (2002). A linear conversion is also used to convert between FPC and DN (equation 4.2) and pixel values that lie between 101 and 200 on an 8-bit scale range yield a woody vegetation FPC value.

\[
FPC = DN \times 0.01 - 1
\]

(eq. 4.2)

4.2.5. Useable image selection

For each vegetation metric, a total of 92 images were provided for the entire time period. Each of these images was visually assessed to identify those which had atmospheric effects that interfered with the visibility of study plots. Atmospheric effects identified include cloud cover and smoke haze. Consequently, these images were removed from the analyses. Atmospheric effects
rendered 42% of imagery provided as un-useable. Of the useable images, 28% occurred in summer; 23% occurred in autumn; 15% occurred in winter and 34% in spring. The most sampled year was 2015, followed by 2014, with 2008-2011 & 2013 having between 4 and 6 useable images each (Table 4.4, Figure 4.3). The low number of useable images is due in part to the large spatial extent of the study area. This meant that there was a much higher probability of the presence of atmospheric effects and if one plot was affected the image was removed. As a result, highly irregular temporal spacing between sampling times became a key feature of the dataset and subsequent analyses.

Table 4.4 Summary Table of useable Landsat imagery for 8 years of data.

<table>
<thead>
<tr>
<th>Season</th>
<th>Images Provided</th>
<th>Images Used</th>
<th>Images Provided</th>
<th>Images Used</th>
<th>Total Useable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Summer</td>
<td>13</td>
<td>6</td>
<td>16</td>
<td>9</td>
<td>15</td>
</tr>
<tr>
<td>Autumn</td>
<td>8</td>
<td>6</td>
<td>10</td>
<td>6</td>
<td>12</td>
</tr>
<tr>
<td>Winter</td>
<td>1</td>
<td>1</td>
<td>14</td>
<td>7</td>
<td>8</td>
</tr>
<tr>
<td>Spring</td>
<td>13</td>
<td>9</td>
<td>17</td>
<td>9</td>
<td>18</td>
</tr>
<tr>
<td>Col. Total</td>
<td>35</td>
<td>22</td>
<td>57</td>
<td>31</td>
<td>53</td>
</tr>
</tbody>
</table>

4.3. Image Sub-Setting and Raster Value Extraction

A GIS system (ArcMap version 10.2) was used to subset images by removing areas of the image tile that fell outside the study area. This reduces file size, increases processing speeds, and is particularly important when working with large datasets. Image subsetting involved the creation of two subset layers, one encompassing the entire MVNP, the other containing each of the 53 x two hectare study plots that analyses would focus on. These layers were both polygonal shapefiles that were subsequently used in value extraction.

4.3.1. Creating 2ha study site layer

The 2 hectare study plot spatial subset (‘2ha’) was created by converting a point file of the corner-point locations of each study plot into a polygon shapefile using the editor tool in ArcMap 10.2. To do this, a new polygon shapefile is created in ArcCatalog using the same coordinate.
system as both the corner-point locations and the Landsat vegetation metrics (GDA 94 – MGA Zone 55S). Polygons were created and labelled for each study plot using the ‘editor’ tool, by joining the corner-points of the 2 ha plots. The 2 ha polygon shapefile produced, can then be used to clip, mask or extract data.

4.3.2. Creating MVNP ‘fishnet’ layer

The MVNP spatial subset (‘MVNP’) was created as a point shapefile that encompassed the extent of MVNP. User accuracy and precision was vital in this process, as the MVNP subset was also used to define the position of data extraction points. Using geometrically calibrated Landsat imagery as a reference, the x and y coordinates (metres) of the most northerly, southerly, easterly and westerly study plots were identified, and outwardly extended by 100 metres. These points placed in the ‘crossroads’ between Landsat pixels, and contained the entire MVNP (+100 m).

4.3.3. Extracting vegetation metric values from within 2ha study sites

To extract individual NDVI and FPC values, the MVNP point shapefile was used as the extent input to create a 'Fishnet' that covered the MVNP. The Fishnet tool creates point and polygon shapefiles of an evenly spaced grid of cells to a specified cell size (30 m$^2$ in this case, in order to line up with pixels in the Landsat rasters which the Fishnet would overlay) (Figure 4.4). In a separate layer, a point is positioned in the centre of Landsat pixel area. The 'Intersect' tool was used to subset the data into 54 x 2 ha polygons containing a single point overlaying each 30 m$^2$ pixel with its majority contained within the 2 ha study plot (Figures 4.5 & 4.6)
**Figures 4.5 & 4.6** ArcMap model to create extraction points for 2 ha study plots; Model output shows extraction points overlaying Landsat pixels of interest.

**Figure 4.4** Input specifications for creating a ‘Fishnet’ in ArcMap 10.2. Note that cell size, spatial extent and label points can all be specified rendering it an effective value extraction tool in ArcMap.
The 'Extract Values to Points' tool was used to create .dbf files of raster values which could be converted back to NDVI or FPC in Excel. There were 53 images for each metric from which data was required. An 'Iterative' component was added to the tool with a defined workspace (Figure 4.7). This basically works like a 'batch' and instructs the model to extract pixel values from each image contained within a defined location on the computer’s hard drive. Multiple pixel values were extracted from each of the 2 ha areas from all 54 study plots for all 53 images and converted to either NDVI or FPC using equations 4.1 & 4.2.

Skewness tests carried out in excel indicated that NDVI and FPC values were variably skewed within the 2 hectare study plots, so the median metric value from each 2 ha study plot was used in the analyses because median values are less impacted by outliers than means.

Figure 4.7 ArcMap model for extracting multiple pixel values from large datasets. Pixel values were then converted back to NDVI or FPC in Excel.
4.4. **Statistical Analyses**

Exploratory analyses and data visualisation were undertaken to understand how RRG canopy condition are assessed based on different metrics, to identify obvious trends and periodicity in the data series, and to investigate whether RRG canopy condition dynamics were impacted by SD or SQ. All statistical analyses were conducted in R version 3.2.3 (R Development Core team, 2015).

4.4.1. **The use of median as a statistical parameter**

Initially, all plot values were tested for skewness to determine a suitable parameter to be analysed. Plots were found to be variably skewed, both positively and negatively across the 53 dates in the time period, indicating the presence of outlying canopy condition values within the plots across time (Appendix 13). The degree of skewness was different for each plot and date. It was decided that median plot values would be analysed rather than means, as the median is more resistant than the mean to outliers.

4.4.2. **Justification for modelling**

Generalised Linear Mixed Modelling (GLMM) was used to account for the nested and autocorrelated structure of the data (Zuur et al. 2009, p. 101) in order to:

1. Determine whether SQ and SD play a role in driving RRG canopy condition dynamics.
2. Understand how RRG canopy condition dynamics in SQ and SD classes respond to hydrologic and climatic variability over time.
3. Identify which predictor variables explain the most variation in trend and periodic components.
4. Determine the amount of random noise in the data series.

Traditionally, a TSA may be used to decompose a time series into its constituents and account for temporal auto-correlation, however, due to the presence of frequent data gaps and highly irregular temporal sampling, it was not possible to use TSA without undertaking a substantial amount of interpolation. Using GLMM, RRG canopy condition dynamics are entirely accounted for in much the same way as TSA would do without the need to rely on interpolated data to fill
data gaps, thus ensuring results are based entirely on empirical. Modelling was implemented using the ‘lme’ framework within the ‘nlme’ package (Pinheiro et al. 2016), and the ‘MuMIn’ package was used to extract $r^2$ values (Barton, 2012).

Temporal auto-correlation describes how dates in a regularly-spaced time series are related to one another over time (Legendre & Legendre, 2012). When these relationships are plotted using the auto-correlation function (ACF), a pattern emerges that indicates the presence or absence of periodicity in the series. If periodicity is a component of the series, the ACF will repeat its cycle over time. In a TSA, data must be de-trended by differencing before determining the ACF. In other words, the ACF depicts only the periodicity and noise components of the data (Legendre & Legendre, 2012). To determine only the amount of noise present in the data, the partial ACF is used. The partial ACF looks at the amount of correlation between different dates while removing the influence of seasonality (Crawley, 2012, p. 785). This temporal component decomposition is an important step in a TSA, particularly when the role of periodicity cannot be ignored, and developing a methodology to account for trend, periodicity and noise was a challenging component of this study.

GLMM was able to identify and account for trend, periodicity and random noise in the data series by including temporal sin and cosine functions for annual periodicity as independent variables in the model formula. Significant coefficients for these variables indicated detected the presence, and relative influence of periodicity, while the importance of climatic and hydrologic variables was also assessed. The model residuals describe the amount of variation not accounted for by the seasonal and trend components, and are therefore considered ‘modelled’ random noise.

4.4.3. Model Selection

The decision to use GLMM was based on the size and complexity of variables in the dataset including nominal, ordinal, interval and ratio variables. The model had to be flexible enough to describe seasonal, trend and noise components in the data, as well as accounting for both fixed and random effects operating on the dataset. The output from a GLMM can be easily interpreted by those with little background in additive statistics, such as land managers and for this reason, GLMM was preferred to Generalized Additive Mixed Modelling (GAMM). Furthermore the modelling procedure had to be able to cope with irregular temporal lags between sampling times.
To date, GAMM statistical packages cannot incorporate spatial correlation structure to account for irregular sampling intervals (Wood, 2016).

4.4.4. Modelling the Data

The ‘lme’ framework in the ‘nlme’ package in R enables analysts to develop GLMMs in a flexible manner. Both fixed and random effects can be incorporated, as well as other important considerations when dealing with irregularly sampled data such as correlation structure. All explanatory variables were treated as fixed effects, with ‘Plot’ treated as a random effect. Interaction effects between stratified variables (SQ and SD) and hydro-climatic variables were explored. To account for irregular temporal lags between sampling times, a spherical correlation structure was specified. Spherical correlation structures are commonly used in spatial statistics but can also be adapted to temporal statistics. By using a spherical correlation structure, the length of a period can be specified within the model. This tells the model that the pattern of correlation present is consistent with each repetition of the period (Crawley, 2012, p. 825, Zuur, et al. 2009, p. 161). It was important for the model to be able to capture the seasonal component present in the data, therefore sin and cosine functions were included. It was presumed that the length of a cycle was equal to 12 months, and so a period equivalent to 365.25 days was specified for sin and cosine (Equation 4.3a, 4.3b). To do this, ‘day’ was converted to a decimal with 365.25 days = 1.0, 730.5 days = 2.0, and so on. The resultant Decimal Dates were multiplied by 2π to convert them to radians when used in the sin and cosine functions.

\[ 'SinTime' = \sin('Decimal Date'.2\pi) \]  
(eq. 4.3a)

\[ 'CosTime' = \cos('Decimal Date'.2\pi) \]  
(eq. 4.3b)

Using ‘SinTime’ and ‘CosTime’ allows the GLMM to model any sinusoidal annual pattern observed in the vegetation metrics irrespective of its amplitude and when the peak occurred during the year (Crawley, 2012, p. 785).
Another important consideration in the modelling process was the link function required to model the FPC data. FPC provides a proportional measurement of the amount of live, vertically projected canopy observed within a Landsat pixel. As a proportional measurement, its distribution curve is compressed relative to the normal distribution (Rodriguez, 2007, Ch. 3), and so a logit transform was applied to all FPC measurements using:

\[
\text{Logit } FPC = \ln \left( \frac{FPC}{1 - FPC} \right)
\]  

(\text{eq. 4.4})

Fitted models were then plotted against observed FPC by applying the inverse logit function:

\[
Fitted \ FPC = \frac{e^\alpha}{e^\alpha + 1}
\]  

(\text{eq. 4.5})

Where \( \alpha \) is the GLMM model estimated using Logit transformed FPC as the \( y \) variable. Manual transformation of the FPC data was necessary as no R packages were known that could do both mixed effects modelling with a spherical correlation structure that would account for irregular temporal lags between sample dates, and allow the logit link function to be specified.

Initial modelling of median values of NDVI and FPC sought to describe the entire 8 year period. However, it became evident that the model did not fit the wet period (2010-2011) very well using the variables available, so modelling each distinct climatic period separately was investigated. This prevented the tendency for periods of water scarcity to negatively influence the model during periods of water abundance.

Models were developed using a top-down approach, whereby the most likely explanatory variables were included first. Predictors with high \( p \)-values were removed one at a time and the model re-fitted with variable eliminated based on significance scores and Akaike’s Information Criterion values (AIC) whereby lower absolute AIC values indicate a better model fit (Akaike, 1974). Models with lower AIC scores and statistically significant variables were deemed superior in terms of describing which variables were having an effect on canopy condition, and how much influence each variable had. Assumptions of normality and homogeneity of variance underpinning the models were verified graphically using quantile-quantile plots and residual vs. fitted plots. R code for the analyses and diagnostic plots is presents in Appendices 1-7.
5. Results

5.1. Relationship between NDVI and FPC

The dynamic response of remotely sensed vegetation metrics over time were compared for the 8-year period. NDVI and FPC behaved in a consistent manner, following the same general pattern for the dates between 2008 – 2010 and 2013 – 2016. In the years 2010 – 2012, FPC experienced a sharp increase whereas NDVI increased in a more subdued manner. It should be noted that FPC is a proportional measurement and ranges between 0 and 1, whereas NDVI has twice this range (-1 to +1), and therefore this difference between 2010 – 2012 is not due to scale, as FPC would have become even more stretched if applied to a -1 to +1 scale. The relatively sharp increase in FPC may suggest that abundant epicormic growth may have occurred in response to increased water availability, roughly resulting in a 50% increase in vertically projected foliage cover from 2010-2011. NDVI also increased over this period, suggesting that the amount of photosynthetically active foliage increased (Figure 5.1).

![Exploratory stage plot of NDVI (blue) and FPC (yellow) for all 54 plots across the entire time period.](image)

**Figure 5.1:** Exploratory stage plot of NDVI (blue) and FPC (yellow) for all 54 plots across the entire time period.
5.2. Visual exploration of general trends and periodicity

Scatterplots (Figure 5.1) and Boxplots (Figure 5.2) of NDVI and FPC were used to identify obvious periodicity or trends present in the data series. The scatterplot revealed the presence of a seasonal cycle in the years 2013 – 2016. This periodicity is not clear in the years 2010 – 2011, but data from 2008 – 2010 hints at a periodic cycle. Boxplots of FPC and NDVI for the 8-year period indicate the presence of three distinct periods of trend in the data; a neutral period from 2008 – 2009, followed by a positive trend occurring in the years 2010 – 2011, and finally a weak negative trend occurring between 2013 – 2016. The boxplots were unable to pinpoint exactly when these trends began and ended, but they provided a good indication of where to search for key points and patterns in the data. Boxplots also suggested that the range increases as NDVI and FPC values increase, and this may be indicative of the amount of variation observed in better condition RRG canopy. Table 5.1 summarises the data used in this stage of analysis.

