AN ECOHYDROLOGICAL MODELLING STUDY OF AN AUSTRALIAN EUCALYPTUS FOREST

Hanieh Kosari

Associate Professor Patricia Saco
Professor Garry Willgoose
Associate Professor Jose Rodriguez

Submitted in partial fulfilment of the requirements for the degree of Master’s by Research

Faculty of Engineering and built environment
School of Engineering
University of Newcastle
March 2018

This research was supported by an Australian Government Research Training Program (RTP) Scholarship
Statement of Original Authorship

I hereby certify that the work embodied in the thesis is my own work, conducted under normal supervision.

The thesis contains no material which has been accepted, or is being examined, for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text. I give consent to the final version of my thesis being made available worldwide when deposited in the University’s Digital Repository, subject to the provisions of the Copyright Act 1968 and any approved embargo.

Signature: Hanieh Kosari
Date: March 2018
Acknowledgements

I would like to thank all my supervisors for their knowledge and guidance. I would like to thank the University of Newcastle and the Australian Government Research Training Program for giving me the scholarships for completing this study.

I would like to thank all my fellow friends for their kind support during my studies. They always brought fun to my life.

Finally, I would specially thank my parents that their love were always with me. And to my husband for his patience and his support. His love gave meaning to my life.
# Table of Contents

Statement of Original Authorship ........................................................................................................i
Acknowledgements ................................................................................................................................. ii
Table of Contents .................................................................................................................................... iii
List of Figures .......................................................................................................................................... v
List of Tables ........................................................................................................................................... viii
Abstract .................................................................................................................................................. ix

## CHAPTER 1: GENERAL OVERVIEW ................................................................................................. 1
1.1 Background ........................................................................................................................................ 1
1.2 Ecohydrological models .................................................................................................................... 4
   1.2.1 Modelling above-ground processes ....................................................................................... 5
   1.2.2 Modelling below-ground processes ....................................................................................... 7
1.3 Previous Studies on Australian eucalyptus forests ......................................................................... 9
1.4 Motivation for choosing the MLCan model ..................................................................................... 13
1.5 sensitivity analysis and model calibration ....................................................................................... 15
1.6 Model initialisation .......................................................................................................................... 16
1.7 Objectives of this research ............................................................................................................. 18
1.8 Thesis Outline .................................................................................................................................. 19

## CHAPTER 2: RESEARCH METHODOLOGY ....................................................................................... 20
2.1 Multilayer canopy-root-soil model (MLCan) .................................................................................... 20
2.2 study area ........................................................................................................................................ 24
2.3 Input data ......................................................................................................................................... 26
   2.3.1 Canopy and root structure ...................................................................................................... 27
   2.3.2 Climate data .......................................................................................................................... 28
   2.3.3 Initial conditions .................................................................................................................... 29
2.4 Model Parameters ........................................................................................................................ 30
   2.4.1 Sensitivity analysis of the parameters ..................................................................................... 32
   2.4.2 Selected parameters .............................................................................................................. 33
       Stomatal conductance parameters ............................................................................................ 33
       Soil respiration parameters .................................................................................................... 34
       Plant resistance to flow ........................................................................................................... 34
       Root water uptake and Root conductivities ............................................................................ 34
2.4.3 Parameter range and sampling ................................................................................................. 36
2.4.4 Model performance indicator .................................................................................................. 37
2.5 Model calibration ............................................................................................................................ 38
2.6 Model validation .............................................................................................................................. 38

## CHAPTER 3: EFFECTS OF THE MULTILAYER CANOPY AND HYDRAULIC REDISTRIBUTION ON THE MODEL’S RESULTS .................................................................................. 39
3.1 Effects of different numbers of canopy layers ............................................................................... 41
3.2 Root conductivity Parameters initial sensitivity analysis .............................................................. 47
   3.2.1 Effects of root conductivities on monthly latent heat fluxes ................................................. 48
   3.2.2 Effects of root conductivities on soil moisture and water uptake ......................................... 50
   3.2.3 Effects of the root conductivities and hydraulic redistribution on the latent heat fluxes and soil moisture ............................................................... 51
3.3 Summary and conclusion ........................................................................................................ 55

CHAPTER 4: THE SENSITIVITY ANALYSIS AND MODEL CALIBRATION AND VALIDATION ........................................................................................................ 57

4.1 Model sensitivity analysis to parameters ............................................................................... 58

4.2 Model calibration ................................................................................................................... 66
  4.2.1 Single-response model calibration ................................................................................ 66
  4.2.1.1 Quantitative assessment ...................................................................................... 66
  4.2.1.2 Visual assessment of simulations with single-response calibrated parameters 70
  4.2.2 Multi-response model calibration .............................................................................. 75
  4.2.2.1 Quantitative assessment ...................................................................................... 75
  4.2.2.2 Visual assessment of simulations with multi-response calibrated parameters 77
  4.2.3 Single-response versus multi-response calibrations ................................................ 80

4.3 Model validation on independent data .................................................................................. 81

4.4 Comparison with Previous modelling in Tumbarumba ........................................................ 92

4.5 Summary and conclusion .................................................................................................... 96

CHAPTER 5: THE INFLUENCE OF THE SOIL INITIAL CONDITIONS ........................................ 98

5.1 Effects of initial soil moisture ............................................................................................. 99
  5.1.1 Effects of initial soil moisture on model calibrations ................................................. 99
  5.1.1.1 Single-response model calibration ................................................................. 100
  5.1.1.2 Multi-response model calibration ................................................................. 103
  5.1.1.3 Visual assessment of simulations with multi-response calibrated parameters .... 106
  5.1.2 Effects of initial soil moisture and calibrated parameters ......................................... 109

5.2 Cross Effects of soil temperature and soil moisture ......................................................... 114
  5.2.1 Effects of soil temperature on soil moisture ............................................................ 115
  5.2.2 Effects of soil moisture on soil temperature ............................................................. 118

5.3 Summary and conclusion ................................................................................................... 121

CHAPTER 6: CONCLUSIONS AND POTENTIAL FUTURE WORKS ................................ 124

BIBLIOGRAPHY ........................................................................................................................... 129
List of Figures

Figure 1. Australia's forest extent and forest type distribution in 2013 (from www.agriculture.gov.au/abares/forestsaustralia/publications) ........................................................ 3

Figure 2. Components of land surface energy exchanges and the water cycle in ecohydrological models (adapted from Fatichi et al., 2015) ............................................................... 4

Figure 3. Latent heat flux estimations with recent version of the CABLE model (red) and latent heat flux observations (black) in Tumbarumba (from Ukkola et al., 2016) ................. 13

Figure 4. Schematic of the MLCan model (from Le et al., 2012) ................................................................................................................................. 22

Figure 5. Daily total precipitation a), daily average values of shortwave radiation b), and air temperature c) at Tumbarumba for 2005 .............................................................................. 25

Figure 6. Canopy structure at the Tumbarumba forest a) Seasonal variation of LAI in 2005 adapted from Wang et al. (2011) and b) vertical profile of LAD adapted from Ryder et al. (2016). ......................................................................................................................... 27

Figure 7. Root fraction profile for eucalyptus in Tumbarumba generated in MLCan based on the model of Schenk and Jackson (2002) ........................................................................ 28

Figure 8. Monthly average latent heat flux (LE) in Tumbarumba a) Comparison of different processing levels (L3, L4, L6) and two reported published data (Li et al., 2012; Ukkola et al., 2016) b) Percentage of missing data in each month in L3 and L4 data ...................................................................................................................... 29

Figure 9. Effects of different numbers of canopy layers on the sunlit fraction ................................................................. 42

Figure 10. Effects of different numbers of canopy layers on leaf temperature a) sunlit fraction b) shaded fraction c) whole canopy ...................................................................................... 44

Figure 11. Effects of different numbers of canopy layers on stomatal conductance (g_s) of a) sunlit fraction, b) shaded fraction, c) whole canopy .................................................................. 45

Figure 12. Effects of different numbers of canopy layers on a) total PAR absorbed b) total canopy fluxes of: net canopy photosynthesis (An), Sensible heat flux (H) and Latent heat flux (LE) ....................................................................................................................... 46

Figure 13. Monthly average latent heat flux estimations for different sets of root conductivities in year 2005 a) Effects of variable radial root conductivities with Scenarios 2, 6, 10, 14 b) Effects of variable axial root conductivities in Scenarios 5, 6, 7, 8 .............................................................................. 49

Figure 14. Soil moisture profiles and root water uptake profiles for Scenario 16 (low root conductivity) and Scenario 9 (high root conductivity) ......................................................... 50

Figure 15. Effects of root conductivity and hydraulic redistribution on a) monthly average and b) diurnal average latent heat fluxes. Note that the two blue lines are on top of each other. ......................................................................................................................... 52

Figure 16. Soil moisture estimations in Scenario 16, with low root conductivity (top plots), and in Scenario 9, with high root conductivity (bottom plots), at a) 10 cm depth and b) 228 cm depth ......................................................................................................................... 53

Figure 17. Water uptake for Scenario 9 (high root conductivity) in Table 7 with HR at 10cm depth (blue line) and 228cm depth (red line) .............................................................. 54

Figure 18. GLUE dotty plots of the behavioural latent heat flux (LE) simulations versus the parameters a) m, b) h, c) K_rad, d) K_ice, e) ψ_f, f) S_f, g) R_0, h) R_p and i) Q_{10} ....................................................................................................................... 62

Figure 19. GLUE dotty plots of the behavioural sensible heat flux (H) simulations versus the parameters a) m, b) h, c) K_rad, d) K_ice, e) ψ_f, f) S_f, g) R_0, h) R_p and i) Q_{10} ....................................................................................................................... 63

Figure 20. GLUE dotty plots of the behavioural CO2 flux (F_c) simulations versus the parameters a) m, b) h, c) K_rad, d) K_ice, e) ψ_f, f) S_f, g) R_0, h) R_p and i) Q_{10} ....................................................................................................................... 64
Figure 21. GLUE dotty plots of the 15 cm behavioural soil moisture simulations versus the parameters a) m, b) b, c) $K_{sclad}$, d) $k_{ass}$, e) $\psi_f$, f) $S_f$, g) $R_s$, h) $R_p$ and i) $Q_{10}$ ........................................ 65

Figure 22. Average daily latent heat flux estimations for the five best LE fits versus the observed data for year 2005 ................................................................. 70

Figure 23. Average daily sensible heat flux estimations for the five best H fits versus the observed data for year 2005 ................................................................. 71

Figure 24. Average daily CO₂ flux estimations for the five best $F_c$ fits versus the observed data for year 2005 ................................................................. 70

Figure 25. Average daily soil moisture estimations at the first layer for the five best SWS fits versus the observed data for year 2005 ........................................ 72

Figure 26. Daily soil moisture profile for the best SWS parameter set at year 2005 ........................................ 72

Figure 27. Average daily stomatal conductance estimations for the five best SWS fits for year 2005 ................................................................. 74

Figure 28. Average daily latent heat flux estimations for the best SWS fits for year 2005 ............ 74

Figure 29. Average daily latent heat flux estimations for the five best NS-all parameter sets versus the observed data for year 2005 ........................................ 78

Figure 30. Average daily sensible heat flux estimations for the five best NS-all parameter sets versus the observed data for year 2005 ........................................ 78

Figure 31. Average daily CO₂ flux estimations for the five best NS-all parameter sets versus the observed data for year 2005 ........................................ 79

Figure 32. Average daily soil moisture estimations at first layer for the five best NS-all parameter sets versus the observed data for year 2005 ........................................ 79

Figure 33. Average daily stomatal conductance estimations for the five best NS-all parameter sets ................................................................. 80

Figure 34. Monthly precipitation between 2001 and 2008 in Tumbarumba ........................................ 82

Figure 35. Observed-estimated X-Y plots for (a-d) hourly latent heat fluxes (LE) for individual years between 2001 and 2008 and (e) monthly LE during the eight years ........................................ 85

Figure 36. Observed-estimated X-Y plots for (a-d) hourly sensible heat fluxes (H) for individual years between 2001 and 2008 and (e) monthly H during the eight years ............. 86

Figure 37. Observed-estimated X-Y plots for (a-d) hourly CO₂ fluxes ($F_c$) for individual years between 2001 and 2008 and (e) monthly CO₂ during the eight years ........................................ 87

Figure 38. Observed-estimated X-Y plots for (a-d) hourly soil moisture (SWS) at first layer for individual years between 2001 and 2008 and (e) monthly SWS during the eight years ....... 88

Figure 39. Average monthly latent heat flux estimations versus observations for validations years (2001-2008). Dashed line shows January to December 2005 which was the calibration year ........................................ 89

Figure 40. Average monthly sensible heat flux estimations versus observations for validation years (2001-2008). Dashed line shows January to December 2005 which was the calibration year ........................................ 90

Figure 41. Average monthly CO₂ flux estimations versus observations for validation years (2001-2008). Dashed line shows January to December 2005 which was the calibration year ........................................ 90

Figure 42. Average monthly soil moisture estimations at different depths versus the corresponding observed data ................................................................. 92

Figure 43. Comparison of monthly average latent heat fluxes; observed by (OzFlux, reported by Li et al. (2012) and estimated by the MLCan model and CABLE model .......... 93

Figure 44. Comparison of monthly observed and estimated soil moisture data at different depths a) 15 cm, b) 30 cm, c) 60 cm, d) 120 cm ........................................ 95
Figure 45. Average daily estimated latent heat fluxes for the five best NS-all parameter sets versus the observed data for year 2005 ................................................................. 107

Figure 46. Average daily estimated sensible heat fluxes for the five best NS-all parameter sets versus the observed data for year 2005 ................................................................. 107

Figure 47. Average daily estimated CO₂ fluxes for the five best NS-all parameter sets versus the observed data for year 2005 ................................................................. 108

Figure 48. Average daily soil moisture estimations at first layer for the five best NS-all parameter sets versus the observed data for year 2005 ................................................................. 108

Figure 49. Average daily soil moisture profiles (left) and estimated versus observed soil moisture plots at first layer (right) for Scenarios 1 to 4 in Table 19 ................................................. 113

Figure 50. Soil moisture estimations at different depths for different scenarios a) 10 cm, b) 27 cm, c) 58 cm ........................................................................................................ 116

Figure 51. Soil temperature estimations at different depths for different scenarios a) 10 cm, b) 27 cm, c) 58 cm ........................................................................................................ 119
# List of Tables

Table 1. Features of MLCan, CABLE and SPA models ................................................................. 14
Table 2. MLCan outputs .............................................................................................................. 23
Table 3. Required input data for MLCan model ........................................................................ 26
Table 4. Depth-varying soil initial conditions used in Chapter 4 .............................................. 30
Table 5. List of parameters used to run the MLCan model ...................................................... 31
Table 6. Sampling ranges for the nine parameters and the reported values in the ................. 37
Table 7. Scenarios of root conductivities ................................................................................. 48
Table 8. Single-response model calibration result ................................................................. 67
Table 9. Best parameters set in single-response model calibration .......................... 68
Table 10. Multi-response model calibration results ............................................................... 76
Table 11. Best parameters set in multi-response model calibrations .............................. 77
Table 12. Initial conditions at the beginning of 2001 for model validation .................... 82
Table 13. NS values for independent model validations for years between 2001 and 2008 using the best parameter sets (α1) from multi-response calibration for 2005 .......... 83
Table 14. Depth-constant soil initial conditions for 2005 considered for this analysis .......... 100
Table 15. Single-response model calibration results with depth-constant initial conditions .......... 101
Table 16. Best parameter sets in single-response model calibration ............................ 102
Table 17. Multi-response model calibration results with depth-constant initial soil moisture ........ 104
Table 18. Best parameter sets in multi-response model calibration with depth-constant initial soil moisture ................................................................. 105
Table 19. Different scenarios for evaluating the effects of the parameters and Initial Conditions (ICs) ....................................................................................... 110
Table 20. Different soil initial conditions and parameters for Scenarios 1 to 5 ............ 115
Abstract

In this study, a multilayer canopy-root-soil model (MLCan) was implemented to simulate the ecohydrological fluxes of a eucalyptus forest located in Tumbarumba, Australia. This model has not been previously tested in this type of ecosystem. This study particularly focused on estimating the forest land-atmosphere exchange fluxes of latent heat ($LE$), sensible heat ($H$) and CO$_2$ ($F_c$), as well as the soil moisture at the first layer ($SWS$), comparing model results to observations and examining the sensitivity of the estimates to selected model parameters. The parameter sensitivity analysis and model calibrations were performed using the Monte-Carlo based GLUE method.

The effects of multiple canopy layers on the model’s estimations were first examined, and the optimum number of canopy layers were determined. Sensitivity analysis on the values of root conductivities indicated the importance of axial root conductivity on the estimations of the latent heat flux, root water uptake, soil moisture and hydraulic redistribution.

As a result of the parameter sensitivity analysis using GLUE, it was found that the slope ($m$) and intercept ($b$) of the Ball-Berry stomatal conductance model were the most sensitive parameters for estimating the $LE$, $H$ and $SWS$. The $R_o$ parameter, soil respiration rate at 10 $^\circ$C, was found to be the only sensitive parameter for estimating $F_c$. Model calibrations to observations were carried out using GLUE, both on individual variables (single-response) and on all variables (multi-response). The results of the single-response calibrations produced slightly better results but were biased towards the calibrated variable. The results of the model validations on the independent data during 2001-2008 showed that the model performed reasonably well in estimating the $LE$, $H$ and $SWS$. However, the model could not estimate the $F_c$ very well. The estimations of the $LE$ and $SWS$ using the MLCan model had a similar level of agreement with observations than previous results at the site using the CABLE model.

Comparing the effects of depth-constant and depth-varying initial soil moisture on model calibrations showed that the depth-constant initial soil moisture degraded the model’s performance in multi-response calibration, mainly due to the degradation in
the soil moisture estimation. However, it did not significantly affect the results in the single-response calibration. An analysis on the effects of parameters and initial soil moisture conditions on the soil moisture estimation showed that the deep layer soil moisture influenced the surface layer soil moisture estimations. This result suggested that vegetation has an effect on the soil moisture estimation through hydraulic redistribution. Results from the MLCan simulations at Tumbarumba also suggested that the soil moisture memory is in the order of 12 months. The results presented in this thesis demonstrate that the MLCan model can be used to adequately capture ecohydrologic fluxes in eucalyptus ecosystems in Australia.
Chapter 1: General Overview

1.1 BACKGROUND

Hydrology, a subcategory of the Earth sciences, is defined as the study of the occurrence, circulation and distribution of water throughout the land and the atmosphere (Dingman, 2015). The hydrological cycle refers to the circulation of water in its different phases through the atmosphere: down, over and through the land, and back up to the atmosphere (Brutsaert, 2005). This circulation of water makes life possible on Earth. The hydrological cycle is intrinsically coupled with the climate, vegetation and land surface, and with all of their inter-related processes. Within this nexus, vegetation and water represent the focus of much of the research in the areas of hydrology, climatology and ecology.

The inherent plant-water relations have long been studied by both ecologists and hydrologists. In this integrated relation, vegetation plays a key role. Vegetation growth is linked to water, and thus its distribution and functions are influenced by the hydrologic cycle. On the other hand, plants transfer water to the atmosphere via transpiration. Considering the latent heat used to change the water phase, from liquid to vapour, and transferring the water vapour to the atmosphere via the stomata (through the same opening aperture plants gain carbon for assimilation), vegetation is also linked to the energy and carbon cycles (Asbjornsen et al., 2011; Fatichi et al., 2015).

Recent studies into the existence of the linkage between plant and water have introduced the highly interdisciplinary field of science, namely ecohydrology, which explicitly focuses on the interactions between ecological and hydrological processes (Asbjornsen et al., 2011). The science of ecohydrology is capable of using integrated approaches to predict the ecohydrological responses of the ecosystem to climate change, to provide engineering solutions for sustainable water resources management, and to reduce environmental problems in the foreseeable future (Asbjornsen et al., 2011; Porporato & Rodriguez-Iturbe, 2002). In the past, vegetation was introduced with a constant term in hydrological studies and, at the same time, hydrology had been represented by a simple bucket model in ecological applications (Fatichi et al., 2015). In hydrological engineering applications and short-term analyses this simple
representation might be amenable, but when understanding climate-land surface processes is the main focus, or when modelling multiple processes or mutual interactions between vegetation and water is needed, a simple representation of vegetation does not suffice, and is misleading (Fatichi et al., 2015).

Eucalyptus is an iconic Australian tree and eucalyptus forests, with a total of 92 million hectare (74% of Australia’s forest area), are the dominant forest type in Australia (http://www.agriculture.gov.au/abares/forestsaustralia/profiles/eucalypt-forest) (see Figure 1). Eucalyptus trees in Australia have significant commercial and ecological values, and comprise more than 700 species throughout the continent (Ghannoum et al., 2010). In the national reports, the eucalypt forest type is divided into 11 forest subtypes based on the form of the dominant individuals (multi-stemmed mallee or single-stemmed tree), height (low, medium or tall) and crown cover (closed, open or woodland). Nearly all eucalypt species are evergreen and retain their leaves through the whole year. The forests of south-eastern Australia contain a wide range of dominant eucalypt species, including major commercial timber species such as mountain ash (E. regnans), messmate stringybark (E. obliqua), alpine ash (E. delegatensis), silvertop ash (E. sieberi), blackbutt (E. pilularis) and spotted gum (Corymbia maculata). Eucalypt forests in south-western Australia are dominated by jarrah (E. marginata) and karri (E. diversicolor). The typical eucalypts of northern Australia include Darwin woollybutt (E. miniata) and Darwin stringybark (E. tetrodonta). Many species of the mallee eucalypts are found across the inland regions of southern Australia (http://www.agriculture.gov.au/abares/forestsaustralia/profiles/eucalypt-forest).

As the eucalyptus forest is the dominant forest type in Australia, simulating the forest interactions with water and climate are of great interest among ecohydrologists. With the tight coupling between vegetation, hydrology and climate, the land surface models and/or ecohydrological models try to simulate the land surface processes. In this study, the land surface models have been used interchangeably with the ecohydrological models. Therefore, having a reliable and validated land surface model contributes to an understanding of the potential changes in the ecosystem water balance as well as the land-atmosphere exchange fluxes of CO₂, water vapour and the energy of the dominant Australian forest under the effects of environmental perturbations, including climate change.
In this study, a point-scale multilayer canopy-root-soil model (MLCan) is used to analyse the ecohydrology of an Australian eucalyptus forest in central New South Wales. There is a particular focus on estimating the forest land-atmosphere exchange fluxes of carbon, water and energy, as well as the soil moisture, to identify and examine the sensitivity of the selected model parameters. The study also evaluates the effects of the initial conditions on the model estimations. The MLCan model was developed by a group of researchers at The University of Illinois in the USA (Drewry et al., 2010a), and has not been used on a eucalyptus forest before.

In the following sections, an overview of the ecohydrological modelling is provided in Section 1.2. This is followed by a review of previous studies on Australian eucalyptus forests in Section 1.3, and a discussion of the motivation for employing the MLCan model for this study in Section 1.4. Light is then shed on the sensitivity analysis and model calibration in Section 1.5 and the model initialisation in Section
1.6. The objectives of this research and the thesis outlines are explained in Sections 1.7 and 1.8, respectively.

1.2 ECOHYDROLOGICAL MODELS

Ecohydrological models have been defined in various ways in the literature, and they are generally used to solve water, energy and carbon cycles at the land surface. The land surface components, based on whether they deal with the canopy or the root-soil system, can be considered as above-ground or below-ground processes, which will be discussed separately in the following sub-sections. Figure 2 shows the components of the land surface energy exchanges, such as shortwave and longwave radiation, canopy and soil latent and sensible heat flux, soil heat flux and the components of the water cycle, such as the rainfall, snowfall, evaporation, transpiration and infiltration. Many models do not include all of the components presented in this figure.

![Figure 2. Components of land surface energy exchanges and the water cycle in ecohydrological models (adapted from Fatichi et al., 2015)](image)

In terms of the water budget, the models account for the water inflows, outflows and changes in water storage within a defined volume, based on Equation (1) as shown below:
Inflow = Outflow + change in storage  

Precipitation and condensation are the water inflows to the ecosystem and evaporation and transpiration are usually the major components of the water outflows. Considered as latent heat, evapotranspiration, which is the sum of evaporation and transpiration, is also a major component of the energy budget. Water in the soil is redistributed vertically and horizontally, and is typically modelled with the Richards equation. However, in many ecological applications the water budget has been represented by a simple bucket approximation. Whether the water is stored in the soil, taken up by the plant and transpired, or is redistributed by the roots, is the main focus of Section 1.2.2.

Assuming a conservation of the energy budget is shown in Equation (2):

\[ R_n - LE - H - G = 0 \]

where \( R_n \) is the net radiation, \( H \) is the sensible heat, \( G \) is the ground heat flux and \( LE \) is the latent heat flux. As a result of the water and energy transfers by the latent heat flux, the water and energy cycles are tightly coupled. The energy balance components can be estimated by an approximation of the soil or canopy temperature. Solving the energy balance components faces one, or a system of, non-linear, temperature-dependent equations. As a simplification, several ecohydrological models use the Penman-Monteith equations (Fatichi et al., 2015).

Fatichi et al. (2015) reviewed the different approaches to simulating vegetation-water interactions at different scales, from a plant cell scale, plot to catchment scale, and regional to global scale, and discussed the different levels of complexities which can be attributed to these approaches. They presented a list of the ecohydrological models that have been developed in the last 15 years in the “plot to catchment” scale and summarized the features and processes that these models simulate. Of the models outlined by Fatichi, the MLCan model is the focus of this study that we hypothesized it has the potential to study the ecohydrology of eucalyptus forests in Australia.

1.2.1 Modelling above-ground processes

The above-ground processes correspond to the canopy model, in which the exchanges of radiation, water and \( \text{CO}_2 \), between the land surface and the atmosphere, are calculated. In the canopy model, the canopy processes, such as photosynthesis, the canopy energy balance components, and the canopy characteristics, such as leaf
temperature, are estimated. The canopy model also calculates how much radiation is absorbed, transmitted and reflected within the canopy radiation regime.

There are two commonly used approaches to simulate the canopy processes in the soil-vegetation-atmosphere transfer scheme, namely: 1) multilayer canopy models; and 2) single-layer canopy models (or big leaf models) (Leuning et al., 1995; Raupach & Finnigan, 1988; Williams et al., 1996).

In the big-leaf models, the details of the canopy profile are simplified to consider only a single layer and to simulate the behaviour of the whole canopy. Due to the non-linearity of the photosynthesis function and the changes in leaf physiology within canopy profiles, the arithmetic mean of the leaf level data in different layers is not applied to estimate the whole canopy fluxes of the radiation, CO₂ and water vapour in this approach. Thus, the canopy properties must be estimated directly in bulk (“big-leaf”) (Friend, 2001; Leuning et al., 1995; Williams et al., 1996). This may cause inaccuracies in the estimation of the energy fluxes (Drewry et al., 2010a).

On the other hand, multilayer canopy models need the spatial distributions of key parameters at the leaf scale in the different layers. This approach integrates the fluxes and variables measured or estimated at the leaf scale in each layer to give the total flux. As it is sometimes difficult to find information in vertical profiles (e.g., vertical profile of LAI), this is assumed to be one of the restrictions of multilayer models (Leuning et al., 1995; Raupach & Finnigan, 1988; Williams et al., 1996). The vertical distribution of canopy states and fluxes is of great importance among hydrologists and plant physiologists who would like to study the interactions between microclimates and physiology, or the hydrology of forested catchments (Raupach & Finnigan, 1988). Therefore, accurate estimations of the physical, biochemical and ecophysiological processes throughout the canopy are needed to predict the surface energy partitioning and surface hydrology under climate change (Drewry et al., 2010a).

The MLCan model, which has been chosen for this study, has a multilayer canopy model. The multilayer model resolves the leaf states and fluxes throughout the canopy, however the number of layers might affect the simulation results (Drewry et al., 2010a; Pyles et al., 2000). To determine the optimum number of canopy layers for the simulations, a sensitivity analysis of the effects of different numbers of canopy layers is required. The effects of different numbers of canopy layers will be examined
with the MLCan model in the estimation of the energy fluxes of a eucalyptus forest in the study area in Chapter 3.

1.2.2 Modelling below-ground processes

The canopy-atmosphere exchange fluxes of carbon, water and energy are regulated by both the above-ground and below-ground vegetation properties. The above-ground processes were discussed in the previous section and in this section the focus will be on the below-ground processes and the moisture transport through the root-soil system. Modelling the root water uptake and hydraulic redistribution in the hydrological and ecological models will also be discussed.

Root zone structure plays an important role in the land surface processes. Roots link the soil to the atmosphere and transfer water from the soil to where the plants use and transpire it. Among the below-ground vegetation properties, the root depth, distribution and functioning, as well as soil properties like soil water potential, soil moisture and hydraulic conductivity, are all important characteristics which can affect the fluxes of water and carbon (Feddes et al., 2001).

The existing ecohydrological models use different amounts of soil and plant root information. These differences affect the estimations of the land surface water and energy fluxes (Feddes et al., 2001). Some models consider the soil column as a bucket, and only consider the total soil water storage using the soil depth, rooting depth and soil texture and the beginning of the water stress (Drewry et al., 2010a; Jackson et al., 2000). However, other models consider the soil column as a multilayer system, which means that they use the vertical distributions of the root profile to estimate the soil water uptake in each layer (Amenu & Kumar, 2008; Drewry et al., 2010a; Feddes et al., 2001). The vertical distribution of the roots in the soil column is defined by the maximum rooting depth and the root fraction in each layer (Jackson et al., 2000). In local point-scale ecohydrological models, the root information and soil hydraulic characteristics in each soil layer are then used to estimate the water extracted by the roots (Feddes et al., 2001). Root water uptake is modelled differently amongst the ecological and hydrological communities. From a more hydrological perspective, the root water uptake is solved in a macroscopic approach, and is usually represented as a sink term in the moisture transport equation in the soil column (Feddes et al., 2001).
Hydraulic redistribution is one of the mechanisms associated with root water uptake that has been observed in the field (Burgess et al., 1998), and it has been found to be essential to be included in ecohydrological models (Li et al., 2012; Teodosio et al., 2017). The distribution of water throughout the root system, named “hydraulic redistribution”, refers to both the upward or downward movement of water via plant roots, from wet to dry soil layers (Amenu & Kumar, 2008). It can change the soil moisture profile, water uptake, soil CO₂ flux, canopy transpiration, carbon assimilation and the resultant water use efficiency (Domec et al., 2010; Quijano et al., 2012; Teodosio et al., 2017). Prentice et al. (2015) highlighted the importance of investigating “new” processes like hydraulic redistribution in the functions of the next-generation of land surface models and how this contributes to improving our understanding of the interactions among ecosystem processes.

Burgess et al. (1998) observed the hydraulic redistribution of river red gum trees (E. camaldulensis) in the south-west of Australia and silky oak trees (G. Robusta) in Kenya. Their results for the sap flow measurements in roots showed that water is redistributed whenever the water potential of the roots is unequal.

Recent ecohydrological models have incorporated the hydraulic redistribution mechanism into their modelling framework and their results have shown the effects of hydraulic redistribution on simulating the ecosystem water fluxes (Li et al., 2012; Quijano et al., 2012). Li et al. (2012) improved the responses of the Australian community land surface model (CABLE) to seasonal drought in Tumbarumba and two other sites out of Australia by considering an alternative root water uptake function (Lai & Katul, 2000), as well as including the hydraulic redistribution function of Ryel et al. (2002) into their modelling. Li et al. (2012) used the eddy covariance flux measurements at each study site and showed that the model estimations of the net ecosystem exchange flux and latent heat flux, when simulated with the alternative root water uptake function in tandem with the hydraulic redistribution function, agreed well with the observed data during the dry season. They related this agreement to the effects of including hydraulic redistribution phenomena in the soil moisture simulation and the larger root water uptake from the deep soil layers, using Lai and Katul’s function (compared to the default function in the CABLE model), during the dry season when the deep soil layers were wetter than the surface layers. However Li’s results did not significantly affect the model simulation during the wet season.
Quijano et al. (2012) extended the canopy-root-soil model (MLCan) of (Drewry et al., 2010a, b) to improve the below-ground ecohydrologic dynamics part of the model by applying the root water uptake and hydraulic redistribution functions of Amenu and Kumar (2008) for multiple plant species. They then applied the extended model in the Mediterranean climate of the Blodgett Forest in the Sierra Nevada Mountains in California, which is dominantly covered in overstorey by Ponderosa Pine, in order to study the interactions between the below-ground and above-ground dynamics as facilitated by hydraulic redistribution. Their results showed that the deep layer uptake of water by the tall vegetation and its release in the shallow layers enhanced the productivity of the understorey vegetation during summer. The multispecies-modelling feature of MLCan demonstrates the dynamics of the processes occurring below-ground, however it adds more complexity to the simulations by requiring more parameters as input data to the model.

The reviewed papers showed that the inclusion of the hydraulic redistribution mechanism in ecohydrological models is recommended to accurately describe the root water uptake, the latent heat flux and soil moisture. Moreover, correct representations of root functioning are important for modelling the responses of vegetation to droughts and the seasonal changes in soil moisture content. In this regard, Chapter 3 investigates the effects of the root conductivity parameters in modelling the below-ground processes, specifically the simulations of the latent heat flux, soil moisture, water uptake and the hydraulic redistribution mechanism.

1.3 PREVIOUS STUDIES ON AUSTRALIAN EUCALYPTUS FORESTS

Information on the ecosystem gas exchange fluxes of energy, water vapour and carbon dioxide is of great importance to ecologists and hydrologists (Drewry & Albertson, 2006). This information helps to improve our understanding of the processes controlling the coupled cycles of carbon, water and energy at multiple temporal and spatial scales. These fluxes are among the outputs of many of the land surface/ecohydrological models. Micrometeorological equipment, along with the eddy covariance method, have provided direct measurements of the carbon and water fluxes between vegetation and the atmosphere over short and long time scales. The measured fluxes are used to evaluate the models’ estimations.
As the focus of this study is the estimation of forest land-atmosphere exchange fluxes, a review is undertaken of the previous studies estimating the carbon, water and energy fluxes of eucalyptus forests in Australia. Tumbarumba is one of the eucalyptus-dominated sites in Australia that has been extensively subjected to gas-exchange measurements and simulations. Therefore, this site was chosen as the study area for this project as the valuable information to run the MLCan model can be found from the literature.