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Images</th>
<th>Images x Sites</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008</td>
<td>4</td>
<td>216</td>
</tr>
<tr>
<td>2009</td>
<td>6</td>
<td>324</td>
</tr>
<tr>
<td>2010</td>
<td>6</td>
<td>324</td>
</tr>
<tr>
<td>2011</td>
<td>6</td>
<td>324</td>
</tr>
<tr>
<td>2012</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>2013</td>
<td>5</td>
<td>270</td>
</tr>
<tr>
<td>2014</td>
<td>11</td>
<td>594</td>
</tr>
<tr>
<td>2015</td>
<td>13</td>
<td>702</td>
</tr>
<tr>
<td>2016</td>
<td>2</td>
<td>108</td>
</tr>
<tr>
<td>Total</td>
<td>53</td>
<td>2862</td>
</tr>
</tbody>
</table>
Figure 5.2 Boxplots for NDVI (top) and FPC (bottom) for each median plot value of all plots per year.
Boxplots give an indication of trend and variation by illustrating the median, upper and lower quartiles, as well as the range and presence of any outliers.

5.3. Visual exploration of stratified variables: site quality and stem density

Plots of FPC and NDVI for the time period were used to investigate patterns between stratified variables. FPC and NDVI were plotted for the 8-year time period and differentiated by site quality (SQ) and stem density (SD) to investigate whether they behave in a distinct manner from one another. Plots suggest that SQ may play a role in canopy condition dynamics over the entire period, with consistently higher values observed in SQ-1 canopies compared with SQ-2 canopies in both vegetation metrics (Figures 5.3a, 5.3b).
Figure 5.3a Relationship between SQ-1 & SQ-2 canopies FPC response for the entire time period. Canopies in SQ-1 consistently demonstrate higher values when compared with canopies in SQ-2.

Figure 5.3b Relationship between SQ-1 & SQ-2 canopies NDVI response for the entire time period. Canopies in SQ-1 consistently demonstrate higher values when compared with canopies in SQ-2.

When different SD classes were compared, no clear pattern could be observed in either FPC or NDVI plots, and values appeared randomly interspersed (Figures 5.4a, 5.4b). More rigorous
statistical methods were required to determine whether SQ or SD have an influence on RRG canopy condition dynamics, and whether any interaction effects might be present.

**Figure 5.4a** Plot indicates the relationship between SD groupings as observed in FPC for the entire time period. A clear or consistent pattern does not exist.

**Figure 5.4b** Plot indicates the relationship between SD groupings as observed in NDVI for the entire time period. A clear or consistent pattern does not exist.
5.4. Investigating drivers of change: Generalised Linear Mixed Effects Modelling

5.4.1. Modelling the entire eight year period

Initial attempts to model canopy condition across the entire data series found the best fit for both NDVI and FPC to be a combination of monthly total precipitation, mean monthly minimum and maximum temperature, SOI, weekly mean river discharge, SQ as well as sine and cosine functions (Table 5.7). As SQ was found to be a significant predictor, both classes (SQ-1 and SQ-2) were modelled separately to depict their behaviour throughout the series. Models for the 8-year period show SQ-1 as having a consistently better canopy condition than SQ-2 (Figures 5.5a, 5.5b). However, the models showed some weaknesses. Both NDVI and FPC models provide a loose fit of the data, and the FPC model fails to explain the strong positive trend occurring late 2010, early 2011 (Figure 5.5b). Neither stem density nor % live basal area were found to be statistically significant drivers of canopy condition.

![Figure 5.5a](image)

**Figure 5.5a** Initial attempts at GLMM modelling for NDVI produced loose fits. Canopies in SQ-1 are modelled as being in a consistently better condition for the entire 8-year period.
Figure 5.5b  Similar to NDVI models, initial attempts at GLMM modelling for FPC produced loose fits and fitted values failed to capture the observed peak in 2010 – 2011. Canopies in SQ-1 are modelled as being in a consistently better condition for the entire 8-year period.

Table 5.7  Summary of variables tested and fitted in initial GLMMs. ‘●’ indicates use in best fit model.

<table>
<thead>
<tr>
<th>Tested</th>
<th>Fitted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monthly Rain</td>
<td>NDVI</td>
</tr>
<tr>
<td>Lagged Monthly Rain</td>
<td></td>
</tr>
<tr>
<td>log (Monthly Rain + 1)</td>
<td>●</td>
</tr>
<tr>
<td>Mean Monthly Max Temperature</td>
<td>●</td>
</tr>
<tr>
<td>Mean Monthly Min Temperature</td>
<td>●</td>
</tr>
<tr>
<td>Lagged Minimum Temperature</td>
<td>●</td>
</tr>
<tr>
<td>Mean Monthly Temperature Range</td>
<td></td>
</tr>
<tr>
<td>SOI</td>
<td>●</td>
</tr>
<tr>
<td>Lagged SOI</td>
<td>●</td>
</tr>
<tr>
<td>Monthly Mean Discharge</td>
<td></td>
</tr>
<tr>
<td>Weekly Mean Discharge</td>
<td></td>
</tr>
<tr>
<td>Lagged Weekly Mean Discharge</td>
<td>●</td>
</tr>
<tr>
<td>log (Weekly Mean Discharge + 1)</td>
<td>●</td>
</tr>
<tr>
<td>Site Quality</td>
<td>●</td>
</tr>
<tr>
<td>Stem Density</td>
<td></td>
</tr>
<tr>
<td>Live Basal Area</td>
<td></td>
</tr>
<tr>
<td>Sin Time</td>
<td>●</td>
</tr>
<tr>
<td>Cosine Time</td>
<td>●</td>
</tr>
<tr>
<td>Interactions</td>
<td></td>
</tr>
</tbody>
</table>
It is likely that the periods from 2008 – 2010 and 2013 - 2016 caused the model to underestimate RRG canopy condition during the 2010 – 2011 period by giving too much weight to data points at either end of the data series. Giving consideration to the hydrologic and climatic variability across the 8-year time period provided a rationale for modelling separately three distinct periods. The Murray Darling Basin was heavily affected by the Millennium drought from 2001 to 2010 whereby areas immediately upstream of MVNP recorded their lowest ever rainfall for the period from 2006 – 2010 (Figure 5.6). This occurred just before the drought was broken by a strong La Nina event (Figure 5.7), in which SE Australia witnessed its wettest two years on record (CSIRO, 2012; BoM, 2012). Subsequently, significant flooding occurred when MVNP received large environmental water allocations in 2010 and 2011 (199 GL and 424.6 GL per respective year) (MDBA, 2012). Since then, SOI has slowly been in decline and reverted back to El Nino conditions in Autumn 2015. On this basis, modelling was applied to the three distinct climatic and hydrologic periods as summarised below (Table 5.8, Figure 5.8). As a result, individual models were developed for SQ-1 and SQ-2 sites for the ‘drought’, ‘wet’ and ‘recent’ periods in the data series.

### Table 5.8 Summary of trend features

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Climatic Feature</th>
<th>Climatic Attribute</th>
<th>Canopy Condition Trend</th>
<th>Obvious Periodicity</th>
</tr>
</thead>
<tbody>
<tr>
<td>2008 - 2010</td>
<td>&quot;Millenium Drought&quot;</td>
<td>Dry</td>
<td>Neutral</td>
<td>No</td>
</tr>
<tr>
<td>2010 - 2011</td>
<td>Strong La Nina</td>
<td>Wet</td>
<td>Positive</td>
<td>No</td>
</tr>
<tr>
<td>2013 - 2016</td>
<td>SOI Decline</td>
<td>Stable/Drying</td>
<td>Weak negative</td>
<td>Yes</td>
</tr>
</tbody>
</table>
**Figure 5.6** Map showing severe rainfall deficiencies immediately upstream of MVNP for the period 2006-2010 (Bom, 2016).

**Figure 5.7** Monthly SOI graph shows a sustained La Nina event occurring between autumn 2010 and autumn 2011, followed by a drawn out decline back to an El Nino phase in autumn 2015. This is evident in RRG canopy condition during the same period.
5.4.2. Modelling distinct periods

A better model fit was achieved for NDVI for all periods based on AIC scores (Tables 5.9, 5.10). It became clear that different predictors were impacting different periods. For instance, temperature did not contribute significantly to NDVI derived canopy condition in the wet period (Table 5.9) and FPC derived canopy condition in the most recent period could be best explained by SOI, SQ and Sin and Cosine functions (Table 5.10). Log transformed weekly mean discharge was found to play a significant role in driving canopy condition for the drought and wet periods, but not in the recent period. SQ, SOI and Cosine function were the only two variables that were influential in all periods for all vegetation metrics. Live Basal Area was not found to be statistically significant in any of the models for either vegetation metric.
Table 5.9 Summary of variables tested and fitted in NDVI periodic GLM models. ‘●’ indicates best fit variable.

<table>
<thead>
<tr>
<th>Variables Tested</th>
<th>NDVI</th>
<th>NDVI</th>
<th>NDVI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Drought period</td>
<td>Wet period</td>
<td>Recent period</td>
</tr>
<tr>
<td></td>
<td>Fit</td>
<td>p-value</td>
<td>Fit</td>
</tr>
<tr>
<td>Monthly Rain</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged Monthly Rain</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log (Monthly Rain + 1)</td>
<td>●</td>
<td>p&lt;0.001</td>
<td>●</td>
</tr>
<tr>
<td>Mean Monthly Max Temperature</td>
<td>●</td>
<td>p&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Mean Monthly Min Temperature</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged Minimum Temperature</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean Monthly Temperature Range</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SOI</td>
<td>●</td>
<td>p&lt;0.001</td>
<td>●</td>
</tr>
<tr>
<td>Lagged SOI</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monthly Mean Discharge</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weekly Mean Discharge</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged Weekly Mean Discharge</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log (Weekly Mean Discharge + 1)</td>
<td>●</td>
<td>p&lt;0.001</td>
<td>●</td>
</tr>
<tr>
<td>Site Quality</td>
<td>●</td>
<td>p&lt;0.001</td>
<td>●</td>
</tr>
<tr>
<td>Stem Density</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Live Basal Area</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sin Time</td>
<td>●</td>
<td>p&lt;0.001</td>
<td>●</td>
</tr>
<tr>
<td>Cosine Time</td>
<td>●</td>
<td>p&lt;0.001</td>
<td>●</td>
</tr>
<tr>
<td>Interactions</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC Score</td>
<td>-2733.028</td>
<td>-1604.617</td>
<td>-4652.508</td>
</tr>
</tbody>
</table>
Table 5.10 Summary of variables tested and fitted in FPC periodic GLM models. ‘●’ indicates best fit variable.

<table>
<thead>
<tr>
<th>Variables Tested</th>
<th>FPC</th>
<th>Drought period</th>
<th>Wet period</th>
<th>Recent period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Fit</td>
<td>p-value</td>
<td>Fit</td>
</tr>
<tr>
<td>Monthly Rain</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Lagged Monthly Rain</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>log (Monthly Rain + 1)</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Mean Monthly Max Temperature</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean Monthly Min Temperature</td>
<td>●</td>
<td>p&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged Minimum Temperature</td>
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<td></td>
<td></td>
<td></td>
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<td>Mean Monthly Temperature Range</td>
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<tr>
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<td>●</td>
<td>p&lt;0.001</td>
<td>0.0044</td>
<td>●</td>
</tr>
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<td>Lagged SOI</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Monthly Mean Discharge</td>
<td></td>
<td></td>
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<tr>
<td>Weekly Mean Discharge</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged Weekly Mean Discharge</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log (Weekly Mean Discharge + 1)</td>
<td>●</td>
<td>p&lt;0.001</td>
<td>p&lt;0.001</td>
<td></td>
</tr>
<tr>
<td>Site Quality</td>
<td>●</td>
<td>p&lt;0.001</td>
<td>p&lt;0.001</td>
<td>●</td>
</tr>
<tr>
<td>Stem Density</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Live Basal Area</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sin Time</td>
<td>●</td>
<td>p&lt;0.001</td>
<td>p&lt;0.001</td>
<td>●</td>
</tr>
<tr>
<td>Cosine Time</td>
<td>●</td>
<td>p&lt;0.001</td>
<td>p&lt;0.001</td>
<td>●</td>
</tr>
<tr>
<td>Interactions</td>
<td></td>
<td></td>
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<td></td>
</tr>
</tbody>
</table>

**AIC Score**

-549.61  786.58  50.29
Figure 5.9 Three periods of modelled NDVI RRG canopy condition. Blue lines represent period boundaries based on changes in hydrology or climate. This model is a better fit than the initial 8-year period models.

Figure 5.10 Three periods of modelled FPC RRG canopy condition. Blue lines represent period boundaries based on changes in hydrology or climate. This model is a better fit than the initial 8-year period models.
5.4.3. RRG canopy condition dynamics in the drought period (2008 – 2010)

When compared with wet and recent periods, the NDVI and FPC measured drought period was characterised by generally weaker seasonal and trend components which accounted for 56% and 77% respectively of the signal as indicated by the conditional $R^2$ value. Unexplained noise component made up 44% and 23% of the modelled period for NDVI and FPC respectively (Tables 5.11a, 5.11b). There is little difference between RRG canopy condition for SQ-1 and SQ-2 during the drought, both classes exhibit uniformly low condition values for the period (Figure 5.9, 5.10, 5.11a, 5.11b).