Leuning et al. (2005) measured the fluxes of energy, carbon and water over a tropical wet and dry savanna with scattered eucalyptus trees in north Queensland and a temperate eucalyptus forest in Tumbarumba during February 2001 to March 2004. They analysed the monthly and seasonal variabilities of the measured fluxes and discussed the environmental/climatic factors driving the variations in the two study sites. Their study provided the first measured datasets of the hourly energy, carbon and water fluxes in two important Australian ecosystems. They found a strong coupling between carbon uptake and water stress in the Tumbarumba site by observing the lowest CO₂ flux during the dry period of 2003. Based on their observations on the Tumbarumba site, they predicted a large reduction in forest production as a result of potential future drought.

Medlyn et al. (2007) measured the tree sap flows and leaf-gas exchanges in the eucalyptus forest in Tumbarumba during five days in May 2002. Using the measured data, they examined the performance of the tree-based model MAESTRA (Medlyn, 2004) to predict forest canopy transpiration. They parameterised the stomatal conductance equation of Ball et al. (1987) and the photosynthesis equation of Farquhar et al. (1980) in the MAESTRA model with the leaf-gas exchange data and confirmed the ability of the model to predict tree water use from leaf-level measurements.

Estimated fluxes have been presented in the literature using both land surface models and ecohydrological models. Kato et al. (2007) compared the sensitivity of different land surface models and the input data to the estimates of the evapotranspiration, sensible heat flux and top layer soil moisture at four reference sites in the Coordinated Enhanced Observing Period (CEOP), including Tumbarumba. CEOP is an initiative of the Global Energy and Water Cycle Experiment (GEWEX) which began, in 2001, to gather satellite and model data to support water and energy cycle, monsoon system and climate prediction studies. The models compared in this
study were Noah, Mosaic and CLM. The input data were the land cover, soil, elevation information, precipitation and downward radiation forcing datasets. They showed that the land surface models are the most important factors affecting the estimated results. They also highlighted the need for improving the land surface models, not just the quality of the inputs, to better estimate the water and energy cycle components.

Kirschbaum et al. (2007) examined the carbon and water budgets of eucalyptus forest in Tumbarumba using the forest growth model (CenW 3.1). This model runs on a daily time step and does not differentiate between the overstorey and understory vegetation species, thus considering the canopy as a single unit. This study highlighted that detailed physiological modelling is a powerful technique for estimating ecosystem carbon budget and to understand the factors affecting site carbon budget in different conditions.

Kowalczyk et al. (2006) examined estimations of the ecosystem exchange fluxes of the eucalyptus forest in Tumbarumba using the CABLE model. They found good agreement between the estimations and observations, however they did not evaluate the model performance in details. Nevertheless, they reported that they did not use a reasonable value for the surface characteristics parameters. This study was the first published results of the CABLE model. The CABLE model is the Australian community land surface model, which has been applied in the form of a one-dimensional stand-alone model to estimate the fluxes of the latent heat, sensible heat and net ecosystem exchange of CO₂. This model has been used in several studies around the world and in Australia.

Abramowitz et al. (2008) compared the performance of three land surface models, CABLE, CLM, and ORCHIDEE, against two statistical models for estimating the fluxes of the sensible heat, latent heat and net CO₂ exchange in Tumbarumba during the years 2002 and 2003, and at other sites in different years. Comparisons were made for different sets of input parameters. Firstly, they examined the performances of the models with the default parameters used in GCMs. Secondly, they focused on a comparison between using the default parameters and locally calibrated parameters at the site. Thirdly, they compared the performances of the models running with different combinations of parameters within their range of uncertainties. The results showed the inferior performances of the land surface models compared to the statistical models.
They then identified the potential causes of the poor performances, which may be useful in understanding the responsible factors in the models’ structures.

Li et al. (2012) improved the response of CABLE to seasonal drought in Tumbarumba by considering an alternative root water uptake function as well as including a hydraulic redistribution function. The two implemented root functions significantly improved the estimation of the latent heat flux and soil moisture during the dry season. In this paper, Li et al. recommended the implementation of these root functions in other land surface models which are used to study the land-atmosphere exchange fluxes in areas with seasonally variable rainfalls.

In another study, De Kauwe et al. (2015) implemented an optimal stomatal conductance model within the CABLE model. They tested the new version of the model on estimating carbon, water and energy fluxes of six different flux stations covered with different plant functional types including the eucalyptus forest in Tumbarumba. Their results showed small differences between simulated fluxes by the new and the standard CABLE models in Tumbarumba as well as five other sites.

Haverd et al. (2016) improved the representation of coupled soil-canopy processes in the CABLE model by using an alternative hydrology model. The results of this study showed improvements in the latent heat flux estimation and highlighted the role of deep soil moisture in mediating drought responses.

Ukkola et al. (2016) improved the evapotranspiration estimation during a precipitation deficit with the CABLE model. The authors combined the modifications performed in Li et al. (2012), De Kauwe et al. (2015) and Haverd et al. (2016), including three prescriptions for the LAI data, and evaluated the model’s performances in several flux tower stations across the world, including Tumbarumba. Their model better estimated the evapotranspiration during a precipitation deficit. The results underscore the significance of evaluating land surface models during precipitation deficits and across multiple plant functional types.

In another study, the mechanistic soil-plant-atmosphere (SPA) model, first introduced by Williams et al. (1996), was applied to and validated an Australian eucalyptus woodland in the Cumberland Plains in north-west of Sydney to examine the sensitivity of the sap flow rates to soil water content and some other factors (M. J. Zeppel et al., 2008). Later, Whitley et al. (2011) modified the SPA model to
incorporate both C3 and C4 photosynthesis and investigated the intra- and inter-annual variations of the ecosystem’s gross primary production (GPP) and evapotranspiration (ET) of a tropical eucalyptus-dominated savannah in Northern Australia.

The reviewed literature showed that the CABLE and SPA models are the most extensively used models for the estimation of the gas exchange fluxes of the eucalyptus forests in Australia. The next section discusses the motivations for choosing the MLCan model for this study and also compares the features of the extensively used models with MLCan.

1.4 MOTIVATION FOR CHOOSING THE MLCAN MODEL

From the discussion in Section 1.3, several points have been identified which require further extensive attention. The results from the recent study employing the most extensively used model (CABLE) in Tumbarumba show that, with all the model developments, there is still a need for improvements in the model’s estimations. Figure 3, which has been taken from Figure 2 in the paper by Ukkola et al. (2016), shows that the latent heat flux estimations for Tumbarumba do not match with the observations very well.

In addition, the SPA model represents a simplistic root-soil hydrology model and does not include the hydraulic redistribution function when simulating the below-ground processes. As discussed in Section 1.2.2, the hydraulic redistribution feature can add to the capabilities of the model by improving the estimations of the soil moisture, latent heat flux and carbon assimilation (Li et al., 2012; Quijano et al., 2012).
Therefore, the SPA model cannot fully couple the below-ground and above-ground processes in simulating the plant and water interactions. Therefore, this led to the choice of a more comprehensive multilayer canopy-root-soil model with the above features.

Most of the models discussed in the previous sections have considered the canopy as a big leaf model, rather than considering multiple layers for the canopy. Of the models that have been employed to study the eucalyptus forest of Tumbarumba, none has used the multilayer canopy feature except for a multilayer energy budget scheme, namely the ORCHIDEE-CAN model (Chen et al., 2016; Ryder et al., 2016). Baldocchi et al. (2002) highlighted the improvements in the CO₂, water and energy flux estimations by the use of complex and detailed ecophysiological models (Baldocchi & Wilson, 2001; Pyles et al., 2000; Williams et al., 2001).

A detailed ecohydrological model that couples the above-ground and below-ground processes with a multilayer canopy-root-soil model is the MLCan model. This model was first developed by (Drewry et al., 2010a) to simulate the soil-vegetation-atmosphere transfer scheme. Table 1 shows the detailed features of the MLCan model compared to the last version of the CABLE model (v2.1), which is the most extensively used land surface model in Australian eucalyptus forests, and the SPA model.

<table>
<thead>
<tr>
<th>Features</th>
<th>MLCan</th>
<th>CABLE</th>
<th>SPA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Study site</td>
<td>USA</td>
<td>Australia and Across the world</td>
<td>Australia and Across the world</td>
</tr>
<tr>
<td>Multispecies simulation</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Multilayer canopy</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Multilayer root-soil system</td>
<td>Yes (root distribution via Jackson equation or observed data)</td>
<td>Yes (only six layers. (root distribution via Jackson equation)</td>
<td>Yes (root distribution via root biomass data)</td>
</tr>
<tr>
<td>Stomatal model (gₛ)</td>
<td>Tuzet-Ball-Berry</td>
<td>Leuning model</td>
<td>Williams et al. 1996</td>
</tr>
<tr>
<td>Vertical distribution of Tₛ, U, CO₂, eₛ</td>
<td>K-theory closure (Poggy et al., 2004)</td>
<td>Localized Near Field theory (LNF)(Raupach 1989a, b)</td>
<td>f(wind speed, leaf width, air temperature)</td>
</tr>
<tr>
<td>Hydraulic redistribution</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Vegetation representative</td>
<td>Specific for each plant</td>
<td>Plant functional type</td>
<td>Stand model</td>
</tr>
</tbody>
</table>
1.5 SENSITIVITY ANALYSIS AND MODEL CALIBRATION

Generally, the land surface models and/or the ecohydrological models require a large number of parameters to simulate the physical processes of the land surface. The model parameters are known as one of the sources of errors in uncertainty assessments of land surface models (Dumedah & Walker, 2014). Therefore, aside from the model chosen, the model parameters are crucial, and are needed to be accurately considered to result in good model correlations. The literature shows that good model fits can result with different parameter values, which is called equifinality (Chen, 2013; Franks et al., 1997).

Sensitivity analysis enhances our understanding of how different model parameterisations affect the model’s results. As a result, sensitive and insensitive parameters can be identified. Chen (2013) has compared the different methods for doing sensitivity analysis found in the literature, including Monte-Carlo methods. Monte-Carlo approaches have added a reliability and accuracy to the sensitivity analysis by including the observed data in the model evaluation. Using a Monte-Carlo approach, the sensitivity analysis and model calibration can be done at the same time.

Model calibration aims to find the best parameter values that match the model’s estimations with the observations. The Generalized Likelihood Uncertainty Estimation (GLUE) method with a Monte-Carlo approach has been extensively used in the literature for the model calibration (Beven & Binley, 1992, 2014). Chen (2013) used a Monte-Carlo based GLUE method to calibrate the IBIS (Foley et al., 1996) and HYDRUS-1D (Simunek et al., 2008) model parameters for the soil moisture estimations in two study areas. In the GLUE method with the Monte-Carlo approach, a large number of simulations are performed with randomly changing parameters. Each simulation runs with different sets of parameter values which have been sampled from specified ranges. The sample range for each parameter can be defined from the literature and/or sample model runs to check the ability of the model to run within that range.

Rosero et al. (2010) used a global variance sensitivity analysis based on a Monte-Carlo approach to identify the sensitivity of the parameters of the three versions of the Noah land surface model.
Prihodko et al. (2008) analysed the sensitivity, uncertainty and time dependence of the parameters in a complex land surface model (SiBv2.5) using a Monte-Carlo carbon cycle data assimilation within the GLUE framework for a study in Wisconsin in the USA. Their results showed that the optimization did not improve the model’s estimations when the problem was associated with the model’s structure and/or the observations.

Franks et al. (1997) used the Monte-Carlo approach to analyse the sensitivity of the parameters of a simple bucket type soil-vegetation-atmosphere transfer (SVAT) model, named TOPUP, to simulate the evapotranspiration fluxes of two study sites in the USA and central Amazonia. Their results highlighted the occurrence of equifinality of the parameters in calibration to the data sets.

McCabe et al. (2005) used a multi-objective calibration framework to assess the performance of the TOPUP SVAT land surface model. They highlighted the improvements in modelling the surface fluxes when other sources of data, like soil moisture, were used in the calibration process with the surface fluxes.

According to the reviewed literature, MLCan requires a sensitivity analysis on the model parameters to successfully simulate the forest land-atmosphere gas exchange fluxes. Therefore in Chapter 4, a comprehensive parameter sensitivity analysis and model calibration is performed using the Monte-Carlo based GLUE approach.

1.6 MODEL INITIALISATION

The initial conditions are one of the input data to any mathematical model. However, observed data is not always available for the variables that needed to be initialised in the model. The model initialisation is critical as it may produce inaccurate results (Rodell et al., 2005; Yang et al., 2011). Performing a sensitivity analysis on the effects of the initial conditions on the model’s simulations can improve our knowledge when discussing the model’s results. For example, Liang et al. (2003) implemented surface and groundwater interactions with a new parameterisation in the land surface model VIC-3L. They evaluated the effects of the groundwater dynamics within a land surface model on the estimations of the groundwater table, streamflow, evapotranspiration and soil moisture and they compared the VIC-3L model and the new version of the model, named VIC-ground, at two study sites. They also performed
a sensitivity study on the effects of the initial groundwater level on the new version of the model by comparing two scenarios initialized with shallow and deep groundwater tables. They found that it is better to initialize the groundwater table in a shallow layer (250 cm below surface) as it takes 1.5 year for the simulations to converge, compared to the 3.5 year for the deeper groundwater table initialization.

The soil initial conditions in MLCan might affect the soil moisture and soil temperature estimations. However, its influence is dependent on the persistence time called “soil memory”. Soil moisture memory is important in climate models and in long-term predictions of precipitation and surface air temperatures (Cosgrove et al., 2003; Koster et al., 2004; Koster & Suarez, 2001; Seneviratne et al., 2010). Zhang (2004) analysed the impacts of soil moisture on the observed and simulated surface air temperatures in the Australian continent. He used 16 different land surface models through the Atmospheric Model Intercomparison Project Phase 2 (AMIP2) and found that complex models, which take into account many processes in their simulations, have a longer soil moisture memory compared to simple models, which assume the soil column as a bucket. Chen (2013) evaluated the effects of LAI seasonality on soil moisture estimations using the HYDRUS model for the Stanley catchment in NSW, Australia. She compared the constant LAI (CLAI) and seasonal LAI (SLAI) on the surface and full profile soil moisture estimations and found significant differences between the CLAI and SLAI soil moisture estimations. The results showed that the effects of the seasonal LAI on the daily soil moisture estimations continue much longer at deeper soil layers than the 30 cm soil layer. As HYDRUS does not have a dynamic vegetation model, it is believed that the longer effects of seasonality at the deeper soil layers is due to the longer memory of the soil at deep layers.

Regarding the soil temperature memory, Yang and Zhang (2016) evaluated the soil temperature memory over China using soil temperature observations from 626 stations during 1981-2005. They found that the soil temperature memory increases with the soil depth, and it could be several months on average.

Moreover, soil moisture and soil temperature are coupled. This is because soil thermal properties are influenced by the soil water. For example, a soil heat capacity and thermal conductivity increase as the soil moisture increases. Therefore, the thermal properties of wet soil are different from those of dry soil. Some studies have used this concept to estimate the soil moisture from the soil temperature using remotely sensed
techniques (Fang & Lakshmi, 2014; Lakshmi et al., 2013; Narayan & Lakshmi, 2006). Fang and Lakshmi (2014) applied an algorithm based on the relationship between the daily temperature change and the average soil moisture, which is called thermal inertia theory, to downscale the remotely sensed soil moisture data. Their results showed good agreement between the simulated and observed data for two growing seasons in 2010 and 2011 in a catchment in Oklahoma.

The importance of evaluating the effects of the initial conditions on the model’s simulations is clear from the previous literature. Studies have shown that the initial conditions are one of the sources of error in the uncertainty assessments of land surface models (Dumedah & Walker, 2014; Pianosi et al., 2016). However, such observed data is often scarce. Therefore, the effects of the soil initial conditions on the model’s estimations are investigated using the MLCan model in Chapter 5. By performing this analysis, light is shed on the lengths of the soil moisture and temperature memories of the MLCan model.

1.7 OBJECTIVES OF THIS RESEARCH

This project aims to test the ability of a detailed ecohydrological model to capture the dynamics of an Australian eucalyptus forest. Therefore, after reviewing the studies that have been done in eucalyptus forests in Australia, and the different ecohydrological models used, the MLCan model was chosen for this study. The MLCan model has not been previously used in Australia. Therefore, it is not immediately apparent that the MLCan model, which until now has been applied to other ecosystems in the northern hemisphere, can be successfully applied to Australian ecosystems to simulate the ecohydrological fluxes (i.e. carbon, water and energy). Therefore, in this research we test the MLCan model in a eucalyptus forest in Tumbarumba. The main goal of this study is divided into three detailed objectives, as described below.

As MLCan is a multilayer canopy model, its results might be affected by the number of canopy layers (Baldocchi et al., 2002; Drewry et al., 2010a; Pyles et al., 2000; Wu et al., 2000). Therefore, a sensitivity analysis is needed to find the optimum number of canopy layers. Moreover, the MLCan model includes the hydraulic redistribution mechanism in the simulation of the above-ground and below-ground processes. However, its magnitude is dependent on the root conductivity parameters,
which we do not have enough information about. Thus, one of the objectives of this study is to examine the effects of the multilayer canopy model and the hydraulic redistribution mechanism on the model’s results, which are carried out in Chapter 3.

This study also performs a comprehensive parameter sensitivity analysis in order to evaluate the effects of the different parameterisations on the model’s estimations. Previous studies have shown the need for improvements in the estimation of the ecosystem gas exchange fluxes. Aside from this, it is not clear how much a new detailed modelling approach can contribute to the gas exchange estimation improvements without having reasonable calibrated parameters. In Chapter 4 the sensitivity analysis is performed on the selected model parameters and the MLCan model is calibrated and validated in the eucalyptus forest in Tumbarumba.