Table 5.11a Summary of model output for NDVI period 1 (Drought)

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>DF</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>log Monthly Rain + 1</td>
<td>0.0024</td>
<td>0.0005</td>
<td>524</td>
<td>4.4165</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>Mean Month Max Temp</td>
<td>-0.0038</td>
<td>0.0003</td>
<td>524</td>
<td>-13</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>SOI</td>
<td>0.0067</td>
<td>0.0009</td>
<td>524</td>
<td>8.9486</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>log Weekly Mean Discharge + 1</td>
<td>0.0248</td>
<td>0.0039</td>
<td>524</td>
<td>6.2999</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>SQ</td>
<td>-0.0386</td>
<td>0.0094</td>
<td>51</td>
<td>-4.1211</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>Sin</td>
<td>0.0383</td>
<td>0.0017</td>
<td>524</td>
<td>22.3886</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>Cos</td>
<td>-0.0548</td>
<td>0.0046</td>
<td>524</td>
<td>-11.9762</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>0.2802</td>
<td>0.0427</td>
<td>524</td>
<td>6.5665</td>
<td>p&lt;0.001</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Random Effects</th>
<th>Std Dev</th>
<th>Residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.0324</td>
<td>0.0224</td>
</tr>
<tr>
<td>Conditional $R^2$</td>
<td>0.56</td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>-2733.028</td>
<td></td>
</tr>
</tbody>
</table>
## Table 5.11b Summary of model output for FPC period 1 (Drought)

### Logit FPC ~ Mean Month Min Temp + SOI + log (Weekly Mean Discharge +1) + SQ + Sin + Cos

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>DF</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Month Min Temp</td>
<td>-0.024</td>
<td>0.002</td>
<td>525</td>
<td>-12.161</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>SOI</td>
<td>0.0527</td>
<td>0.0067</td>
<td>525</td>
<td>7.8256</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>log(Weekly Mean Discharge + 1)</td>
<td>0.1029</td>
<td>0.0265</td>
<td>525</td>
<td>3.8876</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>SQ</td>
<td>-0.2933</td>
<td>0.0719</td>
<td>51</td>
<td>-4.0784</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>Sin</td>
<td>0.1478</td>
<td>0.0131</td>
<td>525</td>
<td>11.3172</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>Cos</td>
<td>-0.1687</td>
<td>0.0272</td>
<td>525</td>
<td>-6.2127</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>-1.6681</td>
<td>0.2801</td>
<td>525</td>
<td>-5.9558</td>
<td>p&lt;0.001</td>
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</tbody>
</table>

### Random Effects

<table>
<thead>
<tr>
<th>(Intercept)</th>
<th>Residual</th>
</tr>
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<tbody>
<tr>
<td>Std Dev</td>
<td>0.2464</td>
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</table>

<table>
<thead>
<tr>
<th>Conditional R^2</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.77</td>
<td>-549.61</td>
</tr>
</tbody>
</table>
Figure 5.11a Uniformly low NDVI in SQ-1 and SQ-2 observed during drought period.
Figure 5.11b Uniformly low NDVI in SQ-1 and SQ-2 observed during drought period.
5.4.4. RRG canopy condition dynamics in the wet period (2010 – 2011)

The wet period from 2010 – 2011 was characterised by a strong positive trend driven by weekly mean river discharge. This is expected as water was abundant during this period, and substantial environmental flows saturated parts of MVNP. Periodicity is also more evident here than in the drought period, particularly in the FPC model, and is indicated by larger coefficients for sin and cosine functions. Combined trend and periodicity were prominent in the wet period, explaining 68 and 74% of the model for NDVI and FPC respectively. Therefore the noise component made up 32% and 26% in respective NDVI and FPC models (Table 5.12a, 5.12b). SQ-1 and SQ-2 behaved similarly to one another, and uniformly high values were observed across both classes in vegetation metrics (Figure 5.10a, 5.10b, 5.12a, 5.12b).

<table>
<thead>
<tr>
<th>NDVI ~ log (Monthly Rain + 1) + SOI + log (Weekly Mean Discharge + 1) + SQ + Sin + Cos</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed Effects</strong></td>
</tr>
<tr>
<td>Coefficient</td>
</tr>
<tr>
<td>log (Monthly Rain + 1)</td>
</tr>
<tr>
<td>SOI</td>
</tr>
<tr>
<td>log (Weekly Mean Discharge + 1)</td>
</tr>
<tr>
<td>SQ</td>
</tr>
<tr>
<td>Sin</td>
</tr>
<tr>
<td>Cos</td>
</tr>
<tr>
<td>(Intercept)</td>
</tr>
<tr>
<td><strong>Random Effects</strong></td>
</tr>
<tr>
<td><strong>(Intercept)</strong></td>
</tr>
<tr>
<td><strong>Residual</strong></td>
</tr>
</tbody>
</table>

Table 5.12a Model output for NDVI period 2 (Wet).
Table 5.12b Model output for FPC period 2 (Wet)

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>DF</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Month Min Temp</td>
<td>-0.1539</td>
<td>0.0138</td>
<td>578</td>
<td>-11.1685</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>SOI</td>
<td>0.0646</td>
<td>0.0226</td>
<td>578</td>
<td>2.8606</td>
<td>0.004</td>
</tr>
<tr>
<td>log(Weekly Mean Discharge + 1)</td>
<td>0.8228</td>
<td>0.032</td>
<td>578</td>
<td>25.7295</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>SQ</td>
<td>-0.4114</td>
<td>0.0548</td>
<td>51</td>
<td>-7.5112</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>Sin</td>
<td>0.4501</td>
<td>0.033</td>
<td>578</td>
<td>13.6336</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>Cos</td>
<td>0.6427</td>
<td>0.1025</td>
<td>578</td>
<td>6.2691</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>-7.6246</td>
<td>0.3541</td>
<td>578</td>
<td>-21.5313</td>
<td>p&lt;0.001</td>
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</table>

Random Effects

<table>
<thead>
<tr>
<th></th>
<th>(Intercept)</th>
<th>Residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. Dev</td>
<td>0.156</td>
<td>0.4136</td>
</tr>
</tbody>
</table>

Conditional R² | 0.74 |

AIC | 786.5789 |
Figure 5.12a: Uniformly high NDVI in SQ-1 and SQ-2 observed during anomalously wet period.
Figure 5.12b: Uniformly high NDVI in SQ-1 and SQ-2 observed during anomalously wet period
5.4.5. RRG canopy condition dynamics in the recent period (2013 – 2016)

Modelling for the most recent period showed a weak negative trend and clear seasonality which explained 62% and 38% of the variance in respective NDVI and FPC signals. Noise was therefore 38% and 62% in the respective NDVI and FPC models (Table 5.13a, 5.13b). SQ was the most influential variable acting during the most recent time period, and SQ-1 canopies were in better condition than those observed in SQ-2 (Figure 5.10a, 5.10b, 5.13a, 5.13b).

Table 5.13a: Model output for NDVI period 3 (Recent)

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Coefficients</th>
<th>Std. Error</th>
<th>DF</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>log (Monthly Rain + 1)</td>
<td>0.0162</td>
<td>0.0017</td>
<td>1586</td>
<td>9.609</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>Mean Monthly Max Temp</td>
<td>0.0069</td>
<td>0.0008</td>
<td>1586</td>
<td>8.696</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>SOI</td>
<td>0.0257</td>
<td>0.0019</td>
<td>1586</td>
<td>13.777</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>SQ</td>
<td>-0.0653</td>
<td>0.0087</td>
<td>51</td>
<td>-7.4923</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>Cos</td>
<td>-0.1504</td>
<td>0.0078</td>
<td>1586</td>
<td>-19.3972</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>0.43</td>
<td>0.0235</td>
<td>1586</td>
<td>18.3077</td>
<td>p&lt;0.001</td>
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<table>
<thead>
<tr>
<th>Random Effects</th>
<th>(Intercept)</th>
<th>Residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std Dev</td>
<td>0.0281</td>
<td>0.0613</td>
</tr>
<tr>
<td>Conditional R²</td>
<td>0.62</td>
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</tr>
<tr>
<td>AIC</td>
<td>-4652.508</td>
<td></td>
</tr>
</tbody>
</table>

Table 5.13b: Model output for FPC period 3 (Recent)

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Coefficients</th>
<th>Std. Error</th>
<th>DF</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOI</td>
<td>0.1159</td>
<td>0.0089</td>
<td>1587</td>
<td>13.0262</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>SQ</td>
<td>-0.3364</td>
<td>0.0419</td>
<td>51</td>
<td>-8.0338</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>Sin</td>
<td>-0.0522</td>
<td>0.0193</td>
<td>1587</td>
<td>-2.7098</td>
<td>0.007</td>
</tr>
<tr>
<td>Cos</td>
<td>-0.2831</td>
<td>0.0199</td>
<td>1587</td>
<td>-14.2476</td>
<td>p&lt;0.001</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>-0.3113</td>
<td>0.0322</td>
<td>1587</td>
<td>-9.6691</td>
<td>p&lt;0.001</td>
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</table>

<table>
<thead>
<tr>
<th>Random Effects</th>
<th>(Intercept)</th>
<th>Residual</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std Dev</td>
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<td>0.3661</td>
</tr>
<tr>
<td>Conditional R²</td>
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</tr>
<tr>
<td>AIC</td>
<td>50.29313</td>
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</tbody>
</table>
Figure 5.13a: SQ-1 canopies more resilient than SQ-2 canopies in average climatic and hydrologic conditions.
Figure 5.13b: SQ-1 canopies more resilient than SQ-2 canopies in average climatic and hydrologic conditions.
5.4.6. Periodicity in the models

Coefficients for sin and cosine functions during each period were used to model NDVI and FPC periodicity. Models show that the periodic component for the series driven by vegetation phenology behaves differently over time. When comparing NDVI periodicity for each time period, two noteworthy features are exposed: 1. Peak NDVI function shifted from late autumn into winter across the 8-year time period; and 2. The amplitude of the signal increased slightly from the drought to the wet period, before nearly tripling in the most recent period (Figure 5.14).

![Figure 5.14](image-url) Comparison of modelled NDVI periodicity for each time period.

The same was investigated for logit transformed FPC. Results showed that the drought period also peaked in late August, and so did the incrementally larger recent period seasonal cycle. However, the wet period seasonal cycle was four times larger than the drought and three and a half times larger than the recent period signal. In addition, the wet period seasonal signal peaks in late summer (Figure 5.15).
Figure 5.15 Comparison of modelled FPC periodicity for each time period.

The increase in signal strength may be partly attributed to increasing average monthly precipitation recorded at Mathoura within each period. A simple model shown below (Figure 5.16) compares average monthly precipitation observations for each period in the lead up to winter. The dotted lines represent the 3-month stationary average. A clear precipitative increase with each period can be observed and this is reflected in the seasonal signal.

Figure 5.16 Comparison of average monthly precipitation observed in each of the periods (Drought, Wet & Recent). 3-month stationary averages (dotted lines) show that precipitation increased in the pre-winter months with each period.
Figure 5.17: Residual plots for Site Qualities 1 & 2. When related back to the three components of a time series analysis, these plots account for the random noise component occurring in SQ-1 and SQ-2 canopy condition dynamics.

Using GLMM to model canopy condition dynamics occurring over distinct periods proved useful in describing trends, periodicity and random noise present in the data series. By including sin and cosine functions any periodicity occurring over the time period was able to be identified and reasonably well accounted for in both models. All trends occurring from observation to observation are described by the stratified, hydrologic and climatic variables coefficients included in the model output. Residuals observed in NDVI models for each Landsat overpass can be seen above (Figure 5.17).
6. Discussion

This study used remotely sensed vegetation indices to determine whether intra-species competition and/or water availability had an impact on RRG canopy condition dynamics in MVNP. The study also sought to determine how hydrologic and climatic variability impacts RRG canopy condition in MVNP. This was done using GLMMs on a data series between 2008 and 2016 and covering highly variable hydro-climatic periods. Despite being faced with a temporally fragmented Landsat data set, trend and seasonal components of the modelling were derived and used to develop a baseline understanding of RRG canopy condition dynamics in MVNP against which the impacts of ecological thinning can be compared.

This discussion considers the hydro-climatic variables that contribute to the modelled trends in relation to relevant research on RRG ecology and forest management. Furthermore, the section provides context to the periodicity modelled by the GLMM by relating it to broader research and considers which variables not included in the models could contribute significantly to the amount of noise present in the data.

6.1. Trends in RRG canopy condition

6.1.1. Reports of decline in condition

A number of recent studies exist that report on trends in RRG Forest and broader ecological condition throughout the Murray-Darling Basin (Cunningham et al. 2010a; Mac Nally, et al. 2011; Bennetts & Jolly, 2012; Colloff et al. 2015; Fu & Burgher, 2015; Wen & Sainvilan, 2015). By analysing trends through the lens of GLMM, this study was able to identify positive and negative canopy condition trajectories as well as drivers of condition within each period. This study analysed three distinct trend periods occurring during the 9-year time frame: the dry period (2008 – 2010); the wet period (2010 – 2011); and the recent period (2012 – 2016). The dry period analysed in this study exhibited low NDVI and FPC values occurring in conjunction with a somewhat neutral trend, with vegetation metrics driven primarily by weekly mean discharge, SOI and site quality (Tables 5.11a, 5.11b above). Other studies undertaken within the Murray-Darling Basin covering the same time period described either negative or neutral trends occurring. Cunningham et al. (2010a) reported an overall decrease in canopy condition between 2009 and 2010 across the Murray River floodplain. The timing of monitoring may have influenced their
assessment as investigations were carried out in summer and autumn of 2009 and 2010 prior to the end of the Millennium Drought. At this time rainfall deficiencies remained anomalously high in southern parts of the Murray-Darling Basin (BoM, 2016) (Figure 5.6). It is not unusual that conditions appeared to decline in Cunningham et al.’s study, as this study found that conditions didn’t begin to improve until after autumn 2010. Mac Nally et al. (2011) considered trend over a much longer time period (1990 – 2009). Authors reported the negative trajectory of RRG Forest condition along the Victorian Murray, suggesting that the presence of dieback increased from affecting 45% of RRG Forests in 1990 to affecting 70% of RRG Forests in 2009. It should be noted that 1990 was the beginning of a long-term El Nino event (Trenberth & Hoar, 1996), and 2009 was the end of a major drought in south-eastern Australia (BoM, 2012). Again it would be expected that trends would have had a negative trajectory when a comparison is made between these two dates.