It is generally assumed that a soil initial conditions only affect the initial weeks of the simulation. However, there is uncertainty as to the effects of the soil initial conditions on the models results. As another objective, this research aims to evaluate the effects of the initial soil conditions on the model calibrations.

1.8 THESIS OUTLINE

This thesis contains six chapters. In the following chapters, the research methodology is first discussed in Chapter 2 and then the results of the initial sensitivity analysis are discussed in Chapter 3. In Chapter 4 the results of the model calibrations and validation are discussed. In Chapter 5 the influence of the soil initial conditions are discussed. Finally, Chapter 6 summarizes the findings of the research and highlights the conclusions.
Chapter 2: Research Methodology

This chapter outlines the methodology used in this study. The MLCan model that is used in this study is presented in Section 2.1. Section 2.2 introduces the study area. Section 2.3 describes the input data, including the canopy and root structure, climate data and initial conditions. Section 2.4 introduces the model parameters, the methodology, and the selection of the parameters for the sensitivity analysis, the sampling ranges and the objective function. Finally, the methodology for the model calibration and model validation are explained in Sections 2.5 and 2.6.

2.1 MULTILAYER CANOPY-ROOT-SOIL MODEL (MLCAN)

In this project, the simulations will be performed using the vertically resolved canopy-root-soil model, MLCan. The 1-D multilayer model was developed by Drewry et al. (2010a) to simulate the soil-vegetation-atmosphere transfer processes. The model formulation enables the user to simulate both C3 and C4 vegetations. Its coupling of the above-ground ecophysiological and biochemical processes with the below-ground root-soil moisture transport functioning accurately addresses the ecohydrologic responses of vegetation to environmental perturbations and climate change (Drewry et al., 2010a, b).

The initial validation was done by Drewry et al. (2010a, 2010b) on soybean and maize crops with the flux data from the Ameriflux tower in Bondville, Illinois. Later, the MLCan was used to study the hydrological implications of bioenergy crops (Switchgrass and Miscanthus) under climate change scenarios (Le et al., 2011). Quijano et al. (2012) extended the MLCan model to incorporate multispecies vegetation and improved the dynamics of the below-ground processes by adding the hydraulic redistribution model of Amenu and Kumar (2008) into their modelling framework. They applied the extended model in Blodgett forest, in the USA, to study the interactions of the soil moisture, latent heat flux and carbon assimilation enabled by hydraulic redistribution.

The MLCan model has been developed in MATLAB programming language, Mathwork, USA (Le et al., 2012), and is driven by giving the input data and by defining the soil initial conditions, which are explained in Section 2.3. The main outputs of the model are the ecosystem-atmosphere exchange fluxes of latent heat ($LE$), sensible heat ($H$) and CO$_2$. The model calculates both the soil surface and the canopy energy balances to estimate the
ecosystem exchange fluxes. The MLCan model also has a multilayer soil-root system, which links to the canopy model and computes the soil moisture transport and root water uptake in the root-soil profile using the Richards equation. Figure 4 shows a schematic of the MLCan model.

To quantify the canopy exchange fluxes, the model resolves the meteorological micro-environment and the leaf-level physical-biochemical processes at vertically discretised canopy layers and incorporates them with the soil-root system functioning to estimate the canopy-atmosphere exchange fluxes (see Figure 4). The model uses a coupled series of formulations to compute the canopy photosynthesis, stomatal conductance, leaf boundary layer conductance, leaf temperature and leaf energy balance (Nikolov et al., 1995), as these processes are all non-linear functions of the leaf temperature, CO$_2$ concentration, or themselves (Baldocchi et al., 2002). The model couples the biochemical model of the C3 photosynthesis of Farquhar et al. (1980) or the C4 photosynthesis of Collatz et al. (1992); the stomatal conductance model of Ball and Berry (1982) and the stomatal sensitivity factor to soil moisture followed by Tuzet et al. (2003); and the boundary layer conductance and leaf energy balance formulations proposed by (Nikolov et al., 1995). The model also calculates the soil surface energy fluxes following the functions by Hinzman et al. (1998) (Drewry et al., 2010a).

In the canopy radiation module, the MLCan model considers the shortwave and longwave radiation for both the sunlit and shaded leaf fractions separately. The shortwave radiation components, including Photosynthetically Active Radiation (PAR) and Near-Infrared Radiation (NIR), are considered for both the direct and diffuse fractions separately, following algorithms by Spitters (1986). The PAR and NIR components are attenuated through the canopy, accounting for the absorbed, transmitted and reflected fractions at each layer. The canopy longwave includes both the incident longwave radiations from the atmosphere and the soil, as well as the longwave emitted radiation. The longwave radiation is computed and is attenuated throughout the canopy layers. The calculations of the canopy radiation regime follow Campbell and Norman (1998).

The meteorological micro-environment data, including wind speed ($U$), CO$_2$ concentration ($C_a$), water vapour ($e_a$) and temperature ($T_a$), are resolved within the canopy layers using a K-theory closure (Katul et al., 2004; Poggi et al., 2004). The canopy model considers the wet and dry fractions separately, and computes the canopy water storage from the intercepted precipitation and dew formations in each foliage layer.
Table 2 shows selected MLCan outputs. The results can be divided into canopy-atmosphere exchange fluxes, soil surface fluxes and soil-root water states. The diurnal mean canopy fluxes are integrated over vertically resolved scalar quantities. More detailed descriptions, with formulations of the model, can be found in the relevant literature (Drewry et al., 2010a, b).

Figure 4. Schematic of the MLCan model (from Le et al., 2012)
<table>
<thead>
<tr>
<th>Outputs</th>
<th>Symbol</th>
<th>Definition</th>
<th>Units</th>
<th>Type of data</th>
</tr>
</thead>
<tbody>
<tr>
<td>canopy-atmosphere exchange fluxes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>main outputs</td>
<td>$A_n$</td>
<td>Net leaf CO₂ uptake</td>
<td>µmol/m² leaf area/s</td>
<td>vertical profile- time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>$F_c$</td>
<td>CO₂ flux</td>
<td>µmol/m²/s</td>
<td>time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>$H$</td>
<td>Sensible heat</td>
<td>W/m² leaf area</td>
<td>vertical profile- time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>$L E$</td>
<td>Latent heat</td>
<td>W/m² leaf area</td>
<td>vertical profile- time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>$R_n$</td>
<td>Net radiation</td>
<td>W/m²</td>
<td>vertical profile- time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>$T_l$</td>
<td>Leaf temperature</td>
<td>°C</td>
<td>vertical profile- time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>$P_s$</td>
<td>Leaf water potential</td>
<td>MPa</td>
<td>vertical profile- time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>$C h 2 o$</td>
<td>Condensation water in canopy</td>
<td>mm/s</td>
<td>vertical profile- time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>$S h 2 o$</td>
<td>Intercepted water in canopy, for all layers</td>
<td>mm</td>
<td>vertical profile- time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>$g s$</td>
<td>Stomatal conductance to vapour</td>
<td>mol/m²/s</td>
<td>vertical profile- time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>$g b$</td>
<td>Boundary layer conductance to vapour</td>
<td>mol/m²/s</td>
<td>vertical profile- time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>$C i$</td>
<td>Leaf internal CO₂ concentration</td>
<td>mol/m²/s</td>
<td>vertical profile- time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>TR</td>
<td>Transpiration</td>
<td>mm/s</td>
<td>time series</td>
</tr>
<tr>
<td></td>
<td>Evap</td>
<td>Evaporation</td>
<td>mm</td>
<td>vertical profile- time series- diurnal</td>
</tr>
<tr>
<td>intermediate outputs (leaf states)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$F c _{soil}$</td>
<td>Soil CO₂ flux</td>
<td>µmol/m²/s</td>
<td>time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>$H _{soil}$</td>
<td>Soil surface sensible heat</td>
<td>W/m²</td>
<td>time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>$L E _{soil}$</td>
<td>Soil surface latent heat</td>
<td>W/m²</td>
<td>time series- diurnal</td>
</tr>
<tr>
<td></td>
<td>$G$</td>
<td>Ground heat flux</td>
<td>W/m²</td>
<td>time series- diurnal</td>
</tr>
<tr>
<td>soil – root water states</td>
<td>$s m p$-store</td>
<td>Soil matric potential</td>
<td>MPa</td>
<td>time series profile</td>
</tr>
<tr>
<td></td>
<td>rpp</td>
<td>Root pressure potential</td>
<td>MPa</td>
<td>time series profile</td>
</tr>
<tr>
<td></td>
<td>dwat</td>
<td>Change of soil water</td>
<td>m³/m³</td>
<td>vertical profile- time series</td>
</tr>
<tr>
<td></td>
<td>volliq_store</td>
<td>Soil water per unit volume</td>
<td>m³/m³</td>
<td>time series profile</td>
</tr>
<tr>
<td></td>
<td>q-infl-store</td>
<td>Infiltrated water</td>
<td>mm/s</td>
<td>time series</td>
</tr>
<tr>
<td></td>
<td>wuptake_store</td>
<td>Water uptake</td>
<td>mm/s</td>
<td>time series</td>
</tr>
</tbody>
</table>

Table 2. MLCan outputs
2.2 STUDY AREA

This project addresses the ecohydrology of a eucalyptus forest in New South Wales based on observations at the Tumbarumba flux station. The Tumbarumba flux station is located in the Bago State Forest, in south-eastern New South Wales. The site is a moderately open, wet sclerophyll forest, in which the dominant overstorey species are *Eucalyptus delegatensis* (Alpine Ash) and *Eucalyptus dalrympleana*, while the patchy understory consists of shrubs and grasses. The forest vegetation composition and density is homogeneous. The trees are up to 40 m tall with leaf area index of 1.4 m²/m² and the shrubs are from 0.5 m to 2 m tall with leaf area index of 1.5 m²/m² (Keith et al., 2009; Van Gorsel et al., 2007). The plant functional type classification of Tumbarumba is characterised as temperate evergreen broadleaf forest (Li et al., 2012). The total canopy leaf area index for the site has been observed during 2001 to 2008 and has been reported as between 2.3 to 3.5, with seasonal variation (Li et al., 2012; Wang et al., 2011).

A Mediterranean climate prevails at this site, with hot and dry summers and wet and cool winters. The dry season is from October to March. The mean annual precipitation at Tumbarumba (www.ozflux.org.au) is 1000 mm. Figure 5 shows the total daily precipitation as well as the average daily incoming shortwave radiation and air temperature for 2005. This year was selected to run the simulations for the sensitivity analysis and model calibrations in this study as it was a normal year with average precipitation.

The soil physical properties and the soil texture values for the site (percentage of sand=37% and percentage of clay=30%) have been taken from (Li et al., 2012; McKenzie et al., 2004). These values have been used in previous studies in Tumbarumba.
Figure 5. Daily total precipitation a), daily average values of shortwave radiation b), and air temperature c) at Tumbarumba for 2005
2.3 INPUT DATA

In the MLCan model, the required input data includes the geographic location, climate data, canopy and root structures and the soil initial conditions. The latitude, longitude and elevation are needed for the calculation of the sun zenith angle. The canopy structure is defined by its vertical distribution of leaf area index as well as its seasonal variation. The user specifies the number of canopy layers and the canopy grid has evenly spaced nodes between the soil surface and the top of the canopy’s height. The optimum number of canopy layers can be determined by sensitivity analysis (Drewry et al., 2010a). The root structure can be defined by the observed root profile data or can be modelled using the Schenk and Jackson (2002a) equation. The meteorological and climate data includes the downwelling short wave radiation ($R_g$), downwelling long wave radiation ($L_{Win}$), precipitation (PPT), air pressure ($P_a$), air temperature ($T_a$), wind speed ($U$), vapour pressure deficit (VPD), vapour pressure ($e_a$) and friction velocity (ustar). The model requires the soil moisture and soil temperature initial conditions. Table 3 summarizes the input data required to run the MLCan model.

Table 3. Required input data for MLCan model

<table>
<thead>
<tr>
<th>Input variable</th>
<th>Symbol</th>
<th>Definition</th>
<th>Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climate data</td>
<td>$R_g$</td>
<td>Downwelling shortwave radiation</td>
<td>W/m$^2$</td>
</tr>
<tr>
<td></td>
<td>$L_{Win}$</td>
<td>Downwelling longwave radiation</td>
<td>W/m$^2$</td>
</tr>
<tr>
<td></td>
<td>$T_a$</td>
<td>Air temperature</td>
<td>°C</td>
</tr>
<tr>
<td></td>
<td>$P_a$</td>
<td>Air pressure</td>
<td>kPa</td>
</tr>
<tr>
<td></td>
<td>$e_a$</td>
<td>Vapour pressure</td>
<td>kPa</td>
</tr>
<tr>
<td></td>
<td>PPT</td>
<td>Precipitation</td>
<td>mm</td>
</tr>
<tr>
<td></td>
<td>$U$</td>
<td>Wind speed at 2 m</td>
<td>m/s</td>
</tr>
<tr>
<td></td>
<td>ustar</td>
<td>Friction velocity</td>
<td>m/s</td>
</tr>
<tr>
<td></td>
<td>VPD</td>
<td>Vapour pressure deficit</td>
<td>kPa</td>
</tr>
<tr>
<td>Canopy structure</td>
<td>LAI</td>
<td>Leaf Area Index</td>
<td>m$^2$/m$^2$</td>
</tr>
<tr>
<td></td>
<td>LAD</td>
<td>Canopy height</td>
<td>m</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Leaf area density</td>
<td>m$^2$/m$^3$</td>
</tr>
<tr>
<td>Root structure</td>
<td>$Z^*$</td>
<td>Root depth</td>
<td>m</td>
</tr>
<tr>
<td></td>
<td>RLD*</td>
<td>Root length density</td>
<td>m/m$^3$</td>
</tr>
<tr>
<td></td>
<td>$Z_{50}^{**}$</td>
<td>50th percentile rooting depth</td>
<td>m</td>
</tr>
<tr>
<td></td>
<td>$z_{95}^{**}$</td>
<td>95th percentile rooting depth</td>
<td>m</td>
</tr>
<tr>
<td></td>
<td>Rd$_{max}^{**}$</td>
<td>Maximum root depth</td>
<td>m</td>
</tr>
</tbody>
</table>

* when measured data is available, ** when measured data is not available
2.3.1 Canopy and root structure

In MLCan, the canopy’s structure is defined by the Leaf Area Density profile (LAD) and the Leaf Area Index (LAI). The total canopy LAI at Tumbarumba varies with time, between 2.3 and 3.5, with marked seasonal variation (Li et al., 2012; Wang et al., 2011). The LAD profile for this study was reported by Ryder et al. (2016), and has been normalized based on the total LAD fractions over the total of the ecosystem canopy height. The whole ecosystem LAI data for the years between 2001 and 2008 was obtained from Wang et al. (2011). Figure 6 shows the vertical LAD profile and seasonal variations of the ecosystem LAI during the year 2005.

![Vertical LAD profile and seasonal variations of the ecosystem LAI](image)

Figure 6. Canopy structure at the Tumbarumba forest a) Seasonal variation of LAI in 2005 adapted from Wang et al. (2011) and b) vertical profile of LAD adapted from Ryder et al. (2016).

The root structure in the MLCan is defined based on the model of Schenk and Jackson (2002a). Keith et al. (2012) reported the tree roots in Tumbarumba exists deeper than the 120 cm depth. Haverd et al. (2016) reported the maximum root depths for evergreen broadleaf forest could be up to 3 m depth. Grant et al. (2012) found the cumulative root fractions of *Eucalyptus dunnii* and *Corymbia citriodora* subsp. in the study area in NSW up to a depth of 1 m. According to the above information, we adjusted the Grant’s root fraction profile to 3 m depth and determined the depths where 50 and 95 percent of all roots were above, to calculate the root fraction profile by the MLCan model for this study as shown in Figure 7.
2.3.2 Climate data

The Tumbarumba station is one of the flux towers in the regional network of flux towers in Australia and New Zealand (OzFlux) and it measures the carbon, energy and water vapour fluxes, as well as meteorological variables (Beringer et al., 2016; Isaac et al., 2017). All of the required meteorological data for running the model ($R_g$, $LW_{in}$, $T_a$, $P_a$, $e_a$, $PPT$, $U$, $ustar$, $VPD$) are available at the Tumbarumba station at hourly resolution. The measured meteorological variables were used as the forcing data to run the model. The measured fluxes of the latent heat, sensible heat and CO$_2$, as well as the measured soil moisture data were used to calibrate and validate the model. There are three principal levels of data processing on the OzFlux data for the Tumbarumba site, named $L3$, $L4$, $L6$, as described below (Isaac et al., 2017):

$L3$ – received post-processing and corrections in meteorological data, however contains gaps

$L4$ – gap-filled flux data

$L6$ – gap-filled fluxes and partitioned NEE

Several different (somewhat conflicting) sets of data reported as observed data in Tumbarumba were found in the literature which were different from the OzFlux data. Figure 8a shows the monthly average latent heat flux ($LE$) for the three levels of data processing ($L3$, $L4$ and $L6$) available on the OzFlux, as well as the data reported in papers by Li et al. (2012) and Ukkola et al. (2016). The histogram in Figure 8b shows the percentage of missing $LE$ in each month for the $L3$ and $L4$ processing levels. It can be seen that approximately half of the data are missing in each month. Almost
all of the missing data occur during the night. Since fluxes are higher during the day than the night, due the effect of sun radiation, the monthly averaged $LE$ for $L3$ and $L4$ are higher and they overestimate the $LE$ fluxes. The differences seen between the reported fluxes in the literature (Li et al., 2012; Ukkola et al., 2016) and the $L6$ data suggest that the researchers have used different gap-filling techniques. In this project, we use $L6$ data to calibrate and validate the MLCan model and compare the results with the other datasets published in the literature in Chapter 4.