The temporal resolution considered in the investigations by Cunningham et al. (2010a) and Mac Nally et al. (2011) do not capture any periods of RRG canopy condition recovery. Although Cunningham et al. (2010a) does speculate on whether extensive flooding along the Murray at the time of publication would bring RRG Forests back from widespread poor condition. Only a handful of studies exist that assess whether there was evidence for RRG recovery post Millennium Drought in the Murray-Darling Basin. This is a fundamental consideration, given the number of reports published around their poor condition during the Millennium Drought (Jurskis et al. 2005; Cunningham et al. 2007; Cunningham et al. 2009; Mac Nally et al. 2009; NRC 2009a).

In contrast with the negative trajectory reported in Cunningham et al. (2010a), Fu & Burgher (2015) found an improvement in condition between 2009 and 2010 of riparian ecosystems in eastern half of the Namoi catchment. However, these authors go on to state that trajectories in western riparian communities agreed with Cunningham et al. (2010a), whereby their condition continued to decline in 2010. Fu and Burgher (2015) relate this longitudinal decline to increases in groundwater depth, whereas Cunningham et al. (2010b) suggests the pattern of longitudinal decline to be due in part to a decrease in flooding frequency occurring in a westward direction along the River Murray. The research carried out in this study did not consider longitude as a predictor of canopy condition, due to the smaller scale of investigation.

By only analysing two years of drought this study found trends during the drought period modelled by GLMM to be relatively neutral between 2008 and 2010. Wen and Saintilan did not investigate the same drought period as that which was investigated in this study (2008-2010). Instead their drought period was determined by automated modelling which identified a
significant decrease in condition occurring between a high rainfall event at the beginning of 2006, until late 2008 before conditions began to improve again (Wen & Saintilan, 2015). Subsequently, the reported negative trend over the drought period ran from 2000 until late 2008, before an improving trend was identified beginning in 2009. Had this study investigated the same period as that of Wen and Saintilan, it would likely have modelled a stronger decline in trend during the drought period. However, the periods used in this investigation were determined by the analyst, rather than by statistical methods, which limits the depth of comparison that can be made about trends during the Millennium Drought. There is scope for extending this study further back in time to better capture RRG canopy condition trends during the drought period. Additionally, classification tree modelling may be used to identify statistical breaks in trends (Wen et al. 2009; Fu & Burgher, 2015).

6.1.2. Period of recovery

Cunningham et al. (2010a) speculate as to whether RRG along the Murray would recover from their poor condition post-drought. This has been partially answered in the results of this study. RRG canopy condition was found to recover from the Millennium Drought in the Central Murray in response to the onset of a strong La Nina event and the subsequent increase in river discharge. The results of Wen and Saintilan (2015) from RRG Forests in the Murrumbidgee catchment agree, whereby a sharp positive trend in NDVI was observed post-2010. The period of recovery in this study was referred to as the ‘wet’ period due to the anomalously high rainfall that occurred therein (BoM, 2012). Bennetts and Jolly (2012) also report a recovery of canopy condition observed in the Gunbower Forest, west of MVNP during the La Nina years. RRG are known to increase leaf area, photosynthetic activity and thus primary productivity in response to increased water availability (Briggs & Maher, 1983; Bacon et al. 1993; Stone & Bacon, 1994; Forrester, et al. 2012; Wen et al. 2012). Thus, it is not unusual that vegetation metrics were observed and modelled to increase sharply during the wet period.

6.1.3. Recent conditions and the innate variability of condition in inland freshwater ecosystems

More recently, RRG canopy condition trends have begun to decline again (Figures 5.9 & 5.10).
Since 2012, SOI has gradually moved back into a negative El Nino phase, resulting in less rainfall occurring in south-eastern Australia (Stone & Auliciems, 1992; Pepler et al. 2015). This change in climatic conditions is driving canopy condition in MVNP (Tables 5.13a, 5.13b above) and more broadly throughout the Murray-Darling Basin, as supported by Wen and Saintilan (2015), who used MODIS 250m² NDVI time series to track a decline in canopy condition between 2012 and 2013. Wen and Saintilan (2015) reported that climate phase drives canopy condition in large semi-arid floodplains, and the evidence found in this study would agree, with observations of decline in condition continuing up until 2016.

Canopy condition in SQ-1 plots tends to have remained resilient post drought recovery when compared to SQ-2 plots. Canopy conditions in SQ-1 were modelled as becoming increasingly distinguishable from that of SQ-2 post-drought recovery, it is likely that SQ-1 has better access to both ground and surface water (Baur, 1984) and may occur in areas where soil water retention is greater (Bacon et al. 1993). Groundwater depth is important in preventing saline leaching which has an adverse effect on RRG canopy condition along the Murray River floodplain (Cunningham et al. 2011). Additionally groundwater depth has been shown to determine the distribution of RRG throughout parts of semi-arid Australia (Kath et al. 2014a, 2014b). In conjunction with better access to groundwater, it is likely that SQ-1 plots may be more frequently inundated and for longer periods due to differences in micro-topography. As a result, RRG are able to increase leaf area, photosynthetic activity and thus primary productivity in response to increased water availability in SQ-1 plots (Briggs & Maher, 1983; Bacon et al. 1993; Stone & Bacon, 1994; Forrester, et al. 2012; Wen et al. 2012).

Along with other studies that consider vegetation condition for more than two years (Bennetts & Jolly, 2012; Colloff et al. 2015; Fu & Burgher, 2015; Wen & Saintilan, 2015), this study was able to observe periods of recovery as well as decline. Colloff et al. (2015) remark that the cycle of short-term decline and recovery is a characteristic feature of floodplain ecosystems, and that the level of resilience displayed by the species that inhabit them permit their existence under highly variable rainfall patterns in semi-arid Australia. While RRG along the Mid-Murray have been able to recover, less resilient species, such as Spiny Mud Grass (*Pseudoraphis spinescens*), have continued to struggle (Colloff et al. 2014, 2015). Similarly, while RRG displays resilience in the Mid-Murray, there is little evidence to suggest that it does so further downstream where water resources become increasingly scarce.
6.2. Intra-stand competition

6.2.1. Stem density

The availability of water resources has previously been found to be the most important driver of RRG canopy condition in semi-arid Australia (Wen et al. 2012). This study expected that trees in high density stands would have access to fewer resources than trees in lower density stands, given the same level of water availability. Subsequently, the increased demand for water in high density stands was expected to result in reduced canopy density, extent and photosynthetic function in those stands. If so, stem density would have been a statistically significant driver of RRG canopy condition dynamics throughout the time period. Modelling did not find stem density to be a significant driver of RRG canopy condition dynamics in any of the models produced by GLMM. This was unexpected as the literature indicates that different stem densities exhibit a different canopy response to water deficit (Horner et al. 2009, 2010; Sohn, 2016). While the absence of a significant relationship between stem density and canopy condition may suggest a lack of interaction, this may not be the whole story.

The lack of significance may be attributed to the type of stand-size structures in MVNP. In a thinning study on Eucalypt plantations in south eastern Australia, Forrester et al. (2012) found that stands with negatively skewed DBH distributions (higher proportion of larger trees) respond to thinning with greater annual increases in basal area than stands with less negatively skewed DBH distributions. This suggests that intra-stand competition is higher where there is a higher proportion of larger trees. MVNP is characterised by higher proportions of smaller trees, and so it may be that the levels of competition for water resources exerted by dense even aged RRG stands on residual large RRG in MVNP are not great enough to significantly impact their canopy condition. This does not suggest that intra-stand competition does not have an impact on RRG, but impacts on canopy condition may be difficult to detect because a large proportion of visible canopy is made up of larger trees.

It is likely that imagery captured from above the canopy may be hindered in its ability to detect the effects of intra-stand competition. Kariuki (2008) modelled the effects of thinning to be more pronounced in smaller, younger Eucalypts immediately post-thinning. Thus competitive effects are likely more apparent in smaller, younger Eucalypts. Thus detecting competitive effects in RRG stands can be limited by using satellite derived vegetation metrics because of their tendency to measure the uppermost parts of the canopy.
While no significant patterns were observed, it may be that the most pronounced affects of intra-stand competition are present in dense, even-aged stands of RRG who's signals may be drowned out by larger, mature tree canopies, somewhat resistant to competitive effects. Further research in this area would consider using direct physiological measurements of tree health such as pre-dawn water potential and basal area periodic annual increment to determine whether intra-specific competition impacts on RRG physiological functioning.

6.2.2. Live Basal Area

Findings in this study suggest that by attempting to use more robust spatial measures to describe intra-stand competition a more accurate quantification of water use may be achieved. LBA explained more variance in the models than stem density but was still insignificant. Measures of LBA hint at the presence of a density dependent effect, but one which is not statistically significant enough to influence RRG canopy condition dynamics. If LBA is in fact a better measure of intra-stand competition than stem density then presumably volume would provide a better measure than LBA. The use of allometric relationships in determining accurate volumetric estimations to describe intra-stand competition may be possible. RRG DBH has been observed to be increasing at a rate of around 0-6mm per year in remnant stands around central NSW, however this rate is variable as RRG efficiently takes up water when it is available (Taylor et al. 2014; Rayner et al. 2014). However, a limitation of using allometry to obtain volumetric measures is that the volume of RRG are ultimately determined by water availability, with the species widely known for dropping entire limbs in response to water scarcity (Briggs & Maher, 1983). Additionally accounting for the volume of root-stock may also be difficult at the stand scale. Research is needed in this area if allometric relationships that accurately relate easily obtainable measures of stand structure to volume are to be developed.

While measures of intra-stand competition were not found to be statistically significant drivers of canopy condition in the GLMM models, the need to address the issue should not be ignored. The immediate negative effects directly related to observed MVNP stem densities should be perceived in terms of paucity of habitat features (Horner et al. 2010, Bennett et al. 1994) and it is likely that self-thinning of these dense even-aged stands will occur slowly (Colloff, 2014, p.59). If this is considered in light of predicted ongoing water scarcity, then declines in faunal biodiversity are likely. Ecological thinning of broadleaf forests has found retained trees to be more resilient during droughts (Sohn, 2016), and increases the growth rates of larger Eucalypts (Forrester et al. 2016).
So while effects on canopy condition were not significant, there is still scope for the management of dense even-aged stands in improving habitat quality and fostering resilience in the face of predicted reductions in surface water availability (CSIRO, 2008, as cited in Rogers & Ralph, 2011, p.315). The research presented here may help to determine whether this is the case in MVNP.

6.2.3. Site quality

Intra-stand competition is governed by both demand and availability of resources. This study used site quality as a surrogate measure of water availability (CSIRO, 2008, as cited in Rogers & Ralph, 2011, p.315). While surrogates of water demand were not found to be statistically significant drivers of RRG canopy condition in MVNP, site quality was. This suggests that water supplies across the eight year period have been sufficient enough to maintain homogeneous canopy condition dynamics throughout MVNP despite stand densities.

RRG are known to be facultative phreatophytes, meaning they opportunistically rely on both surface and sub-surface water (Mensforth, et al. 1994, Thorburn et al. 1994). In MVNP, both surface and groundwater likely influence RRG canopy condition and site quality is a coarse measure of the availability of both surface and groundwater resources based on the height of mature canopy. The relationship between site quality and depth to groundwater was described by Baur (1984) (Table 4.1 above). During the drought, there was little difference in site qualities as modelled by the GLMM. However, site quality 1 canopy was modelled as becoming increasingly distinguishable from site quality 2 canopy following recovery from drought, suggesting site quality 1 water supplies are renewed more often or retained for a longer period of time, which may be due to differences in flood period, frequency and sub-soil water retention (Bacon et al. 1993). Groundwater has been found to be an important determinant of the presence and condition of riparian and wetland vegetation globally (Aguilar et al. 2012, Petus et al. 2013). Groundwater depth can change in response to flooding and has been shown to determine the distribution of RRG throughout semi-arid Australia (Kath et al. 2014a, 2014b). Additionally, groundwater recharge is important in preventing saline leaching which has been found to have an adverse effect on RRG canopy condition along the Murray River floodplain (Cunningham et al. 2011). Flood and groundwater modelling or mapping would provide a valuable insight into the relationship between site quality, access to water and the level of intra-stand competition present. Finding site quality to respond differently to hydrologic and climatic
variables over time is an important finding, and it should be given due consideration in future RRG canopy condition monitoring using satellite derived vegetation metrics.

6.3. Drivers of periodicity

6.3.1. Modelled NDVI periodicity

Seasonal and periodic NDVI signals can be subject to precipitative, phenologic or anthropogenic influence. Modelling periodicity of wetland vegetation in semi-arid landscapes has been used to determine the extent of ground water influence, identify limits of acceptable change and is a key component in understanding how wetlands respond to water (Petus et al. 2013). Recent studies on riparian vegetation in the Murray-Darling Basin have reported a high level of similarity in 13-years of periodicity across watered and unwater sites along the Murrumbidgee using MODIS 250m² NDVI (Wen & Saintilan, 2015). In contrast, this study found a relationship between 3-month average pre-winter rainfall and the amplitude of the periodic NDVI signal. While the increase in signal amplitude observed in response to pre-winter precipitation seemingly points to water use by RRG, this may not be the case. NDVI periodicity may be driven by a flush of ephemeral herbs and grasses. Research exists whereby periodicity derived from NDVI time series has been used to separate out woody and herbaceous seasonal signals in semi-arid Australia (Roderick et al. 1999; Lu et al. 2001, 2003). This is because herbaceous species tend to show a more pronounced seasonal signal than that of woody species. This is a notable feature of Inland Riverine Forests, whereby seeds of ephemeral herbs lay dormant before germinating for a short span in response to increased moisture availability (Keith, 2004, p. 223). This difference in visible greenness of the ephemeral layer can be easily observed when two images are compared from the same location, one taken in early December (Appendix 12, Fig. A12a), the other taken the following winter (Appendix 12, Fig. A12b).

Consideration should be given to the potential role of site quality on the ephemeral NDVI signal. In this study SQ was influential in all models and became increasingly different over time by similar magnitudes to what was observed in the NDVI periodicity. Coefficients for SQ show a slight increase during the wet period, before a more substantial increase during the recent period. Therefore, it is not unreasonable to suggest that there may be an interaction between SQ and the periodic NDVI signals. In the Namoi catchment, NSW, Fu and Burgher (2015) found that NDVI periodicity became amplified in drier sites rather than wetter sites. This is consistent with the
findings of Horner et al. (2012) that flood events have been found to increase understorey species diversity, as increasing water availability permits the presence of perennial ground species. In relation to the RRG study, there may be a relationship between site quality and the presence/absence of ephemeral herbs, with SQ-1 plots likely supporting a lesser proportion of ephemerals than SQ-2 plots due to differences in water availability.

6.3.2. Modelled FPC periodicity

Despite limited available research on the phenological traits of RRG using FPC, periodicity modelled by GLMMs likely detected epicormic growth in response to increases in water availability. Similar to the modelled NDVI periodicity, the drought signal peaked in late autumn, and the most recent signal has higher amplitude and peaked in winter. An obvious difference though, is that a more pronounced signal was observed for the wet period which peaked during late summer. If we consider that the strong La Nina event that broke the Millennium drought ran from spring 2010 until autumn 2011 (BoM, 2012), then the amplified FPC periodicity produced by the model can be explained. Recalling that FPC is a measure of canopy density that describes the fraction of ground cover to green canopy for woody vegetation greater than 2m in height, findings can be directly related to FPC in this study and highlight the variability of RRG canopy density. The species is known to undergo a decrease in leaf area and drop entire limbs when water is scarce (Briggs & Maher, 1983; Bacon et al. 1993; Stone & Bacon, 1994) and this would likely have been the case during the drought period (2008 – 2010). Cunningham et al. (2009) found that up to 70% of RRG forests along the Victorian Murray floodplain were in a state of dieback during the Millennium Drought and RRG in MVNP would have been in a similar state. While other studies indicate that RRG showed an increased NDVI response to the 2010/2011 La Nina event (Wen & Saintilan, 2015), there is little available research relating canopy response to La Nina using remotely sensed FPC metrics. As RRG is known to increase its canopy leaf area in response to water abundance, it is likely that the FPC metric has likely captured an intense period of epicormic growth in response to the increased water availability brought by La Nina.
6.4. Recommendations on reducing random noise

A substantial amount of random noise was detected in the models, suggesting that some determinants of canopy condition have been unaccounted for. There are a number of predictors that may contribute to this noise, with the most obvious being quantitative measures of surface and groundwater. The extent of flooding throughout MVNP has not been recorded over the years, and a history of regulator operations would be an essential component in developing flood models. However, researchers at OEH are currently developing Landsat derived wetland classification maps with the capacity to provide binary inundation data for NSW wetlands (OEH, unpublished data). This may be useful information with the ability to greatly improve the modelling produced in this study. Inundation data may also provide context to variable skewness observed within plots, as skewness may be indicative of the presence of active flood-runners within or nearby plots that contribute to increased canopy condition through lateral percolation (Doody et al. 2014). Additionally, findings from this study suggest that FPC is a useful measure of foliage production and loss, and may be better at detecting the onset of epicormic growth than NDVI. Bacon et al. (1993) suggest that inundation may lead to epicormic growth by percolating through to sandy sub-surface lenses and the phreatic zone where it is used by RRG. By relating FPC to inundation data, a more concise understanding of where and when foliage production and loss is happening throughout the study sites in MVNP can be obtained. Furthermore, reductions in random noise can be made by the inclusion of flood inundation data, and subsequently stronger statistical models can be developed to inform our understanding of RRG canopy condition dynamics in MVNP.

Differences observed in canopy condition between SQ-1 and SQ-2 plots may also be due to available nutrients and sediment deposition. Sedimentation and flooding are known to impact seedling and sapling growth habits for different wetland tree species (Walls et al. 2005), and in the U.S. increased sedimentation rates have been linked to decreases in species richness of tussock vegetation in remnant wetlands (Werner & Zedler, 2002). Rivers of the Murray-Darling Basin are known to have become increasingly turbid, primarily due to bank erosion, but hillslope processes and agricultural runoff are also likely contributors (Prosser et al. 2001). Little is known about the effects of this turbidity on riparian and wetland vegetation, in particular RRG. It would be worth investigating whether there is any association between remotely sensed canopy condition, sedimentation and flooding in MVNP, as it may contribute to reducing the levels of random noise observed in the model.
This study did not consider the impacts of the Southern Annular Mode (SAM), Interdecadal Pacific Oscillation (IPO) or the Indian Ocean Dipole (IOD) in southeastern Australia. Negative SAM events bring cooler conditions and positive events bring warmer conditions to the Murray River catchment (Parker et al. 2014; Hendon et al. 2007). Negative IOD phases also bring wetter conditions to much of Australia and substantially wetter conditions were observed in the Murray Darling Basin on the five occasions whereby a negative IOD coincided with a La Nina event, as was observed during the 2010 – 2011 period (BoM, 2016). Discriminably both the IOD and SAM may have an impact on RRG canopy condition dynamics and may warrant further investigation. However they may be unsuitable in any development of a predictive model as both indices themselves are difficult to predict (Hendon et al. 2007; Shi et al. 2012).

6.5 The global context of this study

Globally, freshwater wetlands provide a number of important ecosystem services that benefits life on earth both directly and indirectly, such as carbon retention, resource provision and water purification (Finlayson et al. 2005, p. 560). It is estimated that half of all global wetlands have been lost, and those which remain exist in a somewhat degraded state (Zedler & Kercher, 2005). Both in Australia and globally, freshwater wetlands have been negatively impacted particularly by river modification since the beginning of the 20th century (Revenga & Kura, 2003, p. 17) and the wetlands we observe today are already depleted ecosystems (Colloff et al. 2015). A distinct gap exists across the international literature with respect to studies which monitor and assess the condition of wetlands over time (Zedler & Kercher, 2005).

Long-term ecological monitoring is becoming increasingly valued for its ability to provide an insight into ecosystem processes operating at longer time intervals (Lindenmayer & Likens, 2010, p. 4). However, maintaining regular in-situ field monitoring despite funding restraints represent significant challenges in long-term research projects (Lindenmayer, 2009, p. 235). This study used satellite-derived imagery to investigate a degraded wetland ecosystem in semi-arid Australia, with the intent of building an understanding of the dynamic long-term behaviour of the canopy condition of a key wetland species, RRG. Satellite sensors such as DigitalGlobe’s WorldView-2 sensor are optimal for terrestrial vegetation monitoring due to high spatial and temporal resolution, however imagery comes at a price and budget restraints may limit its use in long-term monitoring programs. Freely accessible remotely sensed data such as Landsat’s, goes some way toward overcoming these challenges by substantially reducing the cost of long-term
monitoring. Remote sensing for ecosystem monitoring has its own set of challenges that users must overcome (AghaKouchak et al, 2015; Mairoto et al. 2015). Atmospheric interference, cloud cover and noise reduce the temporal frequency of Landsat data series, in turn forcing analysts to rely on alternative techniques such as interpolation. But even interpolation risks reducing data series quality through an inability to detect rapid and subtle changes, and loss of integrity over long data gaps between images (Gao et al. 2015). The methods employed in this research were able to cope with a highly fragmented empirical dataset to model RRG canopy condition dynamics. These methods are of relevance to any large-scale landscape experiment reliant on temporally fragmented, remotely sensed imagery to monitor both inter- and intra-annual ecosystem dynamics.

Colloff et al. (2015) state that despite the natural cycle of decline and recovery observed in semi-arid wetland ecosystems across the Murray-Darling Basin, an overall improvement in condition is not apparent over the last 110 years and wetlands remain in a depleted state. These shifting baselines of condition should be given due consideration when developing management plans for inland wetland ecosystems, particularly on regulated rivers (Finlayson et al. 2005, p. 551) and thus the emphasis should not be on maintaining condition, but improving it. In the face of global climate change, enhancing the state of wetland ecosystems will become increasingly difficult (Rogers & Ralph, 2010) and the need for an integrated approach towards asset, valley and catchment scale wetland monitoring and modelling is essential (Ward & Colloff, 2010; Saintilan et al. 2011). The methods employed in this study have potential to contribute toward the improvement of ecosystem research locally and internationally both through knowledge-base integration and by facilitating the investigation of sub-hectare asset scale phenomena without the need to rely exclusively on time series analyses or sacrificing data integrity.
7. Conclusion

Using satellite derived vegetation metrics, this study investigated canopy condition dynamics of RRG across different levels of intra-species competition and water availability. The investigation focussed on a multi-year period spanning the end of the millennium drought, subsequent high rainfall years, and the relatively stable years preceding 2016. Aims were achieved using the following objectives:

1. Derive values from suitable vegetation metrics using remotely sensed satellite data obtained between 2008 and 2016.
2. Develop an appropriate methodology based on the available data to describe RRG canopy condition.
3. Identify and investigate where and why any differences in canopy condition manifest themselves.
4. Determine whether and how canopy condition dynamics across intra-stand competition levels and water availability respond to hydrologic and climatic variables such as Southern Oscillation Index (SOI), precipitation, or river discharge using Generalized Linear Mixed Modelling.

Time series analyses are useful in learning about how certain systems behave over time and give analysts the option to fully account for a system through the additive components of trend, periodicity and random noise. However the collection of monitoring data over long periods can be an expensive and difficult pursuit. The use of satellite derived remotely sensed data to undertake TSA has become popularized in recent times because there are many that provide frequent, regularly sampled imagery at little or no expense, although there are limitations. A trade-off must be made between the spatial and temporal resolution of the imagery, as satellites with frequent return times tend to capture imagery at a lower spatial resolution and vice-versa. This means that when undertaking terrestrial vegetation investigations using TSA, satellites such as MODIS must be relied upon which are limited to a spatial resolution of 250m². This is insufficient if investigations require data at a multi-temporal, sub-hectare resolution. In such cases, Landsat satellites with a 30m² spatial resolution are often used, however due to their lower temporal frequency, large, irregular data gaps are inherent. Largely spaced and irregular data gaps mean TSA cannot function properly and trends cannot be removed to derive periodicity or noise. One option is to interpolate missing data, but interpolation techniques such
as ‘data fusion’, also have limitations relating to their ability to capture subtle and small scale changes, as well as interpolating over large data gaps. In addition interpolating missing dates can increase the degrees of freedom in a dataset and subsequently demote the weight of statistical results. For these reasons, this study sought alternative methods to gain an understanding of trends and periodicity present in RRG canopy condition dynamics. By using GLMM, this study able to model trend and periodicity of RRG canopy condition dynamics, and quantify the proportion of the signal which had not been accounted for. The methods described can be applied broadly to a number of ecosystem investigations whereby interest lies in understanding the gamut of variables operating in concert with trends. Without sacrificing data integrity, the methods developed in this study have the potential to retrospectively derive phenological information at scales pertinent to vegetation for long-term ecological studies.

GLMM was also able to identify variables that made a statistically significant contribution to RRG canopy condition dynamics in each period, and also suggested phenological behaviour. Condition was driven by a number of site, hydrologic and climatic variables, although stem density was not found to have a significant influence. As with other riparian ecosystems throughout the Murray-Darling Basin, trends were related to river flow, precipitation, SOI and SQ. Based on FPC and NDVI models, RRG canopy condition exhibited reduced extent, density and photosynthetic activity during the Millennium drought, and there was little difference between canopies of SQ-1 and SQ-2. In response to a strong and sustained La Nina event in 2010, RRG canopy condition underwent a flush of epicormic growth, and trees recovered. But since 2013, condition slowly began to decline again with a slow onset of El Nino. Models suggest that trees in SQ-1 have responded better to increases in water availability, by remaining in a better condition than those in SQ-2. The amount of random noise present suggests that statistically significant variables were not able to fully account for canopy condition dynamics and a number of additional variables may be required to do so.

Long-term, inter- and intra-annual monitoring of RRG canopy condition dynamics is fundamentally important to land management projects in semi-arid Australia. This allows anomalous conditions to be identified at both inter- and intra-annual scales. Measuring condition once a year risks oversight of both random noise and cyclical components present in vegetation phenology, thus increasing the chance of misinterpreting condition. The methods used in this study are expected to open up opportunities for data-driven long-term studies involving ecological modelling and monitoring across a range of environments. In meeting the aims and objectives of this study, a baseline understanding of how RRG canopy condition behaves under a
range of climatic conditions has been developed which will allow informed land managers to assess the impacts of ecological thinning on RRG forests in MVNP.
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project.org/package=nlme


APPENDIX 1: Exploratory Analyses Script.

```r
> # Exploratory Analysis
> # 1. SET UP
> # Set the working directory.
> setwd("E:/Honours Files/R")
> library(lme4)
> # Read in the data check
> EDexplore<-read.csv("EvanDataeq.csv", header=T)
> head(EDexplore)
> attach(EDexplore)
> SOIperiod<-read.csv("SOI_allmonths.csv", header=T)

> # CHECKING ASSUMPTIONS
> ### BARTLETT TEST OF HOMOGENEITY OF VARIANCE
> # Bartlett's test has H0 = variance is the same for all treatment groups
> # If p-value = >0.05, we can NOT reject the null hypothesis, and therefore no evidence exists to suggest that
> # variance in NDVI or FPC is different in the 54 plots.
> attach(Full_SD_Data)
> bartlett.test(NDVI_med~Plot)
> bartlett.test(FPC_med~Plot)

> # 2. BOXPLOTS
> # NDVI Boxplot
> par(mfrow=c(2,1), mar=c(3,3,1,1))
> boxplot(NDVI_med~Year, pch=20, cex=0.8, axes=F, ann=F, frame.plot=T, col=rgb(0.2, 0.6, 0.7, 0.2))
> mtext("Year", side=1, line=2)
> axis(side=2, at=seq(0,1,0.1), cex.axis=0.7)
> mtext("NDVI Median", side=2, line=2)
> # Equivalent FPC boxplot
> boxplot(FPC_med~Year, pch=20, cex=0.8, axes=F, ann=F, frame.plot=T, col=rgb(1,0.75,0,0.2))
> mtext("Year", side=1, line=2)
> axis(side=2, at=seq(0,1,0.1), cex.axis=0.7)
> mtext("FPC Median", side=2, line=2)

> # 3. VARIABLE PLOTS
> # FPCvNDVI over time period
> par(mfrow=c(1,1), mar=c(3,3,1,1))
> plot(Decimal_Date, FPC_med, pch=20, cex=0.8, col=rgb(1,0.75,0,0.2), axes=F, ann=F, frame.plot=T)
> points(Decimal_Date, NDVI_med, pch=20, cex=0.8, col=rgb(0.2,0.6,0.7,0.2))
> axis(side=1, at=c(0:8), labels=c(2008:2016), cex.axis=0.7)
> mtext("Year", side=1, line=2)
> axis(side=2, at=seq(0,1,0.1), cex.axis=0.7)
> mtext("FPC or NDVI median", side=2, line=2)
> legend(0,0.9, legend=c("FPC","NDVI"), col=c("orange", "lightblue"), pch=c(20,20)
```