![Graph](image)

Figure 8. Monthly average latent heat flux ($LE$) in Tumbarumba a) Comparison of different processing levels ($L3$, $L4$, $L6$) and two reported published data (Li et al., 2012; Ukkola et al., 2016) b) Percentage of missing data in each month in $L3$ and $L4$ data

### 2.3.3 Initial conditions

The MLCan model needs, as in many ecohydrology models, the initial soil moisture and temperature data down the soil profile to run the simulations. On the OzFlux website, we have only access to the observed soil moisture profile. Therefore, we performed a warm-up simulation during 2001-2005 and assumed the data at the start of the year 2005 as the initial condition for the soil temperature profile. It will be shown later in Chapter 5 that the initial soil temperature profile did not affect the results significantly.
The observed soil moisture data at Tumbarumba has been measured at an initial depth of 15 cm, and down to 120 cm depth, at 30 cm intervals. There was a gap in the data at the end of 2004 and in the beginning of 2005. Therefore, the last existing data for year 2004 was averaged with the first data for year 2005, and was considered for the beginning of year 2005. As the measured depths are not the same as the soil depths in the model, the closest depths or the average soil moisture data in multiple depths have been used as the initial soil moisture in the simulations for this study. Table 4 shows the initial conditions used for this study, which are referred to as the depth-varying initial conditions later in Chapter 4. To investigate the effects of the initial conditions on the model’s simulations, which is the topic of Chapter 5, the depth-constant initial conditions are used throughout the soil profile equal to the available observed data at the 15 cm depth.

Table 4. Depth-varying soil initial conditions used in Chapter 4

<table>
<thead>
<tr>
<th>Soil depth (m)</th>
<th>Soil temperature (°C)</th>
<th>Soil moisture (m³/m³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.10</td>
<td>25.24</td>
<td>0.15</td>
</tr>
<tr>
<td>0.27</td>
<td>27</td>
<td>0.15</td>
</tr>
<tr>
<td>0.58</td>
<td>25.08</td>
<td>0.21</td>
</tr>
<tr>
<td>1.18</td>
<td>23.08</td>
<td>0.17</td>
</tr>
<tr>
<td>2.28</td>
<td>20.57</td>
<td>0.19</td>
</tr>
<tr>
<td>3.72</td>
<td>17.23</td>
<td>0.25</td>
</tr>
</tbody>
</table>

### 2.4 MODEL PARAMETERS

Ecohydrological models and/or land surface models, depending on their complexity, require multiple parameters which are not always easy to measure. MLCan requires over 40 parameters, and some of them can be directly measured, e.g., leaf width, canopy height and soil texture. This study has looked for the required parameters in the literature and has collected the data from the previous measurements/analyses that had been done in the study area. Table 5 shows the parameters, which were found in the literature, that are used to run the MLCan for the eucalyptus forest in the study area.

In the literature review performed to find the parameter values, we could not find information for nine parameters. As a result, the sensitivity analysis was performed to investigate the model’s behaviours as a result of the changes in these parameters. The
GLUE method was then used to find the optimum values for the sensitive parameters through the model calibration process. The sensitivity analysis and the selection of parameters are explained in Section 2.4.2.

Table 5. List of parameters used to run the MLCan model

<table>
<thead>
<tr>
<th>Name</th>
<th>Units</th>
<th>values</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Canopy</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum water storage capacity for foliage</td>
<td>mm / LAI</td>
<td>0.15</td>
<td>Kirschbaum et al., (2007)</td>
</tr>
<tr>
<td>Leaf width or needle diameter</td>
<td>m</td>
<td>0.02</td>
<td>Medlyn et al., (2007)</td>
</tr>
<tr>
<td>Shoot diameter for conifers or leaf width for</td>
<td>m</td>
<td>0.02</td>
<td>Medlyn et al., (2007)</td>
</tr>
<tr>
<td>broad leaf</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum wetted fraction</td>
<td>unitless</td>
<td>0.2</td>
<td>Drewry et al., (2010)</td>
</tr>
<tr>
<td>Rainfall interception factor</td>
<td>unitless</td>
<td>0.2</td>
<td>Drewry et al., (2010)</td>
</tr>
<tr>
<td>Canopy height, $h_c$</td>
<td>m</td>
<td>48</td>
<td>OzFlux</td>
</tr>
<tr>
<td>Flux tower observation height</td>
<td>m</td>
<td>70</td>
<td>OzFlux</td>
</tr>
<tr>
<td>Canopy roughness length</td>
<td>m</td>
<td>0.076$h_c$ (3.65)</td>
<td>Eamus, (2006)</td>
</tr>
<tr>
<td><strong>Conductance</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slope parameter in Ball-Berry model, $m$</td>
<td>unitless</td>
<td></td>
<td>Calibrated</td>
</tr>
<tr>
<td>Intercepts in Ball Berry model, $b$</td>
<td>mol m$^{-2}$ s$^{-1}$</td>
<td></td>
<td>Calibrated</td>
</tr>
<tr>
<td>Sensitivity parameter for initial decrease in</td>
<td>MPa$^{-1}$</td>
<td></td>
<td>Calibrated</td>
</tr>
<tr>
<td>leaf potential, $S_f$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Leaf potential at which half of the hydraulic</td>
<td>MPa</td>
<td></td>
<td>Calibrated</td>
</tr>
<tr>
<td>conductance is lost, $\psi_f$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Radial root conductivity, $K_{rad}$</td>
<td>s$^{-1}$</td>
<td></td>
<td>Calibrated</td>
</tr>
<tr>
<td>Axial root conductivity, $K_{ax}$</td>
<td>Mm s$^{-1}$</td>
<td></td>
<td>Calibrated</td>
</tr>
<tr>
<td>Plant resistance to water flow, $R_p$</td>
<td>MPa m$^{-1}$</td>
<td></td>
<td>Calibrated</td>
</tr>
<tr>
<td><strong>Photosynthesis (C3)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fraction absorbed $Q$ available to photosystem</td>
<td>unitless</td>
<td>0.5</td>
<td>Drewry et al., (2010), Bernacchi et al., (2003)</td>
</tr>
<tr>
<td>II, $\beta_f$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum rate of Rubisco-limited carboxylation</td>
<td>$\mu$mol m$^{-2}$ s$^{-1}$</td>
<td>81.5</td>
<td>Medlyn et al., (2007)</td>
</tr>
<tr>
<td>at 25 °C $- V_{\text{cmax}}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum electron transport rate $- J_{\text{max}}$</td>
<td>$\mu$mol m$^{-2}$ s$^{-1}$</td>
<td>194.6</td>
<td>Medlyn et al., (2007)</td>
</tr>
<tr>
<td>Mitochondrial respiration in light, $Rd_{25}$</td>
<td>$\mu$mol m$^{-2}$ s$^{-1}$</td>
<td>2.55</td>
<td>Medlyn et al., (2007)</td>
</tr>
<tr>
<td>Decay coefficient for leaf nitrogen concentration</td>
<td>unitless</td>
<td>0.5</td>
<td>Drewry et al., (2010)</td>
</tr>
<tr>
<td><strong>Respiration</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Soil respiration rate at 10 °C, $R_o$</td>
<td>$\mu$mol m$^{-2}$ s$^{-1}$</td>
<td></td>
<td>Calibrated</td>
</tr>
<tr>
<td>Sensitivity of soil respiration to temperature,</td>
<td>unitless</td>
<td></td>
<td>Calibrated</td>
</tr>
<tr>
<td>$Q_{10}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Microenvironment</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drag coefficient, $C_d$</td>
<td>unitless</td>
<td>0.25</td>
<td>Harman &amp; Finnigan., (2007)</td>
</tr>
<tr>
<td>Name</td>
<td>Units</td>
<td>values</td>
<td>Reference</td>
</tr>
<tr>
<td>-------------------------------------------</td>
<td>-------</td>
<td>--------</td>
<td>--------------------------</td>
</tr>
<tr>
<td><strong>Soil</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum root depth ($Rd_{\text{max}}$)</td>
<td>m</td>
<td>3</td>
<td>Haverd et al., (2016)</td>
</tr>
<tr>
<td>Percent of sand</td>
<td>unitless</td>
<td>37</td>
<td>Li et al., (2012)</td>
</tr>
<tr>
<td>Percent of clay</td>
<td>unitless</td>
<td>30</td>
<td>Li et al., (2012)</td>
</tr>
<tr>
<td>Soil surface roughness length</td>
<td>m</td>
<td>0.005</td>
<td>Drewry et al., (2010)</td>
</tr>
<tr>
<td><strong>Radiation</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Atmospheric transmissivity</td>
<td>unitless</td>
<td>0.65</td>
<td>Campbell &amp; Norman., (1998)</td>
</tr>
<tr>
<td>Vegetation emissivity</td>
<td>unitless</td>
<td>0.95</td>
<td>Medlyn et al., (2007)</td>
</tr>
<tr>
<td>Soil emissivity</td>
<td>unitless</td>
<td>0.95</td>
<td>Campbell &amp; Norman., (1998)</td>
</tr>
<tr>
<td>Atmospheric emissivity</td>
<td>unitless</td>
<td>0.8</td>
<td>Campbell &amp; Norman., (1998)</td>
</tr>
<tr>
<td>Leaf clumping parameter</td>
<td>unitless</td>
<td>0.9</td>
<td>Campbell &amp; Norman., (1998)</td>
</tr>
<tr>
<td>Extinction coefficient for diffuse</td>
<td>unitless</td>
<td>0.36</td>
<td>Hopkins et al., 2013</td>
</tr>
<tr>
<td>Leaf absorptivity to Photosynthetically Active Radiation (PAR)</td>
<td>unitless</td>
<td>0.85</td>
<td>Campbell &amp; Norman., (1998)</td>
</tr>
<tr>
<td>Leaf absorptivity to Near Infrared Radiation (NIR)</td>
<td>unitless</td>
<td>0.23</td>
<td>Campbell &amp; Norman., (1998)</td>
</tr>
<tr>
<td>PAR reflection coefficient</td>
<td>unitless</td>
<td>0.05</td>
<td>Campbell &amp; Norman., (1998)</td>
</tr>
<tr>
<td>NIR reflection coefficient</td>
<td>unitless</td>
<td>0.2</td>
<td>Campbell &amp; Norman., (1998)</td>
</tr>
<tr>
<td>Soil reflection coefficient</td>
<td>unitless</td>
<td>0.17</td>
<td>Campbell &amp; Norman., (1998)</td>
</tr>
</tbody>
</table>

**2.4.1 Sensitivity analysis of the parameters**

In this study the GLUE method (Beven & Binley, 1992) has been used with the Monte-Carlo approach to perform the sensitivity analysis of model results to the model parameters. As explained in Section 1.4, in GLUE, a large number of simulations are performed with given random values from the specified ranges of the model parameters in each simulation. The sensitivity of the MLCan model to the parameters in estimating the four key outputs, including the latent heat flux, sensible heat flux, CO$_2$ flux and soil moisture estimations, are then examined statistically and visually. The Nash-Sutcliff ($NS$) performance indicator (see Section 2.4.4) and dotty plots are used to display the model’s behaviours to the parameter range and to evaluate the
model’s performance against the observations. Here, dotty plot is a scatter plot which shows the (NS) values versus the parameter values.

In this study, we changed the MLCan source code to separate the graphical user interface and to set up the Monte-Carlo simulations to run the model 2000 times. The sensitivity analysis was performed using the 2005 forcing data, as mentioned previously, as it was a normal year with average precipitation. The sampling method and the ranges of parameter values are discussed in Section 2.4.3.

2.4.2 Selected parameters

As mentioned, the sensitivity analysis was performed for nine parameters, which included the stomatal conductance, root conductivity, plant resistance to flow, and soil respiration parameters, which are described in more detail below.

Stomatal conductance parameters

In MLCan, the stomatal conductance \( g_s \) is estimated using the Tuzet-Ball-Berry model (Equation (3)) (Ball & Berry, 1982; Drewry et al., 2010a; Tuzet et al., 2003). The model estimates the stomatal responses of both the C3 and C4 plants in different environmental conditions:

\[
g_s = f_{sv} \cdot m \frac{A_n h_s}{C_s} + b
\]

In this empirical equation, the stomatal conductance \( g_s \) is linked to the net CO2 assimilation, the leaf surface relative humidity \( h_s \), and the CO2 concentration at the leaf surface \( C_s \). The slope and intercept of the equation are the \( m \) and \( b \) parameters, respectively. The stomatal sensitivity factor \( f_{sv} \) is used to calculate the stomatal conductance reduction due to plant hydraulic constraint, as proposed by Tuzet et al. (2003). The \( f_{sv} \) factor incorporates the stomatal response to the leaf water potential from Equation (4) below:

\[
f_{sv} = \frac{1 + \exp[s_f \psi_f]}{1 + \exp[s_f (\psi_f - \psi_l)]}
\]

where \( \psi_f \) is the leaf reference potential and \( S_f \) is the sensitivity parameter (Tuzet et al., 2003). This function changes, between 1 (no sensitivity when well-watered) and 0 (no stomatal conductance), as the \( \psi_l \) decreases to the critical water potential.
Soil respiration parameters

MLCan estimates the soil respiration using a simple function that is based on the soil temperature (Equation (5)) (Janssens & Pilegaard, 2003). The two unknown parameters of the soil respiration function are the soil respiration rate at 10 C° \( (R_o) \) and the sensitivity of the soil respiration to temperature \( (Q_{10}) \), which are determined through the sensitivity analysis. \( T_{s,i} \) is the soil temperature in the top layer.

\[
F_{e,s} = R_o Q_{10}^{10} \frac{T_{s,i} - 10}{10} \tag{5}
\]

Plant resistance to flow

Water flow through the canopy-root-soil system in MLCan is formulated using the Ohm’s law analogy (Equation (6)), which relates transpiration \( (T_r) \) to differences between the leaf water potential \( (\psi_l) \) and the root water potential \( (\psi_{r,wgt}) \) (Drewry et al., 2010a; Kramer & Boyer, 1995; Van den Honert, 1948).

\[
T_r = \frac{\psi_{r,wgt} - \psi_l}{R_p} \tag{6}
\]

In Equation (6), \( R_p \) is the parameter for the plant resistance to water flow and is determined through the sensitivity analysis and model calibration. \( T_r \) is determined from the energy balance calculations and \( \psi_l \) is calculated as the remaining variable from the equation above. \( \psi_{r,wgt} \) is the weighted average root water potential over the root fraction \( (r_j) \) at each layer \( (i) \), and is derived from Equation (7). In Equation (7), \( n_s \) is the number of soil layers and \( \psi_{r,i} \) is the root pressure potential at layer \( i \) which is explained below.

\[
\psi_{r,wgt} = \frac{\sum_{i=1}^{n_s} \psi_{r,i} r_j}{r_j} \tag{7}
\]

Root water uptake and Root conductivities

The root water uptake \( (S_r) \) is represented as a sink term in Richards equation, and its value depends on the root conductivities. The model needs two root conductivity parameters, named “radial root conductivity” and “axial root conductivity”. Equation (8) shows the Richards equation with the sink term:
where $\theta$ is the volumetric soil moisture content, $K_{sh}$ is the soil hydraulic conductivity, $\Psi_s$ is the soil matric potential and $z$ is the vertical coordinate. In MLCan, the soil hydraulic conductivity and soil matric potential are estimated using the model of the Brooks-Corey based on soil hydraulic properties at saturation point as shown in Equations (9) and (10) (Amenu & Kumar, 2008; Clapp & Hornberger, 1978; Oleson et al., 2004).

\[ K_{sh} = K_{sat} \left( \frac{\theta}{\theta_{sat}} \right)^{2b+3} \tag{9} \]
\[ \Psi_{sm} = \Psi_{sat} \left( \frac{\theta}{\theta_{sat}} \right)^{-b} \tag{10} \]

where $K_{sat}$, $\Psi_{sat}$ and $\theta_{sat}$ are soil hydraulic conductivity, soil matric potential and soil volumetric content at saturation respectively. $b$ is the Brooks-Corey model parameter. The saturation values are obtained using the functions based on the soil texture (percentage of sand and clay) as shown in Equations (11), (12), (13), (14). In Equation (11), $\xi$ is length scale for exponential decrease in $K_{sat}$ with depth and has been considered 0.5 in the MLCan model.

\[ K_{sat} = 0.0070556 \times 10^{-0.884+0.0153(\%sand)} \exp(-\xi z) \tag{11} \]
\[ \Psi_{sat} = -10 \times 10^{1.88-0.013(\%sand)} \tag{12} \]
\[ \theta_{sat} = 0.489 - 0.00126 \times (\%sand) \tag{13} \]
\[ b = 2.91 + 0.159 \times (\%clay) \tag{14} \]

The root water uptake can be similarly expressed as Equations (15) or (16).

\[ S_r = r_f \left( \frac{\theta - \theta_s}{\theta - \theta_d} \right) T_r \tag{15} \]

where, in Equation (15), $\theta_d$ is the soil moisture at wilting point (i.e., the soil moisture beyond which extraction is not possible) and $\theta_s$ is the saturated soil moisture and $r_f$ is
the root fraction through the soil profile estimated from the function proposed by Schenk and Jackson (2002a).

\[ S_r = K_{rad} (\psi_s - \psi_r) \]  

In Equation (16), \( S_r \) is the water uptake, \( K_{rad} \) is the radial root conductivity, \( \psi_s \) is the soil matric potential and \( \psi_r \) is the root pressure potential. By combining the two above equations (Equations (15) and (16)), the root pressure potential \( \psi_r \) is estimated (Drewry et al., 2010a):

\[ \psi_r = \psi_s - \frac{r_r T_r}{K_{rad}} \left( \frac{\theta - \theta_d}{\theta_s - \theta_d} \right) \]  

The axial root conductivity is also used to estimate the root water uptake. Generally, information on root conductivities is scarce and is confined to measures on isolated conditions (Quijano & Kumar, 2015). As no measurements of root conductivities were found in the study area, the sensitivity analysis was done to understand how sensitive the model is to root conductivity values, and to find out the best value to use in simulations.