126
# FPC AND NDVI BY SITE QUALITY

```r
> par(mfrow=c(2,1), mar=c(3,3,1,1))
> plot(Decimal_Date, FPC_med, pch=20, cex=0.8, col=SQ_mapped, axes=F, ann=F, frame.plot=T)
> axis(side=1, at=c(0:8), labels=c(2008:2016), cex.axis=0.7)
> mtext("Year", side=1, line=2)
> axis(side=2, at=seq(0,1,0.1), cex.axis=0.7)
> mtext("FPC median", side=2, line=2)
> legend(0,0.9,legend=c("Site Quality 1", "Site Quality 2"),col=1:length(SQ_mapped),pch=20, cex=0.8, bty="n")

> # NDVI
> plot(Decimal_Date, NDVI_med, pch=20, cex=0.8, col=SQ_mapped, axes=F, ann=F, frame.plot=T)
> axis(side=1, at=c(0:8), labels=c(2008:2016), cex.axis=0.7)
> mtext("Year", side=1, line=2)
> axis(side=2, at=seq(0,1,0.1), cex.axis=0.7)
> mtext("NDVI median", side=2, line=2)
> legend(0,0.9,legend=c("Site Quality 1", "Site Quality 2"),col=1:length(SQ_mapped),pch=20, cex=0.8, bty="n")

## PLOT NDVI AND FPC BY MAPPED STEM DENSITY CLASS

```r
> par(mfrow=c(2,1), mar=c(3,3,1,1))
> plot(Decimal_Date, FPC_med, pch=20, cex=0.8, col=SD_class, axes=F, ann=F, frame.plot=T)
> axis(side=1, at=c(0:8), labels=c(2008:2016), cex.axis=0.7)
> mtext("Year", side=1, line=2)
> axis(side=2, at=seq(0,1,0.1), cex.axis=0.7)
> mtext("FPC median", side=2, line=2)
> legend(0,0.9,legend=c("0 - 449", "450 - 749", "> 750"),col=1:length(SD_class),pch=20, cex=0.7, bty="n")
```

#add the equivalent plot for NDVI
```
> plot(Decimal_Date, NDVI_med, pch=20, cex=0.8, col=SD_class, axes=F, ann=F, frame.plot=T)
> axis(side=1, at=c(0:8), labels=c(2008:2016), cex.axis=0.7)
> mtext("Year", side=1, line=2)
> axis(side=2, at=seq(0,1,0.1), cex.axis=0.7)
> mtext("NDVI median", side=2, line=2)
> legend(0,0.9,legend=c("0 - 449", "450 - 749", "> 750"),col=1:length(SD_class),pch=20, cex=0.7, bty="n")
```
```
APPENDIX 2: NDVI full period Model.

```r
> NDVI.corr.lme9 <- lme(NDVI_med ~ log(Mrain+1) + MeanMonthMaxT + MeanMonthMinT + SOI + log(WeeklyMD+1) + SQ_mapped + SinTime + CosTime, na.action = na.omit, random = ~1 | Plot, data = lmeruns, correlation = corSpher(form = ~Pass|Plot))
> summary(NDVI.corr.lme9)

Linear mixed-effects model fit by REML
Data: lmeruns

AIC BIC logLik
-7043.652 -6972.403 3533.826

Random effects:
Formula: ~1 | Plot
  (Intercept) Residual
StdDev: 1.027486e-05 0.100792

Correlation Structure: Spherical spatial correlation
Formula: ~Pass | Plot
Parameter estimate(s):
  range
10.61119

Fixed effects: NDVI_med ~ log(Mrain + 1) + MeanMonthMaxT + MeanMonthMinT + SOI + log(WeeklyMD + 1) + SQ_mapped + SinTime + CosTime

Value Std.Error DF t-value p-value
(Intercept) -0.00116766 0.04332829 2749 -0.026949 0.9785
log(Mrain + 1) 0.00758318 0.00123004 2749 6.164 988 0.0000
MeanMonthMaxT 0.00614149 0.00099520 2749 6.171078 0.0000
MeanMonthMinT -0.01420669 0.00113944 2749 -12.468137 0.0000
SOI 0.01831873 0.00173633 2749 10.550235 0.0000
log(WeeklyMD + 1) 0.05037718 0.00300397 2749 16.770212 0.0000
SQ_mappedSQ-2 -0.05303597 0.00668548 51 -7.933009 0.0000
SinTime 0.04620003 0.00404443 2749 11.423125 0.0000
CosTime -0.07843413 0.00651610 2749 -12.036980 0.0000

Correlation:
  (Intr) log(M+1) MnMnthMxT MnMnthMnT SOI log(WM+1 SQ_SQ-
SinTim
log(Mrain + 1) -0.421
MeanMonthMaxT -0.660 0.457
MeanMonthMinT 0.460 -0.354 -0.818
SOI -0.096 0.078 0.161 -0.196
log(WeeklyMD + 1) -0.909 0.220 0.353 -0.299 0.049
SQ_mappedSQ-2 -0.090 0.000 0.000 0.000 0.000
SinTime -0.225 0.128 0.123 -0.309 0.035 0.291 0.000
CosTime 0.396 -0.120 -0.456 0.020 -0.024 -0.184 0.000

Standardized Within-Group Residuals:
  Min Q1 Med Q3 Max
-5.2140547 -0.4706760 0.1416152 0.6869274 2.9354929

Number of Observations: 2809
Number of Groups: 53
```
APPENDIX 3: Logit FPC full period model script.

```r
> logitfpc.corr.lmelag1 <- lme(LogitFPCmed ~ Mrain6lag + MeanMonthMaxT + MeanMonthMinT + SOI6lag + WMDL1 + SQ_mapped + SinTime + CosTime, na.action = na.omit, random = ~1 | Plot, data = lmeruns, correlation = corSpher(form = ~Pass|Plot))
> summary(logitfpc.corr.lmelag1)
```

Linear mixed-effects model fit by REML
Data: lmeruns

AIC  BIC   logLik
-2764.437 -2693.188 1394.218

Random effects:
  Formula: ~1 | Plot
  (Intercept) Residual
  StdDev: 0.0558466  0.1676291

Correlation Structure: Spherical spatial correlation
  Formula: ~Pass | Plot
  Parameter estimate(s):
    range
  4.797177

Fixed effects: LogitFPCmed ~ Mrain6lag + MeanMonthMaxT + MeanMonthMinT + SOI6lag + WMDL1 + SQ_mapped + SinTime + CosTime

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>Std.Error</th>
<th>DF</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>-0.25396840</td>
<td>0.03922956</td>
<td>2749</td>
<td>-6.47390</td>
<td>0.000</td>
</tr>
<tr>
<td>Mrain6lag</td>
<td>0.00346478</td>
<td>0.00013572</td>
<td>2749</td>
<td>25.52984</td>
<td>0.000</td>
</tr>
<tr>
<td>MeanMonthMaxT</td>
<td>0.00594295</td>
<td>0.00206569</td>
<td>2749</td>
<td>28.7699</td>
<td>0.000</td>
</tr>
<tr>
<td>MeanMonthMinT</td>
<td>-0.02622152</td>
<td>0.00248704</td>
<td>2749</td>
<td>-10.54325</td>
<td>0.000</td>
</tr>
<tr>
<td>SOI6lag</td>
<td>0.00465149</td>
<td>0.00206569</td>
<td>2749</td>
<td>21.52984</td>
<td>0.000</td>
</tr>
<tr>
<td>WMDL1</td>
<td>0.00000209</td>
<td>0.00000005</td>
<td>2749</td>
<td>44.69355</td>
<td>0.000</td>
</tr>
<tr>
<td>SQ_mappedSQ-2</td>
<td>-0.14793358</td>
<td>0.01782054</td>
<td>2749</td>
<td>-8.30129</td>
<td>0.000</td>
</tr>
<tr>
<td>SinTime</td>
<td>0.08780335</td>
<td>0.00653580</td>
<td>2749</td>
<td>13.43421</td>
<td>0.000</td>
</tr>
<tr>
<td>CosTime</td>
<td>-0.11163784</td>
<td>0.01421325</td>
<td>2749</td>
<td>-7.85449</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Correlation:
  (Intr) Mrn6lg MnMnthMxT MnMnthMnT SOI6lg WMDL1 SQ_SQ_Sin Tim
  Mrain6lag -0.822 -0.055
  MeanMonthMaxT -0.337  0.029 -0.753
  MeanMonthMinT -0.173 -0.070  0.140 -0.010
  SOI6lag -0.395 -0.017  0.281 -0.092 -0.013
  WMDL1 -0.266  0.000  0.000  0.000  0.000
  SQ_mappedSQ-2 -0.163  0.100  0.044 -0.373 -0.052 -0.052  0.000
  SinTime  0.746 -0.046 -0.527 -0.073 -0.178 -0.341  0.000  0.307

Standardized Within-Group Residuals:
  Min Q1 Median Q3 Max
  -4.7355187 -0.6260200 -0.1142250 0.5115628 4.1192829

Number of Observations: 2809
Number of Groups: 53
APPENDIX 4: NDVI periods script & model output.

```r
> setwd("E:/Honours Files/R")
> lmeruns <- read.csv("EvanDataeq.csv", header=T)
> head(lmeruns) #check it looks OK
> library(nlme)
> # 2. Subset data into 3 periods.
> attach(lmeruns)
> p1 <- lmeruns[ which(Pass > 1 & Pass < 50), ]
> p2 <- lmeruns[ which(Pass > 47 & Pass < 86), ]
> p3 <- lmeruns[ which(Pass > 86 & Pass < 190), ]
> # Period 1 (Drought)
> p1.NDVI.lme1<- lme(NDVI_med ~ log(Mrain+1) + MeanMonthMaxT + SOI + log(WeeklyMD+1)
> + + SQ_mapped + SinTime + CosTime, na.action = na.omit,
> + random = ~1 | Plot, data = p1, correlation = corSpher ( form = ~Pass|P
> + lot))
> summary(p1.NDVI.lme1)
> Linear mixed-effects model fit by REML
> Data: p1
>   AIC      BIC   logLik
> -2733.028 -2685.13 1377.514
> Random effects:
>  Formula: ~1 | Plot
>  (Intercept) Residual
>  StdDev: 0.03239984 0.02241527
> Correlation Structure: Spherical spatial correlation
>  Formula: ~Pass | Plot
>  Parameter estimate(s):
>  range 6.292552
> Fixed effects: NDVI_med ~ log(Mrain + 1) + MeanMonthMaxT + SOI + log(Wee
> klyMD + 1) + SQ_mapped + SinTime + CosTime
>  Value  Std.Error  DF    t-value p-value
> (Intercept) 0.28024292 0.04267755 524   6.566519   0e+00
> log(Mrain + 1) 0.00240950 0.00054557 524   4.416475   0e+00
> MeanMonthMaxT -0.00382258 0.00029195 524 -13.093366   0e+00
> SOI 0.00857100 0.00095781 524   8.948563   0e+00
> log(WeeklyMD + 1) 0.02481957 0.00393967 524   6.299911   0e+00
> SQ_mapped -0.03861933 0.00937123  51  -4.121054   1e-04
> SinTime 0.03828004 0.00170980 524  22.388640   0e+00
> CosTime -0.05484766 0.00457973 524 -11.976171   0e+00
> Correlation:
>  (Intr) l(M+1) MnMnMT SOI l(WM+1 SQ_SQ- SinTim
> log(Mrain + 1) -0.056
> MeanMonthMaxT -0.187 -0.054
> SOI -0.037 -0.001 -0.322
> log(WeeklyMD + 1) -0.970 0.033 0.017 0.089
> SQ_mapped -0.128 0.000 0.000 0.000
> SinTime -0.173 0.199 -0.394 0.063 0.243 0.000
> CosTime 0.609 0.137 -0.510 0.130 -0.567 0.000 0.038
> Standardized Within-Group Residuals:
>   Min      Q1  Med      Q3     Max
>  -5.82427187 -0.61944052 0.01415329 0.59945797 4.71979152
> Number of Observations: 583
> Number of Groups: 53
> # Period 2 (Wet)
> p2.NDVI.lme2 <- lme(NDVI_med ~ log(Mrain+1) + SOI +
```
+ log(WeeklyMD+1) + SQ_mapped + SinTime + CosTime, na.action = na.omit,
+ random = ~1 | Plot, data = p2, correlation = corSpher ( form = ~Pass|Plot))
>
> summary(p2.NDVI.lme2)
Linear mixed-effects model fit by REML
Data: p2

AIC    BIC  logLik
-1604.617 -1560.176 812.3085

Random effects:
Formula: ~1 | Plot
(Intercept)   Residual
StdDev: 0.01574982 0.06298781

Correlation Structure: Spherical spatial correlation
Formula: ~Pass | Plot
Parameter estimate(s):
range

1.000006

Fixed effects: NDVI_med ~ log(Mrain + 1) + SOI + log(WeeklyMD + 1) + SQ_mapped + SinTime + CosTime

(Intercept)    -0.5046278 0.05663095 578   -8.910812       0
log(Mrain + 1)  0.0173222 0.00420482 578    4.119616       0
SOI             0.0207396 0.00441917 578    4.693103       0
log(WeeklyMD + 1) -0.0907807 0.00477003 578   19.031489       0
SQ_mappedSQ-2   -0.0420516 0.00670602  51   -6.270723       0
SinTime         0.0234019 0.00365878 578    6.396093       0
CosTime         -0.0853877 0.00587654 578   -14.530268       0

Correlation:

(log(Mrain + 1) 0.342
SOI               0.514
log(WeeklyMD + 1) 0.976
SQ_mappedSQ-2     0.069
SinTime          -0.446
CosTime           0.449

Standardized Within-Group Residuals:

Min          Q1         Med          Q3         Max
-4.91282370  -0.55895731  -0.04366027  0.55572300  2.59364490