The hydraulic redistribution has been formulated in MLCan using two equations, as shown below:

\[ \begin{align*}
\frac{\partial \theta}{\partial t} - \frac{\partial}{\partial z} \left[ K_{st} \left( \frac{\partial \psi_s}{\partial z} - 1 \right) \right] &= -K_{rad} (\psi_s - \psi_r) \\
- \frac{\partial}{\partial z} \left[ K_{axs} \left( \frac{\partial \psi_r}{\partial z} + 1 \right) \right] &= K_{rad} (\psi_s - \psi_r)
\end{align*} \]  

These equations model the water flow in the soil system, as well as in the root system, and combines them with the root water uptake function, resulting in the model for hydraulic redistribution (Amenu & Kumar, 2008).

**2.4.3 Parameter range and sampling**

As explained in Section 2.4.1, the sensitivity analysis was performed using GLUE with a Monte-Carlo approach, where random values were used for the parameters chosen from a specified range. The nine parameters were: stomatal conductance parameters (Ball-Berry slope and intercept parameters \( m \) and \( b \) and Tuzet function parameters \( S_f \) and \( \Psi_f \)), root conductivity parameters \( K_{rad} \) and \( K_{axs} \), soil
respiration parameters \((Q_{10 \& R_0})\), and the plant resistance to water parameter \((R_p)\).
The sampling range for each parameter was chosen based on the reported values in the literature (See Table 6), the sample model runs to check the computational ability of the model to run within that range, and the observed sensitivity of the model’s output within that range. Generally, a uniform sampling method is used to generate a random value, but for the \(b, K_{rad}\) and \(K_{axs}\) parameters a sampling method based on logarithmic scale was considered more appropriate. This sampling method gives an opportunity to see the behaviours of the model in different ranges of parameter values. Table 6 shows the sampling range for each parameter and the reported parameter values from previous studies with MLCan on different vegetation.

Table 6. Sampling ranges for the nine parameters and the reported values in the literature

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Unit</th>
<th>sampling Range</th>
<th>Soybean (1)</th>
<th>Maize (1)</th>
<th>Ponderosa Pine (2)</th>
<th>Shrubs (2)</th>
<th>Miscanthus (3)</th>
<th>Switch-grass (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(R_0)</td>
<td>(\mu\text{mol m}^{-2}\text{s}^{-1})</td>
<td>0 – 20</td>
<td>1.2</td>
<td>1.2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Q_{10})</td>
<td>(\cdot)</td>
<td>0 – 2</td>
<td>2</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(m)</td>
<td>(\text{mol m}^{-2}\text{s}^{-1})</td>
<td>1 – 20</td>
<td>10.6</td>
<td>7</td>
<td>13</td>
<td>13</td>
<td>5.7</td>
<td>8</td>
</tr>
<tr>
<td>(b)</td>
<td>(\text{mol m}^{-2}\text{s}^{-1})</td>
<td>0.0001 – 0.2</td>
<td>0.008</td>
<td>0.008</td>
<td>0.001</td>
<td>0.001</td>
<td>0.007</td>
<td>0.008</td>
</tr>
<tr>
<td>(S_f)</td>
<td>MPa(^{-1})</td>
<td>0 – 10</td>
<td>3.5</td>
<td>6.5</td>
<td>1</td>
<td>1</td>
<td>6.5</td>
<td>6.5</td>
</tr>
<tr>
<td>(\Psi_f)</td>
<td>MPa</td>
<td>-10 – 0</td>
<td>-1.3</td>
<td>-1.3</td>
<td>-2</td>
<td>-2</td>
<td>-1.3</td>
<td>-1.3</td>
</tr>
<tr>
<td>(R_p)</td>
<td>MPa (\text{m}^{-1})</td>
<td>1 – 20</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(K_{rad})</td>
<td>s(^{-1})</td>
<td>(10^{-9} – 10^{-6})</td>
<td>5(\times)10(^{-8})</td>
<td>2.5(\times)10(^{-8})</td>
<td>0(^{-8})</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(K_{axs})</td>
<td>mm (\text{s}^{-1})</td>
<td>10(^{-4}) – 1</td>
<td>0.2</td>
<td>0.1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(1) Drewry et al. (2010a)
(2) Quijano et al. (2012)
(3) Le et al. (2012)

2.4.4 Model performance indicator

Results from the parameter sensitivity analysis using the GLUE require the identification of an appropriate performance indicator. In this study, the Nash-Sutcliffe performance indicator (Nash & Sutcliffe, 1970) shown in Equation (19) was used to analyse the sensitivity of the model’s behaviours for the selected parameters.

\[
NS = 1 - \frac{\sum_{i=1}^{n} (O_i - S_i)^2}{\sum_{i=1}^{n} (O_i - \bar{O})^2}
\]  \(19\)
In this equation, \( n \) is the number of observations, \( S_i \) is the simulated values and \( O_i \) is the observed values at time step \( i \). The \( NS \) values change, from minus infinity to 1, and the values close to 1 show the best agreement between the estimated and observed values. A threshold value is usually set at zero or a positive value, so that the simulations with negative \( NS \) values can be ignored.

2.5 MODEL CALIBRATION

Model calibration refers to finding the values for the model parameters that best fit the model’s estimations with the observations. The Nash-Sutcliff performance indicator was used as an objective function during the model calibration.

The objective function was used to measure the goodness-of-fit between the model’s estimation and the observation. In this study, we have done a single-objective model calibration using a single-response or multi-response approach. The single-response model calibration was performed to maximize the \( NS \) values for the \( LE, H, Fc, SWS \) separately. In the multi-response model calibration, the average of the \( NS \) values for the \( LE, H, Fc, SWS \), which was named \( NS-all \), were maximized.

2.6 MODEL VALIDATION

Model validation refers to examining the model’s performances on the estimation of the model’s outputs against the observations using the calibrated parameters. In this study, the model calibration has been done with year 2005 data. The calibrated parameters were then used to validate the model between the years 2001 to 2008 as we could find the Leaf Area Index data (LAI) in the literature for this period. The results of the model calibration and validation are discussed in Chapter 4.
Chapter 3: Effects of the Multilayer Canopy and Hydraulic Redistribution on the Model’s Results

As discussed in previous chapters, this project studies the ecohydrology of an Australian eucalyptus forest. In Chapter 1, the land surface/ecohydrological models were reviewed and a multilayer canopy-root-soil model, named MLCan, was chosen to study the eucalyptus forest in Tumbarumba.

The MLCan model simulates the CO₂, water and energy fluxes and the moisture transport through the canopy-root-soil system. As discussed in Section 1.2.1, the multilayer canopy model of MLCan was initially developed to improve the estimations of canopy-atmosphere exchange fluxes. The flux estimations, however, might be affected by the number of canopy layers chosen for the simulation (Baldocchi et al., 2002; Drewry et al., 2010a; Pyles et al., 2000; Wu et al., 2000). Therefore, a sensitivity analysis on the effects of different numbers of canopy layers is required to find the optimum number of canopy layers.

Norman (1979) suggested that dividing the canopy into a number of layers, so that the LAI for each layer does not exceed a maximum of 0.5 [m² m⁻²], is sufficient to accurately estimate the canopy radiation regime and the canopy-atmosphere exchange fluxes. More recent research has identified the optimum number of canopy layers by examining the sensitivity of the model’s results to different numbers of layers (Pyles et al., 2000; Wu et al., 2000), and then by comparing this number with the Norman rule (Drewry et al., 2010a).

Pyles et al. (2000) analysed the performance of the Advanced Canopy-Atmosphere-Soil Algorithm (ACASA), which has a multilayer canopy model, at sites with different climate and vegetation types. They tested the effects of the vertical resolution on the energy flux estimations and found that, in general, a minimum of 20 canopy layers is required to accurately estimate the \( \text{LE} \) and \( \text{H} \) fluxes. Increasing the number of canopy layers improved the flux estimations at tropical sites, however at other sites no significant changes were found. Their analysis also showed that, with a
canopy model with less than 20 layers, the results degraded at most sites. They did not compare their conclusions with the condition proposed by Norman, but their maximum LAI in the six studied sites ranged from 0.9 to 5 which is compatible with the Norman rule.

Baldocchi et al. (2002) examined the effects of a canopy’s structure on the canopy-atmosphere exchange fluxes in a temperate broad-leaved forest in the USA using the multilayer model CANOAK. They did not study the sensitivity of carbon, water and energy fluxes on the number of canopy layers. However, they based their analysis on previous studies (Pyles et al., 2000; Wu et al., 2000) and concluded that 20 to 30 canopy layers satisfied the LAI less than 0.5 [m² m⁻²] in each layer.

Drewry et al. (2010a) examined the effects of the vertical canopy resolution on the midday canopy sunlit fraction, sunlit and shaded PAR absorption, net canopy-atmosphere exchange of CO₂ and the energy for two agricultural crops (maize and soybean) with the MLCan model. They found that the difference between a 15-layer canopy model and a 50-layer canopy model was only a few percent, however the difference for fewer layers was much more significant. They highlighted that the maximum LAI per layer in their study area for a 15-layer canopy resolution reaches 0.43 [m² m⁻²], which is in agreement with the Norman rule. Therefore, they concluded that 15 canopy layers was sufficient for their study.

The root-soil model in MLCan, which focuses on the below-ground processes, is used to simulate the soil moisture and root water uptake. With the tight coupling between the below-ground and above-ground processes, these simulations affect the land surface processes. To have a good simulation result, the model parameters are as important as the model’s structure. The root-soil model in MLCan needs root conductivity parameters (K_rad and K_axi) to simulate the below-ground processes, such as the soil moisture, root water uptake, latent heat flux and hydraulic redistribution. Root conductivity information is generally limited to a specific vegetation type and/or experimental study (Quijano & Kumar, 2015). Therefore, a sensitivity analysis can increase our knowledge of the effects of these parameters on the model’s results.

Associated with the root water uptake, hydraulic redistribution (HR) has been identified in various ecosystems and across different climates (Burgess et al., 1998; Burgess et al., 2000; Neumann & Cardon, 2012; Quijano & Kumar, 2015; Quijano et al., 2012). As explained in Chapter 1, the hydraulic redistribution mechanism refers to
the upward and downward transport of water through the root system as a result of the soil water potential gradient (Amenu & Kumar, 2008; Quijano et al., 2012), and it is formulated based on the root conductivity parameters (12)). Therefore, the accurate estimation of the hydraulic redistribution also needs further analysis. This mechanism can affect the soil moisture, water uptake, transpiration and carbon assimilation, and has been highlighted as a process which needs to be accounted for in the land surface and ecohydrological models (Prentice et al., 2015; Scott et al., 2008).

In this chapter, the effects of different numbers of canopy layers are first analysed for the simulations of the canopy processes in Section 3.1. The optimum number of canopy layers is then identified. In Section 3.2, a sensitivity analysis is performed on the effects of the root conductivity parameters and hydraulic redistribution on the estimations of the below-ground and above-ground processes. The effects of the root conductivity parameters on the latent heat flux, soil moisture estimation and root water uptake profile are also evaluated. As hydraulic redistribution is a mechanism associated with the root water uptake, the effects of the root conductivity parameters are also evaluated while considering the hydraulic redistribution on the soil moisture and latent heat flux estimations.

To estimate the canopy-atmosphere exchange fluxes, the model considers the entire ecosystem as a single unit. Therefore, the model requires a representative ecosystem canopy and root structure, as well as the ecosystem parameters. In this project, eucalyptus, which is the dominant species in the Tumbarumba site, is considered as the representative of the whole ecosystem. The canopy and root structure described in Section 2.3.1 are used for the simulations.

3.1 EFFECTS OF DIFFERENT NUMBERS OF CANOPY LAYERS

A set of simulations was designed to examine the effects of different numbers of canopy layers on the results associated with the canopy (such as the sunlit fraction, PAR absorption, canopy leaf temperature and canopy stomatal conductance) as well as the canopy gas exchange fluxes (canopy energy balance and canopy net carbon assimilation). This sensitivity analysis was performed to find the optimum number (or the minimum number) of canopy layers to run the simulations. For this study, we considered a canopy model with maximum 48-layer as the highest number of canopy layers and compared simulations with 2, 3, 4, 6, 8, 12 and 24-layer with 48-layer to
find the optimum number of canopy layers. Therefore, the multilayer simulations were conducted with 2, 3, 4, 6, 8, 12, 24, 48 canopy layers. We did not have observations to compare the results and we intended to show the effects of multilayer canopy model on estimations of the eucalyptus forest. The simulation was done on 2002 in DOY 41 to 46 (11-15 February 2002). Alternatively, this analysis can be performed for different periods of time in any other year. To compare the results of the different simulations within the canopy profiles, the vertical distances of the canopy layers ($zh_c/h_c$) were normalised by dividing the vertical distance of the middle of the each canopy layer from the ground ($zh_c$) by the canopy height ($h_c$).

Figure 9 shows the diurnal average sunlit fraction through the entire canopy for the different numbers of canopy layers. It should be noted that the total LAD is constant for all simulations. Figure 9 indicates that the mean sunlit fraction of the entire canopy at midday increased from 33% to 52% when the number of canopy layers increased from 2 to 48. The figure also shows that the sensitivity of the sunlit fraction to the number of canopy layers reduces for the number of canopy layers greater than 12. The sensitivity of the estimated sunlit fraction to the number of canopy layers seems to be affected by the canopy height and shape of the canopy (LAD profile). For example, Drewry et al. (2010a) performed a similar sensitivity analysis on Maize crop with 2.5 m canopy height and found that the sensitivity of the sunlit fraction to number of canopy layers decreased for the canopy layers greater than 15.
Figures 10a and 10b show the vertical distributions of the leaf temperatures at midday in the sunlit and shaded leaf fractions, respectively. The figures show that the leaf temperature was less at the top of the canopy at midday for both the sunlit and shade fractions during the simulation period. The trend was the same for the coarser and finer canopy discretisation. However, for the shaded leaf fraction, the leaf temperature profile varies for different numbers of canopy layers, but for the sunlit fraction, the leaf temperature profile did not change significantly.

Figure 10c shows the vertical distribution of the canopy leaf temperatures at midday. To calculate the mean canopy leaf temperature, the sunlit and shaded leaf temperatures, weighted by the corresponding leaf fraction (sunlit or shaded) in each layer, are averaged (Drewry et al., 2010a). The difference of the leaf temperatures in the middle of the canopy, between the finest resolution and the coarsest resolution, was half a degree, but in the upper or the lower canopy the difference was nearly 1 degree. The shaded leaf temperature of the 2-layer canopy was less than the 48-layer canopy, given the larger shaded fraction in the 2-layer canopy (see Figure 9), which results in a lower canopy leaf temperature in the 2-layer canopy than in the 48-layer canopy.

Figure 10c also shows that the leaf temperature in the middle of the canopy was less than in the upper and lower canopy by nearly half a degree. This might have been caused by the shape of the vertical leaf area density profile, which was denser at the top and the bottom of the profile (see Figure 6b).

Figures 11a and 11b show the vertical distributions of the sunlit and shaded stomatal conductance, and Figure 11c shows the vertical distribution of the canopy stomatal conductance. There was no significant difference between the stomatal conductances in the finer resolution canopy and the coarser resolution canopy. For the sunlit leaf fraction, the stomatal conductance was the same throughout the canopy’s height, however for the shaded leaf fraction it varied. As a result, the mean canopy stomatal conductance changed throughout the canopy’s height.
Figure 10. Effects of different numbers of canopy layers on leaf temperature a) sunlit fraction b) shaded fraction c) whole canopy
Figure 11. Effects of different numbers of canopy layers on stomatal conductance ($g_s$) of a) sunlit fraction, b) shaded fraction, c) whole canopy.
Figure 12a shows the differences between the total PAR absorbed at midday in each simulation, compared to the total PAR absorbed in the 48-layer canopy model. The figure also shows the same differences for the sunlit and shaded PAR absorbed. As shown in Figure 9, when the number of canopy layers was enhanced, the sunlit fraction at midday increased which in turn increased the sunlit absorbed PAR. Thus, the differences, which were always negative compared to the 48-layer canopy, decreased. The opposite pattern happened for the shaded leaf fraction, in which the difference was always positive. The net total sunlit and shaded PAR absorption difference was approximately 28%, with the 48-layer canopy relative to the 2-layer canopy. The net total difference was within 5% with the 12-layer canopy model.

![Graph showing total PAR absorbed at 12:00](image)

![Graph showing total canopy fluxes at 12:00](image)

Figure 12. Effects of different numbers of canopy layers on a) total PAR absorbed b) total canopy fluxes of: net canopy photosynthesis ($An$), Sensible heat flux ($H$) and Latent heat flux ($LE$)
Figure 12b shows the differences in the canopy fluxes of the latent heat, sensible heat and CO₂ assimilation. The effects of the greater PAR absorbed in the 48-layer canopy can be seen in the canopy fluxes. The difference in $A_n$ between the 2-layer canopy and the 48-layer canopy was less than 4%, and the same difference in the available energy ($LE+H$) was nearly 11%. With the 12-layer canopy model, the difference in the available energy was less than 3%.

The results of this section are consistent with a similar discussion made by Drewry et al. (2010a). According to the analysis performed in this section on the estimations of the sunlit fraction, total absorbed PAR radiation and total canopy CO₂ assimilation and energy fluxes, a 12-layer canopy model will affect the results by less than 5% compared to a 48-layer canopy model, while it makes the simulation time much faster. Given that the maximum LAI in the study area is 3.5 [m² m⁻²], following the Norman (1979) rule suggests that a canopy model with at least 7 layers is required, which is less than the 12 layers identified following the previous analysis. Therefore, for modelling the canopy of the eucalyptus forest in this study, it was decided to use a 12-layer canopy model.

3.2 ROOT CONDUCTIVITY PARAMETERS INITIAL SENSITIVITY ANALYSIS

To model the below-ground processes, such as the soil moisture and root water uptake, the root-soil model needs several parameters, including the root conductivity parameters. There is little information about root conductivities (Quijano & Kumar, 2015). Therefore, in this section, a sensitivity analysis is presented on the root conductivity parameters (see Equations (15), (16) and (17)) to see their effects on the latent heat flux, soil moisture and root water uptake.

To perform the sensitivity analysis, MLCan was run with the climate data of year 2005 and the input data introduced in Section 2.3. The model parameters introduced in Table 5, Section 2.4, were used. For the nine parameters where no information for the Tumbarumba site could be found in the literature, the default values in the model were used during this phase. The root conductivity parameters are two of the nine aforementioned parameters that are analysed in this section.

It was found that in the literature, the $K_{rad}$ and $K_{axs}$ values changed between $[10^{-9}-10^{-6}]$ [1/s] and $[10^{-4}-10^{-1}]$ [mm/s], respectively (Quijano & Kumar, 2015). Therefore,
different sets of values were considered for the radial root conductivity \((K_{rad})\) and axial root conductivity \((K_{axs})\), named as Scenarios 1 to 16 in Table 7. Quijano et al. (2012) used the factors of the root conductivity values in Scenario 9 \((k_{rad} = 5\times10^{-8} \,[1/s] \text{ and } K_{axs} = 2\times10^{-1} \,[mm/s])\) to study the Ponderosa Pine in the Blodgett forest in the USA using the MLCan model. The default root conductivity values in the MLCan model are similar to Scenario 16 \((k_{rad} = 1.76\times10^{-9} \,[1/s] \text{ and } K_{axs} = 2.4\times10^{-4} \,[mm/s])\). Therefore, 16 different combinations of the \(K_{rad}\) and \(K_{axs}\) values were considered.

Table 7. Scenarios of root conductivities

<table>
<thead>
<tr>
<th>Scenario NO.</th>
<th>(K_{rad}) (1/s)</th>
<th>(K_{axs}) (mm/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(10^{-6})</td>
<td>(10^{-1})</td>
</tr>
<tr>
<td>2</td>
<td>(10^{-6})</td>
<td>(10^{-2})</td>
</tr>
<tr>
<td>3</td>
<td>(10^{-6})</td>
<td>(10^{-3})</td>
</tr>
<tr>
<td>4</td>
<td>(10^{-6})</td>
<td>(10^{-4})</td>
</tr>
<tr>
<td>5</td>
<td>(10^{-7})</td>
<td>(10^{-1})</td>
</tr>
<tr>
<td>6</td>
<td>(10^{-7})</td>
<td>(10^{-2})</td>
</tr>
<tr>
<td>7</td>
<td>(10^{-7})</td>
<td>(10^{-3})</td>
</tr>
<tr>
<td>8</td>
<td>(10^{-7})</td>
<td>(10^{-4})</td>
</tr>
<tr>
<td>9</td>
<td>(10^{-8})</td>
<td>(10^{-1})</td>
</tr>
<tr>
<td>10</td>
<td>(10^{-8})</td>
<td>(10^{-2})</td>
</tr>
<tr>
<td>11</td>
<td>(10^{-8})</td>
<td>(10^{-3})</td>
</tr>
<tr>
<td>12</td>
<td>(10^{-8})</td>
<td>(10^{-4})</td>
</tr>
<tr>
<td>13</td>
<td>(10^{-9})</td>
<td>(10^{-1})</td>
</tr>
<tr>
<td>14</td>
<td>(10^{-9})</td>
<td>(10^{-2})</td>
</tr>
<tr>
<td>15</td>
<td>(10^{-9})</td>
<td>(10^{-3})</td>
</tr>
<tr>
<td>16</td>
<td>(10^{-9})</td>
<td>(10^{-4})</td>
</tr>
</tbody>
</table>

3.2.1 Effects of root conductivities on monthly latent heat fluxes

Figure 13 shows the effects of changing the axial and radial root conductivities on the monthly average latent heat fluxes \((LE)\). In Figure 13a, the effects of the radial root conductivity on the latent heat flux are shown by assuming four scenarios with a fixed axial root conductivity (e.g., \(K_{axs} = 10^{-2}\) in Scenarios 2, 6, 10, 14). Similarly, in Figure 13b, the effects of the axial root conductivity on the latent heat flux are shown by assuming four scenarios with a fixed radial root conductivity (e.g., \(K_{rad} = 10^{-7}\) in Scenarios 5, 6, 7, 8). The figures for the other scenarios are similar.
Figure 13a presents the results for the fixed axial root conductivities and shows that when the radial root conductivity increased, the monthly latent heat flux displayed little change. This behaviour suggests that the radial root conductivity does not constrain the water flow and that is why the radial root conductivity does not affect the average monthly $LE$.

![Figure 13a](image)

Figure 13b shows that for the fixed radial root conductivities, increasing the axial root conductivities enhanced the monthly latent heat fluxes during the first half of the year and the last month of the year (summer and autumn months in Australia), but that it did not affect the latent heat fluxes during the winter and spring months. This behaviour can be linked to the root water uptake process. When the root conductivities increase, water can be transferred more easily between the roots and the soil. In the summer (with high evaporative demand), an increase in the root conductivities facilitates the mechanism of root water uptake: the roots absorb more water and the leaves transpire more water. In the winter, the evaporative demand is less and the soil moisture is high and the amount of water uptake, even with low root conductivities, compensates for the evaporative demand. Consequently, increasing the root conductivity does not result in more water uptake. Figure 13 also shows the monthly averages of the observed $LE$ data from the OzFlux station at the Tumbarumba site. The comparison of the observed versus modelled $LE$ will be done in the next chapters.
which are devoted to a sensitivity analysis of the nine selected parameters (which include $K_{rad}$ and $K_{ass}$).

### 3.2.2 Effects of root conductivities on soil moisture and water uptake

From the previous section, it was found that the axial root conductivity plays the main role in the root water uptake process, and therefore changing the axial root conductivity value affects the latent heat flux ($LE$). Therefore, this section shows the effects of the changes in the root conductivity values on the root water uptake and soil moisture profile as a function of depth. Figure 14 shows the effects of increasing the root conductivity on the soil moisture and water uptake profiles for Scenarios 9 and 16 in Table 7.

![Soil moisture and water uptake profiles for Scenario 16 (low root conductivity) and Scenario 9 (high root conductivity)](image)

Figure 14. Soil moisture profiles and root water uptake profiles for Scenario 16 (low root conductivity) and Scenario 9 (high root conductivity)
Scenario 16 had both the lowest axial and radial root conductivity (which here is briefly named as low root conductivity). Scenario 9 had values similar to those from the Ponderosa Pine study in the USA (Quijano et al., 2012), and had the highest axial root conductivity (briefly named high root conductivity). As seen in Figure 14, in Scenario 9, with higher root conductivities, the water was taken up through the whole three-metre profile during the summer and autumn. Therefore, the soil moisture profile was drier in the deep layers.

3.2.3 Effects of the root conductivities and hydraulic redistribution on the latent heat fluxes and soil moisture

As discussed earlier in Section 1.2.2, hydraulic redistribution is one of the mechanisms associated with root water uptake, and it can affect the soil moisture profile, water uptake, canopy transpiration and soil CO₂ flux (Amenu & Kumar, 2008; Neumann et al., 2014; Quijano & Kumar, 2015; Quijano et al., 2012; Teodosio et al., 2017). In this study, we did not have access to the soil texture profile to examine the impact of soil heterogeneity and hydraulic redistribution on model profile estimations. However, we believe that soil heterogeneity and parameters are also important factors in controlling soil moisture and land surface fluxes.

As discussed in Section 2.4.2, the hydraulic redistribution in MLCan has been formulated based on the radial and axial flows through the root system (Amenu & Kumar, 2008; Mendel et al., 2002; Quijano et al., 2012). Therefore, the magnitude of the hydraulic redistribution depends on the root conductivity parameters (see Equation (18) in Section 2.4.2). Therefore, the effects of the root conductivity values and the hydraulic redistribution were evaluated on the soil moisture and latent heat fluxes with the same scenarios of high and low root conductivities used for the soil moisture and water uptake plots in Section 3.2.2 (Scenarios 9 and 16 in Table 7). Figure 15 shows the diurnal and average monthly latent heat fluxes with the scenarios simulated with hydraulic redistribution (HR) and the scenarios without hydraulic redistribution (NOHR).

Figure 15a shows a tiny increase in the monthly average latent heat flux during the summer when hydraulic redistribution is considered. The tiny increase in the latent heat flux is also seen in the diurnal average latent heat flux plot shown in Figure 15b. During the dry season, the upper part of the soil profile tends to be drier than the deeper
part, and the roots absorb water from the deep layers, transport it upwards, and then release it in the shallow layers during periods of low ET. This process which is called “hydraulic lift” and it can increase transpiration or soil evaporation during the summer (Amenu & Kumar, 2008; Burgess et al., 1998). However, no significant differences in the LE estimations were seen, with or without the hydraulic redistribution.

![Figure 15. Effects of root conductivity and hydraulic redistribution on a) monthly average and b) diurnal average latent heat fluxes. Note that the two blue lines are on top of each other.](image)

Unlike in the present study, Amenu and Kumar (2008) tested their HR model in a study area dominated by deep-rooted vegetation in Sierra Nevada, USA, and found increased transpiration during the dry season when simulating with HR during the period of 1979-2005. Burgess et al. (1998) observed negative sap flows in roots during the night before a rain event starts in a set of experiments on silky oak trees (G. Robusta) in Kenya, and they inferred the presence of hydraulic lift by the root system. They also observed a similar pattern in another experiment conducted in Western Australia on eucalyptus trees (E. camaldulensis) before a rainfall event, which proved the upward movement of water from deeper soil to shallower soil.

The effects of HR were also checked on the soil moisture estimations in different layers. Figure 16 shows the soil moisture estimates for the scenarios with low and high root conductivity, while considering HR, and without considering HR (NOHR) in a shallow and a deep layer within the modelled root-soil profiles with 10 and 228 cm depth, respectively.
As shown in Figure 16a, and explained above, since with hydraulic redistribution the roots transport water from the deep layers to shallow layers during the dry season (hydraulic lift), the soil moisture estimation is higher in scenarios with HR than with NOHR in shallow layers during the dry summer. This effect was more significant for high root conductivities (bottom plots in Figure 16) as increasing the root conductivity (radial and axial) facilitates the transference of water in the radial and vertical directions, respectively. Therefore, in the scenarios with low root conductivity, the roots are not conductive enough to transfer water through the root profile (see Figure 14), and there is not much difference in the soil moisture between the two scenarios, with and without HR.

Figure 16. Soil moisture estimations in Scenario 16, with low root conductivity (top plots), and in Scenario 9, with high root conductivity (bottom plots), at a) 10 cm depth and b) 228 cm depth

In Figure 16a it is also seen that in the winter months, after rainfall (see Figure 5), the soil moisture with HR was smaller than the soil moisture without HR (NOHR) in the scenario with a high root conductivity. This opposite pattern indicates “hydraulic
descent”, which refers to the transport of water through the root system, from shallow layers to deep layers, during the wet season or after rainfall events in the dry season (Quijano et al., 2012; Schulze et al., 1998; Scott et al., 2008). Burgess et al. (1998) observed positive sap flows in the roots after a rain event in silky oak and eucalyptus trees, which was inferred as the transport of water from a shallow wet soil layer to a deep dry soil layer in their experimental study.

Figure 16b shows similar plots for the deep layer (228 cm). As a result of hydraulic lift, the estimated soil moisture in the deeper layer was slightly smaller, in scenario with HR rather than NOHR during the first few months of the year in the dry season. Looking at the sharp rise in the estimated soil moisture with HR (blue line) in the high root conductivity plot (after DOY 150) shows hydraulic descent during the wet season after precipitation.

Figure 17 shows the daily root water uptake for Scenario 9, with high root conductivity while considering HR. This figure shows the root water uptake in the 10 cm and 228 cm depths. The negative values in the figure show water being released from the roots to the soil, which is hydraulic redistribution (Amenu & Kumar, 2008).

![Figure 17. Water uptake for Scenario 9 (high root conductivity) in Table 7 with HR at 10cm depth (blue line) and 228cm depth (red line)](image)

As is shown, during the second half of the year (winter season) the evaporative demand was small and the soil profile was wet, and the root water uptake was very small in the shallow and deep layers. During this season, when precipitation occurs...
(e.g., DOY = 160), and the shallow layers become wet, the roots absorb water (positive value) in the shallow layers (blue line) and transfer it downward and release it (negative value) in the deep layers (red line). This behaviour, which is called “hydraulic descent”, can also happen during the summer when precipitation occurs and the shallow layers are wet. Hydraulic lift can also be seen by the negative blue line as a release of moisture in the shallow layers during the dry months. These results highlight the importance of considering hydraulic redistribution in land surface models and of studying the responses of ecosystems under current and future climates (Scott et al., 2008).

3.3 SUMMARY AND CONCLUSION

This chapter first investigated the effects of the canopy vertical resolution on the canopy radiation regime, leaf temperature and total canopy fluxes. The results of this analysis showed that the canopy vertical resolution significantly affected the sunlit and shaded leaf fractions. The estimated leaf fractions resulted in different total absorbed PAR radiations, averaged leaf temperatures and total canopy fluxes between the finer and coarser canopy resolutions. The results showed that with the 12-layer canopy model, the total PAR absorption at midday was within 5% difference and the total latent and sensible heat fluxes (available energy) was less than 3% different from the 48-layer canopy model. Therefore, the conclusion was that the 12-layer canopy model has the optimum number of canopy layers. These results agreed well with the previous analysis of the sensitivities of different numbers of canopy layers and their suggestion, as a general rule, to limit the LAI at each layer to a maximum of 0.5 [m$^2$ m$^{-2}$] (Baldocchi et al., 2002; Drewry et al., 2010a; Norman, 1979; Pyles et al., 2000).

The sensitivity analysis on the values of the radial and axial root conductivities showed that increasing the axial root conductivity enhanced the monthly average latent heat fluxes during the summer and autumn. However, it did not significantly affect the results during the winter. This behaviour was linked to the facilitated root water uptake as a result of higher axial root conductivity during the months with high evaporative demands. In addition, increasing the radial root conductivity did not significantly affect the average monthly $L.E$. This analysis highlighted the effects of axial root conductivity on the water uptake, soil moisture and latent heat flux, especially during the dry period.
The comparison of the soil moisture estimations, with and without hydraulic redistribution, supported the presence of the hydraulic lift phenomenon during the dry periods and the hydraulic descent phenomenon during the wet season (after rainfall) in this study area. However, the effects on scenarios with high root conductivities were found to be more significant. The analysis increased our knowledge of the importance of root conductivities on hydraulic redistribution, especially axial root conductivity. Moreover, the results of the latent heat flux estimations, with and without hydraulic redistribution, showed only minor differences.

Although the effects of hydraulic redistribution showed minor differences on the latent heat flux and soil moisture estimations, HR is included in the MLCan model for further simulations as other authors have found HR to be an important mechanism that needs to be included in the models (Li et al., 2012; Prentice et al., 2015). Therefore, the model used to do the sensitivity analyses in Chapters 4 and 5 has a 12-layer canopy model and accounts for hydraulic redistribution.
Chapter 4: The Sensitivity Analysis and Model Calibration and Validation

To study the land surface processes using an ecohydrological model, a reliable model structure and parameter definitions are required. The potential advantages of the detailed multilayer canopy-root-soil model of MLCan for this study were discussed in previous chapters. In this chapter, the focus is on the sensitivity analyses of the parameters and calibrations and the validation of the MLCan model.

The Generalized Likelihood Uncertainty Estimation (GLUE) method (Beven & Binley, 1992) is used for the model calibration and sensitivity analyses in this study. The GLUE analysis enhances our understanding of the model’s performance by evaluating the possible model outcomes produced by different random model parameterisations. The model’s performances are evaluated in estimating four key variables, namely the latent heat flux ($LE$), sensible heat flux ($H$), CO$_2$ flux ($F_c$) and soil moisture ($SWS$). These variables are typical ecohydrological model outputs for which there is also the observed data from the flux tower at the Tumbarumba site to compare with the model’s estimations. The sensitivity analyses and the model calibration and validation performed in this chapter include the hydraulic redistribution.