Number of Observations: 636
Number of Groups: 53

> # Period 3 (Stable)
> p3.NDVI.lme3a<-lme(NDVI_med ~ log(Mrain+1) + MeanMonthMaxT + SOI +
+   SQ_mapped + CosTime, na.action = na.omit,
+   random = ~1 | Plot, data = p3, correlation = corSpher ( form = ~Pass|Plot))
>
> summary(p3.NDVI.lme3a)
Linear mixed-effects model fit by REML
Data: p3

AIC    BIC  logLik
-4652.508 -4603.902 2335.254

Random effects:
Formula: ~1 | Plot
(Intercept)   Residual
StdDev: 0.02804848 0.06298781

Correlation Structure: Spherical spatial correlation
Formula: ~Pass | Plot
Parameter estimate(s):

Fixed effects: NDVI_med ~ log(Mrain + 1) + MeanMonthMaxT + SOI + SQ_mapped + CosTime

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>Std.Error</th>
<th>DF</th>
<th>t-value</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>0.4300234</td>
<td>0.023488642</td>
<td>1586</td>
<td>18.307716</td>
<td>0</td>
</tr>
<tr>
<td>log(Mrain + 1)</td>
<td>0.0161827</td>
<td>0.001684109</td>
<td>1586</td>
<td>9.609027</td>
<td>0</td>
</tr>
<tr>
<td>MeanMonthMaxT</td>
<td>0.0068728</td>
<td>0.000790348</td>
<td>1586</td>
<td>8.695955</td>
<td>0</td>
</tr>
<tr>
<td>SOI</td>
<td>0.0256956</td>
<td>0.001865100</td>
<td>1586</td>
<td>13.777042</td>
<td>0</td>
</tr>
<tr>
<td>SQ_mappedSQ-2</td>
<td>-0.0652830</td>
<td>0.008713367</td>
<td>51</td>
<td>-7.492278</td>
<td>0</td>
</tr>
<tr>
<td>CosTime</td>
<td>-0.1503994</td>
<td>0.007753667</td>
<td>1586</td>
<td>-19.397197</td>
<td>0</td>
</tr>
</tbody>
</table>

Correlation:

<table>
<thead>
<tr>
<th></th>
<th>(Intr)</th>
<th>l(M+1)</th>
<th>MnMnMT</th>
<th>SOI</th>
<th>SQ_SQ-</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(Mrain + 1)</td>
<td>0.621</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MeanMonthMaxT</td>
<td>-0.940</td>
<td>0.487</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SOI</td>
<td>0.039</td>
<td>0.010</td>
<td>-0.013</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SQ_mappedSQ-2</td>
<td>-0.217</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>CosTime</td>
<td>0.857</td>
<td>-0.356</td>
<td>-0.932</td>
<td>0.022</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Standardized Within-Group Residuals:

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>Q1</th>
<th>Med</th>
<th>Q3</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-8.45561328</td>
<td>-0.62521278</td>
<td>0.02787508</td>
<td>0.57468362</td>
<td>3.21970436</td>
</tr>
</tbody>
</table>

Number of Observations: 1643
Number of Groups: 53

> ##########################
> # Diagnostic plots of p1.NDVI.lme1 (DROUGHT with drought model)
> ##########################
> #Residuals v Fitted
> par(mfrow=c(1,1), mar=c(3,3,1,1))
> plot(fitted(p1.NDVI.lme1), residuals(p1.NDVI.lme1), ann=F, pch=19, cex =0.8, col="DarkGray")
> mtext(side=1,line=2,text="Fitted", cex=0.8)
> mtext(side=2,line=2,text="Residuals", cex=0.8)
> abline(h=0, col="blue")
> ##QQ
> par(mfrow=c(1,1))
> qqnorm(residuals(p1.NDVI.lme1))
> #Seasonality
> acf(residuals(p1.NDVI.lme1), lag.max=50)
> text(30,0.9, "ACF")
> mtext(side=1, line=2, text="Lag", cex=0.8)
> #Error
> pacf(residuals(p1.NDVI.lme1), lag.max=50)
> text(30, 0.5, "PACF")
> mtext(side=1, line=2, text="Lag", cex=0.8)
> ##########################
> # Diagnostic plots of p2.NDVI.lme2 (Wet with wet model)
> ##########################
> #Residuals v Fitted
> par(mfrow=c(1,1), mar=c(3,3,1,1))
> plot(fitted(p2.NDVI.lme2), residuals(p2.NDVI.lme2), ann=F, pch=19, cex =0.8, col="DarkGray")
> mtext(side=1,line=2,text="Fitted", cex=0.8)
> mtext(side=2,line=2,text="Residuals", cex=0.8)
> abline(h=0, col="blue")
> ##QQ
> par(mfrow=c(1,1))
```r
> qgnorm(residuals(p2.NDVI.lme2))
> #Seasonality
> acf(residuals(p2.NDVI.lme2), lag.max=50)
> text(30,0.9, "ACF")
> mtext(side=1, line=2, text="Lag", cex=0.8)
> #Error
> pacf(residuals(p2.NDVI.lme2), lag.max=50)
> text(30, 0.5, "PACF")
> mtext(side=1, line=2, text="Lag", cex=0.8)
> ####################
> # Diagnostic plots of p3.NDVI.lme3a(STABLE with stable model)
> ####################
> #Residuals v Fitted
> par(mfrow=c(3,1), mar=c(3,3,1,1))
> plot(fitted(p3.NDVI.lme3a), residuals(p3.NDVI.lme3a),ann=F, pch=19, cex =0.8, col="DarkGray")
> mtext(side=1,line=2,text="Fitted", cex=0.8)
> mtext(side=2,line=2,text="Residuals", cex=0.8)
> abline(h=0, col="blue")
> ###QQ
> par(mfrow=c(1,1))
> qqnorm(residuals(p3.NDVI.lme3a))
> #Seasonality
> acf(residuals(p3.NDVI.lme3a),lag.max=50)
> text(30,0.9, "ACF")
> #Error
> pacf(residuals(p3.NDVI.lme3a),lag.max=50)
> text(30, 0.5, "PACF")
> mtext(side=1, line=2, text="Lag", cex=0.8)
> ####################
> #(drought-drought)
> ####################
> #extract the fitted and residual values (from the object produced by lmer)
> #and put them in new data frames
> fitted.p1.NDVI.lme1<-as.data.frame(fitted(p1.NDVI.lme1))
> residuals.p1.NDVI.lme1<-as.data.frame(residuals(p1.NDVI.lme1))
> #bind the two together by column into one object
> #(which will have all 2809 values in it: 53 sites with 11 time steps each)
> fr.p1.NDVI.lme1<-cbind(fitted.p1.NDVI.lme1, residuals.p1.NDVI.lme1)
> head(fr.p1.NDVI.lme1)
> #write the file to a csv
> write.csv(fr.p1.NDVI.lme1, "Fitted Residual for p1.NDVI.lme1 010916.csv")
> ############
> #(wet-wet)
> ############
> #extract the fitted and residual values (from the object produced by lmer)
> #and put them in new data frames
> fitted.p2.NDVI.lme2<-as.data.frame(fitted(p2.NDVI.lme2))
> residuals.p2.NDVI.lme2<-as.data.frame(residuals(p2.NDVI.lme2))
> #bind the two together by column into one object
```
> # (which will have all 2809 values in it: 53 sites with 11 time steps each)
> fr.p2.NDVI.lme2 <- cbind(fitted.p2.NDVI.lme2, residuals.p2.NDVI.lme2)
> head(fr.p2.NDVI.lme2)
>    fitted(p2.NDVI.lme2) residuals(p2.NDVI.lme2)
> 1       0.3609264          -0.008426398
> 2       0.5410800          -0.071080016
> 3       0.6671017          -0.087101720
> 4       0.5463799            0.008620093
> 5       0.6013428          -0.056342779
> 6       0.6194426            0.045557385
> # write the file to a csv
> write.csv(fr.p2.NDVI.lme2, "Fitted Residual for p2.NDVI.lme2 010916.csv")

> # # (stable-stable) 
> # First you have to extract the fitted and residual values (from the
> # object produced by lmer) 
> # and put them in new data frames
> fitted.p3.NDVI.lme3a <- as.data.frame(fitted(p3.NDVI.lme3a))
> residuals.p3.NDVI.lme3a <- as.data.frame(residuals(p3.NDVI.lme3a))
> # bind the two together by column into one object 
> # (which will have all 2809 values in it: 53 sites with 12 time steps each)
> fr.p3.NDVI.lme3a <- cbind(fitted.p3.NDVI.lme3a, residuals.p3.NDVI.lme3a)
> head(fr.p3.NDVI.lme3a)
>    fitted(p3.NDVI.lme3a) residuals(p3.NDVI.lme3a)
> 1       0.7065695          -0.041569527
> 2       0.7031395            0.004360487
> 3       0.6627897          -0.015289740
> 4       0.5259764            0.061523587
> 5       0.5149450            0.092554967
> 6       0.5411040            0.068895965
> # write the file to a csv
> write.csv(fr.p3.NDVI.lme3a, "Fitted Residual for p3.NDVI.lme3a 010916.csv")
> # Edit csv writes to include landsat passes without satellite image. 
> # IE to match scale of model plots.
> # To plot the fitted values and the residuals (wet/wet)
> par(mfrow=c(1,1), mar=c(3,3,1,1))
> plot(lmeruns$Pass[1:11], fr.p1.NDVI.lme1[1:11,1], type="l", lwd=2,
+ ylim=c(0,1), xlab="Time", ylab="NDVI_med", ann=F, cex.axis=0.9)
> lines(lmeruns$Pass[1:11], fr.p1.NDVI.lme1[23:33,1], lwd=1)
> axis(side=1, at=seq(0,186,22.8), labels=c(2008:2016), cex.axis=0.9)
> mtext("Time", side=1, line=2, cex=0.9)
> mtext("NDVI_med", side=2, line=2, cex=0.9)
> points(lmeruns$Pass[1:11], lmeruns$NDVI_med[1:11], col="red", pch=20,
+ cex=0.8)
> lines(lmeruns$Pass[11:22], lmeruns$NDVI_med[11:22], col="red")
> abline(v=48, col="light blue")
> abline(v=85, col="light blue")
> points(lmeruns$Pass[23:53], fr.p.3.NDVI.lme3a[1:31,1], type="l", lwd=2,  
+ ylim=c(0,1), xaxt="n", ann=F, cex.axis=0.8, bty="n")
> lines(lmeruns$Pass[23:53], fr.p.3.NDVI.lme3a[63:93,1])
> points(lmeruns$Pass[23:53], lmeruns$NDVI_med[23:53], col="red", pch=20,  
+ cex=0.8)
> lines(lmeruns$Pass[23:53], lmeruns$NDVI_med[23:53], col="red")
> abline(v=123, col="light blue")
> abline(v=186, col="light blue")
> ##
> #Read edited csv back in to plot residuals.
> #SQ Resids Barplot
> SQ_resids <- read.csv("SQResdis.csv", header=T)
> head(SQ_resids)
>   Resids.SQ.2. Resids.SQ.1.
> 1  0.000000000  0.000000000
> 2  0.000000000  0.000000000
> 3  0.000000000  0.000000000
> 4  0.005359946 -0.003158502
> 5  0.000000000  0.000000000
> 6  0.000000000  0.000000000
> par(mfrow=c(2,1), mar=c(3,3,1,1))
> B=barplot(SQ_resids[1:186,1], ylim=c(-0.5,0.5), cex.axis=0.8, col="light blue")
> axis(side=1, line=0, at=B, labels=1:186,cex.axis=0.5)
> mtext(side=1, line=2, "Landsat Pass", cex=0.9)
> mtext(side=2, line=2, "Residuals SQ-1", cex=0.9)
APPENDIX 5: Logit FPC periods script and output.

> # 1. Set up.
> setwd("E:/Honours Files/R")
> lmeruns <- read.csv("EvanDataeqFLPC-SDfinal.csv", header=T)
> head(lmeruns)  #check it looks OK
> library(lme4)
Loading required package: Matrix

Attaching package: ‘lme4’

Warning message:
package ‘lme4’ was built under R version 3.3.1

> library(nlme)
> library(gtools)

> # 2. Subset data into 3 periods.
> attach(lmeruns)
> p1 <- lmeruns[ which(Pass > 1 & Pass <50), ]
> p2 <- lmeruns[ which(Pass > 47 & Pass < 86), ]
> p3 <- lmeruns[ which(Pass > 86 & Pass < 190), ]

> # Now the same but for FPC.

> # LFPC Models
> # Period 1 (Drought)
> p1.LFPC.lme1 <- lme(LogitFPC ~ MeanMonthMinT + SOI + log(WeeklyMD + 1) + SQ_mapped + SinTime + CosTime, na.action = na.omit,
+ random = ~ 1 | Plot, data = p1, correlation = corSpher ( form = ~Pass|Plot))
> summary(p1.LFPC.lme1)

Linear mixed-effects model fit by REML
Data: p1
AIC       BIC   logLik
549.6098  506.0487  284.8049

Random effects:
Formula: ~1 | Plot
(Intercept)  Residual
StdDev:     0.24642 0.1723027

Correlation Structure: Spherical spatial correlation
Formula: ~Pass | Plot
Parameter estimate(s):
  range
10.18777

Fixed effects:  LogitFPC ~ MeanMonthMinT + SOI + log(WeeklyMD + 1) + SQ_mapped + SinTime + CosTime
   Value  Std.Error  DF    t-value p-value
(Intercept) -1.6680858 0.28007765 525 -5.955798   0e+00
MeanMonthMinT -0.0239560 0.00196991 525 12.160977   0e+00
SOI                0.0527494 0.00674065 525   7.825560   0e+00
log(WeeklyMD + 1)  0.1029338 0.02647753 525   3.887589   1e-04
SQ_mappedSQ -0.2933162 0.07191987  51 -4.078375   0e+00
SinTime            0.1478113 0.01306076 525 11.317209   0e+00
CosTime -0.1687016 0.027715441 525 -6.212676   0e+00

Correlation:
 (Intr) MnMmMT SOI 1(W+1) SQ_SQ- SinTim
MeanMonthMinT  0.101
SOI              0.036 -0.279
log(WeeklyMD + 1) -0.978 -0.174 -0.020
SQ_mappedSQ -0.150  0.000  0.000  0.000
SinTime -0.285 -0.430  0.069  0.317  0.000
CosTime  0.516 -0.365  0.078 -0.515  0.000 -0.043

Standardized Within-Group Residuals:
    Min      Q1     Med      Q3     Max
-7.1171544 -0.3853636  0.0635452  0.5253655  3.5888087

Number of Observations: 583
Number of Groups: 53
> # Period 2 (Wet)
> p2.LFPC.lme1 <- lme(LogitFPC ~ MeanMonthMinT + SOI + log(WeeklyMD) + SQ_mapped + SinTime + CosTime, na.action = na.omit,
+ random = ~ 1 | Plot, data = p2, correlation = corSpher ( form = ~Pass|Plot))
> summary(p2.LFPC.lme1)
Linear mixed-effects model fit by REML
Data: p2
AIC  BIC  logLik
786.5789 831.0202 -383.2895

Random effects:
Formula: ~1 | Plot
(Intercept)  Residual
StdDev: 0.156003 0.4136206

Correlation Structure: Spherical spatial correlation
Formula: ~Pass | Plot
Parameter estimate(s):
  range
1.000076

Fixed effects: LogitFPC ~ MeanMonthMinT + SOI + log(WeeklyMD) + SQ_mapped + SinTime + CosTime
Value  Std.Error   DF  t-value p-value
(Intercept) -7.624549 0.3541148 578 -21.531292 0.0000
MeanMonthMinT -0.153924 0.0137820 578 -11.168467 0.0000
SOI 0.064625 0.0225914 578  2.860597  0.0044
log(WeeklyMD) 0.822794 0.0319786 578  25.729481  0.0000
SQ_mappedSQ 2 -0.411352 0.0547652  51 -7.511193  0.0000
SinTime 0.450145 0.0301748 578  13.633585  0.0000
CosTime 0.642709 0.1025202 578   6.269098  0.0000

Correlation:
                      (Intr) MeanMonthMinT SOI  log(WeeklyMD) SQ_mappedSQ 2 SinTime
MeanMonthMinT -0.146
SOI  0.215  0.682
log(WeeklyMD) -0.910 -0.256 -0.522
SQ_mappedSQ 2 -0.090  0.000  0.000  0.000
SinTime -0.130 -0.743 -0.585  0.427  0.000
CosTime  0.198 -0.942 -0.658  0.179  0.000  0.624

Standardized Within-Group Residuals:
    Min      Q1     Med      Q3     Max
-3.86605081 -0.60628506  0.03295294  0.63568004  3.05486035

Number of Observations: 636
Number of Groups: 53

> # Period 3 (Stable)
> p3.LFPC.lme1 <- lme(LogitFPC ~ SOI + SQ_mapped + SinTime + CosTime, na.action = na.omit,
+ random = ~ 1 | Plot, data = p3, correlation = corSpher ( form = ~Pass|Plot))
> summary(p3.LFPC.lme1)
Linear mixed-effects model fit by REML
Data: p3
AIC  BIC  logLik
50.29313 93.50298 -17.14656

Random effects:
Formula: ~1 | Plot
(Intercept)  Residual
StdDev: 0.0888332 0.3661379

Correlation Structure: Spherical spatial correlation
Formula: ~Pass | Plot
Parameter estimate(s):
  range
9.738143

Fixed effects: LogitFPC ~ SOI + SQ_mapped + SinTime + CosTime
Value  Std.Error   DF  t-value p-value
(Intercept) -0.311334 0.03210000 1587 -9.669088  0.0000
SOI 0.1158556 0.00889798 1587 13.026190  0.0000
SQ_mappedSQ-2  -0.3363939  0.04187212  51  -8.033840  0.0000
SinTime   -0.0522074  0.01926632  1587  -2.709773  0.0068
CosTime   -0.2831295  0.00000000  1587  -14.247618  0.0000

Correlation:

(Intr) SOI   SQ_SQ  SinTim

SOI      0.102
SQ_mappedSQ-2 -0.761  0.000
SinTime  -0.023  -0.042  0.000
CosTime  0.015  0.045  0.000

Standardized Within-Group Residuals:

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>Q1</th>
<th>Med</th>
<th>Q3</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-4.86420433</td>
<td>-0.50876503</td>
<td>0.48781114</td>
<td>4.23305697</td>
<td></td>
</tr>
</tbody>
</table>

Number of Observations: 1643
Number of Groups: 53

> # Diagnostic plots of p1.LFPC.lme1 (DROUGHT with drought model)
> # Residuals v Fitted
> par(mfrow=c(1,1), mar=c(3,3,1,1))
> plot(fitted(p1.LFPC.lme1), residuals(p1.LFPC.lme1), ann=F, pch=19, cex=0.8, col ="DarkGray")
> mtext(side=1,line=2,text="Fitted", cex=0.8)
> mtext(side=2,line=2,text="Residuals", cex=0.8)
> abline(h=0, col="blue")
> #QuantileQuantile
> par(mfrow=c(1,1))
> qqnorm(residuals(p1.LFPC.lme1))
> #Seasonality
> acf(residuals(p1.LFPC.lme1), lag.max=50)
> text(30,0.9, "ACF")
> mtext(side=1, line=2, text="Lag", cex=0.8)
> #Error
> pacf(residuals(p1.LFPC.lme1), lag.max=50)
> text(30, 0.5, "PACF")
> mtext(side=1, line=2, text="Lag", cex=0.8)
> # Diagnostic plots of p2.LFPC.lme1 (WET model)
> # Residuals v Fitted
> par(mfrow=c(1,1), mar=c(3,3,1,1))
> plot(fitted(p2.LFPC.lme1), residuals(p2.LFPC.lme1), ann=F, pch=19, cex=0.8, col ="DarkGray")
> mtext(side=1,line=2,text="Fitted", cex=0.8)
> mtext(side=2,line=2,text="Residuals", cex=0.8)
> abline(h=0, col="blue")
> #Seasonality
> acf(residuals(p2.LFPC.lme1), lag.max=50)
> text(30,0.9, "ACF")
> mtext(side=1, line=2, text="Lag", cex=0.8)
> #Error
> pacf(residuals(p2.LFPC.lme1), lag.max=50)
> text(30, 0.5, "PACF")
> mtext(side=1, line=2, text="Lag", cex=0.8)
> #QuantileQuantile
> par(mfrow=c(1,1))
> qqnorm(residuals(p2.LFPC.lme1))
> # Diagnostic plots of p3.LFPC.lme1 (STABLE model)
> # Residuals v Fitted
> par(mfrow=c(1,1), mar=c(3,3,1,1))
> plot(fitted(p3.LFPC.lme1), residuals(p3.LFPC.lme1), ann=F, pch=19, cex=0.8, col ="DarkGray")
> mtext(side=1,line=2,text="Fitted", cex=0.8)
> mtext(side=2,line=2,text="Residuals", cex=0.8)
> abline(h=0, col="blue")
> #Seasonality
> acf(residuals(p3.LFPC.lme1), lag.max=50)
> text(30, 0.9, "ACF")
> # Error
> pacf(residuals(p3.LFPC.lme1), lag.max=50)
> text(30, 0.5, "PACF")
> # Quantile
> par(mfrow=c(1,1))
> qqnorm(residuals(p3.LFPC.lme1))
> # 4. Plotting the model over time (drought-drought)
> # extract the fitted and residual values (from the object produced by nlme)
> # and put them in new data frames
> fitted.p1.LFPC.lme1< as.data.frame(inv.logit(fitted(p1.LFPC.lme1)))
> residuals.p1.LFPC.lme1< as.data.frame(inv.logit(residuals(p1.LFPC.lme1)))
> # bind the two together by column into one object
> # (which will have all 2809 values in it: 53 sites with 11 time steps each)
> fr.p1.LFPC.lme1<cbind(fitted.p1.LFPC.lme1, residuals.p1.LFPC.lme1)
> head(fr.p1.LFPC.lme1)
> inv.logit(fitted(p1.LFPC.lme1)) inv.logit(residuals(p1.LFPC.lme1))
> 1 0.3010796 0.5105091
> 2 0.2787224 0.5376010
> 3 0.2707213 0.5417441
> 4 0.2588302 0.5510119
> 5 0.2674587 0.5280133
> 6 0.2982528 0.5020835
> # write the file to a csv
> write.csv(fr.p1.LFPC.lme1, "Fitted Residual for p1.LFPC.lme1 010916.csv")
> # 4. Plotting the model over time (wet-drought)
> # extract the fitted and residual values (from the object produced by lmer)
> # and put them in new data frames
> fitted.p2.LFPC.lme1< as.data.frame(inv.logit(fitted(p2.LFPC.lme1)))
> residuals.p2.LFPC.lme1< as.data.frame(inv.logit(residuals(p2.LFPC.lme1)))
> # bind the two together by column into one object
> # (which will have all 2809 values in it: 53 sites with 12 time steps each)
> fr.p2.LFPC.lme1<cbind(fitted.p2.LFPC.lme1, residuals.p2.LFPC.lme1)
> head(fr.p2.LFPC.lme1)
> inv.logit(fitted(p2.LFPC.lme1)) inv.logit(residuals(p2.LFPC.lme1))
> 1 0.2299603 0.4399230
> 2 0.4015328 0.4178015
> 3 0.6511627 0.2712837
> 4 0.4095968 0.5855579
> 5 0.6282326 0.3173875
> 6 0.7078025 0.5801955
> # write the file to a csv
> write.csv(fr.p2.LFPC.lme1, "Fitted Residual for p2.LFPC.lme1 010916.csv")
> # 4. Plotting the model over time (stable-drought)
> # extract the fitted and residual values (from the object produced by lmer)
> # and put them in new data frames
> fitted.p3.LFPC.lme1< as.data.frame(inv.logit(fitted(p3.LFPC.lme1)))
> residuals.p3.LFPC.lme1< as.data.frame(inv.logit(residuals(p3.LFPC.lme1)))
> # bind the two together by column into one object
> # (which will have all 2809 values in it: 53 sites with 31 time steps each)
> fr.p3.LFPC.lme1<cbind(fitted.p3.LFPC.lme1, residuals.p3.LFPC.lme1)
> head(fr.p3.LFPC.lme1)
> inv.logit(fitted(p3.LFPC.lme1)) inv.logit(residuals(p3.LFPC.lme1))
> 1 0.4179329 0.4710207
> 2 0.4360922 0.4577744
> 3 0.4109277 0.4782186
> 4 0.3275130 0.5929374
> 5 0.2927223 0.5866133
> 6 0.3209875 0.5901446
> #write the file to a csv
> write.csv(fr.p3.LFPC.lme1, "Fitted Residual for p3.LFPC.lme1 010916.csv")
> ##BONUS SECTION
> #LFPC Model Plotting
> par(mfrow=c(1,1), mar=c(3,3,1,1))
> plot(lmeruns$Pass[1:11], (fr.p1.LFPC.lme1[1:11,1]), type="l", lwd=2,
+ ylim=c(0,1), xlim=c(4,186), xaxt="n", ann=F, cex.axis=0.8, bty="n")
> lines(lmeruns$Pass[1:11], (fr.p1.LFPC.lme1[23:33, 1]), lwd=1)
> axis(side=1, at=seq(0,186,22.8), labels=c(2008:2016), cex.axis=0.8)
> mtext("Time", side=1, line=2, cex=0.9)
> mtext("FPC Median", side=2,line=2, cex=0.9)
> abline(v=48, col="light blue")
> points(lmeruns$Pass[1:11], lmeruns$FPC_med[1:11], col="red", pch=20, cex=0.8)
> lines(lmeruns$Pass[1:11], lmeruns$FPC_med[1:11], col="red")
> legend(0,0.9, c("Observed FPC", "Fitted SQ2", "Fitted SQ1"), lty=1, lwd=c(1,2,1
+ ), col=c("red","black","black"), bty="n", cex=0.9)
> points(lmeruns$Pass[11:22],(fr.p2.LFPC.lme1[1:12,1]), type="l", lwd=2,
+ ylim=c(0,1), xlim=c(4,186), xaxt="n", ann=F, cex.axis=0.8, bty="n")
> lines(lmeruns$Pass[11:22],(fr.p2.LFPC.lme1[25:36, 1]), lwd=1)
> points(lmeruns$Pass[11:22], lmeruns$FPC_med[11:22],col="red", pch=20, cex=0.8)
> lines(lmeruns$Pass[11:22], lmeruns$FPC_med[11:22],col="red")
> abline(v=85, col="light blue")
> points(lmeruns$Pass[23:53],(fr.p3.LFPC.lme1[1:31,1]),type="l", lwd=2,
+ ylim=c(0,1), xaxt="n", ann=F, cex.axis=0.8, bty="n")
> lines(lmeruns$Pass[23:53],(fr.p3.LFPC.lme1[63:93,1]))
> points(lmeruns$Pass[23:53], lmeruns$FPC_med[23:53],col="red", pch=20, cex=0.8)
> lines(lmeruns$Pass[23:53], lmeruns$FPC_med[23:53],col="red")
> abline(v=123, col="light blue")
> abline(v=186, col="light blue")
APPENDIX 6: Normal Quantile-Quantile Plots and Residual v Fitted scatterplots for NDVI GLMMS – all periods.
APPENDIX 7: Normal Quantile-Quantile Plots and Residual v Fitted scatterplots for Logit FPC GLMMS – all periods.
APPENDIX 8: El Nino Southern Oscillation conditions for the study period.

El Nino Southern Oscillation (2007 - 2016)

APPENDIX 9: Daily River Discharge at Yarrawonga Weir for the study period.

Yarrawonga Weir Daily Discharge (ML)
APPENDIX 10: Mean monthly temperature for the period recorded at Deniliquin Airport.

Mean Monthly Max and Min Temperature
Deniliquin AWS (stn. 74258)

APPENDIX 11: Monthly precipitation for the period recorded at Mathoura for the study period.

Monthly Precipitation Mathoura (stn. 74129)
APPENDIX 12: Contrast between ephemeral summer and winter ground cover.

**Figure A12a** Summer ground cover.  
**Figure A12b** Winter ground cover.

APPENDIX 13: Skewness testing

**Figure A13** Spider chart highlights the skewness variability in a random selection of plots for each of the 53 dates in the data series. Values > 0.5 and < -0.5 were considered indicative of skewness.