In GLUE, a large number of simulations are required. For this study, 2000 simulations for the eucalyptus forest in Tumbarumba were run. As explained in Chapter 2, the sensitivity analyses and model calibrations were performed using the year 2005 data as this year had average precipitation. The canopy and root structure data for the eucalyptus species in the study area were extracted, as far as possible, from the literature, as explained in Section 2.3, and were used as the input data for the MLCan model. The climate data for the year 2005 were given to the model as the forcing file. The depth-varying soil moisture and temperature data down the soil profile at the beginning of the year 2005, as shown in Table 4 (Section 2.3.3), were used as the initial conditions in the model.
As explained in Section 2.4, many of the model parameters which were required to run the model for the eucalyptus species in Tumbarumba were obtained from the literature (shown in Table 5). However, for nine of the parameters, no values could be found in the literature. Accordingly, in this chapter the sensitivity analyses were performed on these parameters. The nine parameters that were evaluated in the sensitivity analyses are listed below:

- Stomatal conductance parameters: slope \( (m) \) and intercept \( (b) \) of the Ball-Berry stomatal conductance model (Equation (3)); sensitivity parameter \( (S_f) \) and the specific leaf water potential \( (\Psi_f) \) in the Tuzet function (Equation (4)),
- Root conductivity parameters: radial \( (K_{rad}) \) and axial \( (K_{ax}) \) root conductivities (Equations (16), (17) and (18)),
- Soil respiration parameters: soil respiration at 10°C \( (R_o) \) and temperature sensitivity of soil respiration rate \( (Q_{10}) \) (Equation (5)),
- Plant resistance parameter to flow \( (R_p) \) (Equation (6)).

The sampling range for each parameter was chosen based on the reported values in the literature for similar studies (see Table 6) but considered a slightly bigger range to ensure that the entire feasible range was covered. The four key variables, \( LE, H, F_c \) and \( SWS \), which were used for the model calibration and parameter sensitivity analysis, were also used for model validation.

The structure of this chapter is organised as follows. Section 4.1 presents the sensitivity analysis results for the nine selected model parameters. In Section 4.2 the multi-response and single-response model calibrations are performed. Section 4.3 presents the results of the model validation for the independent data, and Section 4.4 is a comparison of the MLCan model estimations with the previous modelling efforts at Tumbarumba.

### 4.1 MODEL SENSITIVITY ANALYSIS TO PARAMETERS

In this section, the results of the GLUE analysis for 2000 simulations are presented. The Nash-Sutcliffe values \( (NS) \) have been calculated and used as the performance indicators to analyse the sensitivity of the model’s behaviours to the selected parameters. The \( NS \) values for the key model outputs, including the latent heat flux, sensible heat flux, \( CO_2 \) flux and soil moisture estimations, have been named as
NS-LE, NS-H, NS-Fc, and NS-SWS, respectively. For the soil moisture analysis, we had only access to the soil moisture observation up to 120 cm depth. As the top soil layer always shows the biggest soil moisture fluctuations, modelling studies frequently try to capture these fluctuations by calibrating the model to the top layer soil moisture. Therefore, in this study, the first layer soil moisture data (10 cm depth) was used to compare the model’s estimations to the observed data. The hourly values of the estimated and observed data are used to calculate the NS values. The sensitivity of the MLCan model in estimating these four variables, corresponding to each of the nine parameters, are investigated statistically (using NS values) and graphically (using dotty plots). Larger NS values indicate a better agreement between the observed data and the simulations. Therefore, we are looking for the range of parameters that result in greater NS values and the NS values less than -0.5 are not shown in the dotty plots. A horizontal line in these plots reflects the insensitivity of the model to the parameter within the specified range.

Figure 18 shows the dotty plots for the NS-LE values corresponding to the nine parameters. The dotty plots show the sensitivity of the latent heat flux (LE) estimations to the parameters. It can be seen that no particular pattern existed between the parameters and the NS-LE values, except for the m, b and ψf parameters, as shown in Figure 18 (a, b & e). It is interesting that there was no sensitivity found between the estimated LEs and the root conductivity parameters in this analysis when considering the effects of the nine parameters together, although in Chapter 3 it was found that the root conductivity parameters, especially the axial root conductivity (Kaxs), affects the LE estimations. Figure 18a shows that from the sampling range of between 1 and 20 for the m parameter, the best LE estimation results from the m parameter values were between 9 and 11. Figure 18b shows that for the b parameter from the sampling range of between 10^{-4} and 0.2 [mol m^{-2} s^{-1}], the values between 0.001 [mol m^{-2} s^{-1}] and 0.010 [mol m^{-2} s^{-1}] gave the best LE estimations, whereas b values greater than 0.01 [mol m^{-2} s^{-1}] resulted in poor LE estimations. In Figure 18e, for the ψf parameter for the sampling range between -10 and 0 [MPa], the NS-LE values were slightly reduced for ψf values between -3 to 0 [MPa]. As shown previously in Table 6, the m and b values for the study of the Ponderosa Pine forest in the USA using the MLCan model were reported as 13 and 0.001, respectively (Quijano et al., 2012). Medlyn et al. (2007) fitted the leaf gas exchange data measured in the eucalyptus forest in Tumbarumba to
the Ball-Berry model (without the Tuzet function) and reported the $m$ and $b$ parameters as 11.1 and 0.051 [mol m$^{-2}$ s$^{-1}$], respectively. The values for the $m$ and $b$ parameters in this study were in general agreement with the values in the literature.

Figure 19 shows the dotty plots for the $NS-H$ values corresponding to each of the nine selected parameters. A similar pattern to the $LE$ simulations was found between the $NS-H$ and the $m$, $b$ and $\psi_f$ parameters, as shown in Figure 19 (a, b & e). It was also observed that the $NS-H$ values were generally higher, which indicates better sensible heat estimations compared to the latent heat fluxes.

The $NS$ values for the CO$_2$ flux estimations ($NS-F_c$) corresponding to each of the nine parameters are shown in dotty plots in Figure 20. In Figure 20b, there is no value for $b$ greater than 0.2 because it was out of the sampling range. $R_o$ appeared to be the only sensitive parameter in the CO$_2$ flux estimations as it relates to the soil surface CO$_2$ flux equation. Figure 20g shows that the $NS-F_c$ values were relatively high and flat for the $R_o$ values between 0 and 2 [µmol m$^{-2}$ s$^{-1}$], and the $NS-F_c$ was highest when the $R_o$ was close to 1 [µmol m$^{-2}$ s$^{-1}$]. The $NS-F_c$ slightly increased for $Q_{10}$ values greater than 1 in Figure 20i. No specific pattern was observed for the $F_c$ estimations using other parameters.

The dotty plots of soil moisture estimations ($NS-SWS$) corresponding to each of the nine parameters are shown in Figure 21. Figure 21a shows that $NS-SWS$ increases for $m$ values greater than 10. A similar pattern to $NS-LE$ and $NS-H$ with respect to the $b$ parameter has also been observed between $NS-SWS$ and $b$ in Figure 21b. Figure 21e shows that $NS-SWS$ improves for $\psi_f$ greater than -2 [MPa].

In general, the results of the sensitivity analyses with MLCan showed that, among the nine selected parameters, $m$ and $b$ were the most sensitive parameters for estimating the $LE$, $H$ and $SWS$. The $m$ and $b$ parameters are related to the stomatal conductance estimation, and the stomatal conductance regulates transferring water between the leaves and the atmosphere via the transpiration process. As this process affects the whole transfer of water through the plant, it was in agreement with our expectation to see that the $LE$, $H$ and $SWS$ estimations were sensitive to the $m$ and $b$ parameter values. Therefore, for the best estimations of $LE$, $H$ and $SWS$, the model needs the values of these parameters that give the maximum $NS$ values.
The results of the sensitivity analysis of the CO$_2$ estimations showed that the $R_o$ parameter was the only sensitive (identifiable) parameter for the CO$_2$ estimation. This was expected as the soil surface CO$_2$ flux estimation is dependent on the $R_o$ parameter.

For the other parameters, this sensitivity analysis showed no identifiability/sensitivity between the parameters and the estimations, therefore any value from the sampling range might produce a good result.
Figure 18. GLUE dotty plots of the behavioural latent heat flux (LE) simulations versus the parameters a) $m$, b) $b$, c) $K_{rad}$, d) $k_{ass}$, e) $\psi_f$, f) $S_f$, g) $R_o$, h) $R_p$ and i) $Q_{10}$
Figure 19. GLUE dotty plots of the behavioural sensible heat flux \((H)\) simulations versus the parameters a) \(m\), b) \(b\), c) \(K_{rad}\), d) \(k_{axs}\), e) \(\psi_f\), f) \(S_f\), g) \(R_o\), h) \(R_p\) and i) \(Q_{10}\)
Figure 20. GLUE dotty plots of the behavioural CO₂ flux ($F_c$) simulations versus the parameters a) $m$, b) $b$, c) $K_{rad}$, d) $k_{axs}$, e) $\psi_f$, f) $S_f$, g) $R_o$, h) $R_p$ and i) $Q_{10}$.
Figure 21. GLUE dotty plots of the 15 cm behavioural soil moisture simulations versus the parameters a) \( m \), b) \( b \), c) \( K_{rad} \), d) \( k_{axs} \), e) \( \psi_f \), f) \( S_f \), g) \( R_o \), h) \( R_p \) and i) \( Q_{10} \).
4.2 MODEL CALIBRATION

As previously explained, model calibration refers to finding the values for the model parameters that best fit the model’s estimations to the observations. The NS values have been used as the objective function for evaluating the goodness-of-fit between the model’s estimations and the observations. In this section, the results of the model calibrations with the GLUE method are discussed. As mentioned in the methodology chapter (Section 2.5), the single-objective model calibration has been done using single-response and multi-response approaches. The single-response model calibration is first discussed in Section 4.2.1, and then the focus is on the multi-response model calibration in Section 4.2.1. In both of the following subsections, the model’s performances are compared quantitatively using the Nash-Sutcliffe statistic, and visually by plotting the annual patterns of the average daily estimated and observed data.

4.2.1 Single-response model calibration

4.2.1.1 Quantitative assessment

A single-response calibration is the traditional form of model calibration, in which the model’s performance is evaluated by simulating a single independent variable. The single-response model calibration aims to find the set of model parameters which best fit a single model output to the observation by obtaining a best fit objective function (i.e., maximising the NS value). Ecohydrological models are often calibrated against either of the surface flux measurements (latent or sensible heat flux) (McCabe et al., 2005).

In this section, the single-response model calibration is performed against the observations for each of the four key model outputs, including the latent heat flux (LE), sensible heat flux (H), CO₂ flux (Fₑ) and soil moisture at first layer (10 cm deep as reported in Table 4) (SWS). Table 8 shows the five maximum NS values for each output (i.e., LE, H, Fₑ and SWS) with the abbreviations L1,L2,...,L5, H1,H2,...,H5, F1,F2,...,F5 and S1,S2,...,S5, respectively. The table also shows in other columns the corresponding simulation numbers, the NS values for other uncalibrated model outputs using the calibrated parameters and the NS-all values (the average of all NS values which will be discussed in Section 4.2.2).
As seen in Table 8, when the model was calibrated for latent or sensible heat fluxes, the top five maximum $NS-LE$ or $NS-H$ values were 0.49 and 0.76, respectively. As the $LE$ and $H$ estimations are related, the simulations with the maximum $NS-LE$ values also had the maximum $NS-H$ values, and vice versa. However, the simulations with the best $LE$ and $H$ estimations did not yield very good fits to the soil moisture. The best calibrated models for $LE$ and $H$ showed poor CO$_2$ flux estimations, with very low or negative $NS-F_c$ values.

Table 8. Single-response model calibration result

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Objective function</th>
<th>max values</th>
<th>Sim NO.</th>
<th>$NS-LE$ for sim NO</th>
<th>$NS-H$ for sim NO</th>
<th>$NS-F_c$ for sim NO</th>
<th>$NS-SWS$ for sim NO</th>
<th>$NS-all$ for sim NO</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1</td>
<td>$NS-LE$</td>
<td>0.49</td>
<td>331</td>
<td>0.49</td>
<td>0.75</td>
<td>-2.52</td>
<td>0.25</td>
<td>-0.25</td>
</tr>
<tr>
<td>L2</td>
<td>$NS-LE$</td>
<td>0.49</td>
<td>315</td>
<td>0.49</td>
<td>0.76</td>
<td>-3.18</td>
<td>0.64</td>
<td>-0.32</td>
</tr>
<tr>
<td>L3</td>
<td>$NS-LE$</td>
<td>0.49</td>
<td>1940</td>
<td>0.49</td>
<td>0.76</td>
<td>-0.24</td>
<td>0.51</td>
<td>0.38</td>
</tr>
<tr>
<td>L4</td>
<td>$NS-LE$</td>
<td>0.49</td>
<td>328</td>
<td>0.49</td>
<td>0.76</td>
<td>-2.67</td>
<td>0.62</td>
<td>-0.20</td>
</tr>
<tr>
<td>L5</td>
<td>$NS-LE$</td>
<td>0.49</td>
<td>133</td>
<td>0.49</td>
<td>0.75</td>
<td>-27.51</td>
<td>0.51</td>
<td>-6.44</td>
</tr>
<tr>
<td>H1</td>
<td>$NS-H$</td>
<td>0.76</td>
<td>1320</td>
<td>0.49</td>
<td>0.76</td>
<td>0.06</td>
<td>0.68</td>
<td>0.50</td>
</tr>
<tr>
<td>H2</td>
<td>$NS-H$</td>
<td>0.76</td>
<td>1613</td>
<td>0.48</td>
<td>0.76</td>
<td>0.51</td>
<td>0.51</td>
<td>0.57</td>
</tr>
<tr>
<td>H3</td>
<td>$NS-H$</td>
<td>0.76</td>
<td>328</td>
<td>0.49</td>
<td>0.76</td>
<td>-2.67</td>
<td>0.62</td>
<td>-0.20</td>
</tr>
<tr>
<td>H4</td>
<td>$NS-H$</td>
<td>0.76</td>
<td>315</td>
<td>0.49</td>
<td>0.76</td>
<td>-3.18</td>
<td>0.64</td>
<td>-0.32</td>
</tr>
<tr>
<td>H5</td>
<td>$NS-H$</td>
<td>0.76</td>
<td>890</td>
<td>0.49</td>
<td>0.76</td>
<td>-1.32</td>
<td>0.46</td>
<td>0.10</td>
</tr>
<tr>
<td>F1</td>
<td>$NS-F_c$</td>
<td>0.53</td>
<td>1892</td>
<td>0.38</td>
<td>0.69</td>
<td>0.53</td>
<td>-0.13</td>
<td>0.37</td>
</tr>
<tr>
<td>F2</td>
<td>$NS-F_c$</td>
<td>0.53</td>
<td>1380</td>
<td>0.09</td>
<td>0.47</td>
<td>0.53</td>
<td>-0.24</td>
<td>0.21</td>
</tr>
<tr>
<td>F3</td>
<td>$NS-F_c$</td>
<td>0.53</td>
<td>1804</td>
<td>0.47</td>
<td>0.74</td>
<td>0.53</td>
<td>0.43</td>
<td>0.54</td>
</tr>
<tr>
<td>F4</td>
<td>$NS-F_c$</td>
<td>0.53</td>
<td>596</td>
<td>0.46</td>
<td>0.74</td>
<td>0.53</td>
<td>0.71</td>
<td>0.61</td>
</tr>
<tr>
<td>F5</td>
<td>$NS-F_c$</td>
<td>0.53</td>
<td>218</td>
<td>0.44</td>
<td>0.70</td>
<td>0.53</td>
<td>0.50</td>
<td>0.54</td>
</tr>
<tr>
<td>S1</td>
<td>$NS-SWS$</td>
<td>0.85</td>
<td>1616</td>
<td>0.29</td>
<td>0.50</td>
<td>-4.32</td>
<td>0.85</td>
<td>-0.67</td>
</tr>
<tr>
<td>S2</td>
<td>$NS-SWS$</td>
<td>0.85</td>
<td>1975</td>
<td>0.26</td>
<td>0.45</td>
<td>-0.56</td>
<td>0.85</td>
<td>0.25</td>
</tr>
<tr>
<td>S3</td>
<td>$NS-SWS$</td>
<td>0.85</td>
<td>1312</td>
<td>0.27</td>
<td>0.48</td>
<td>-1.62</td>
<td>0.85</td>
<td>-0.01</td>
</tr>
<tr>
<td>S4</td>
<td>$NS-SWS$</td>
<td>0.84</td>
<td>1505</td>
<td>0.24</td>
<td>0.41</td>
<td>-2.13</td>
<td>0.84</td>
<td>-0.16</td>
</tr>
<tr>
<td>S5</td>
<td>$NS-SWS$</td>
<td>0.84</td>
<td>990</td>
<td>0.26</td>
<td>0.43</td>
<td>-1.61</td>
<td>0.84</td>
<td>-0.02</td>
</tr>
</tbody>
</table>

When the model was calibrated to the CO$_2$ flux measurements, the five top $NS-F_c$ values were 0.53 (see Table 8). It can also be seen that the $NS-LE$ and $NS-H$ values varied for the best CO$_2$ flux estimations. The simulations with the best CO$_2$ flux estimations also did not always have good soil moisture estimations.

Table 8 also shows the $NS$ values when the model was calibrated to the soil moisture observations on the first layer (simulations $S1$ to $S5$). As shown, the maximum $NS-SWS$ were 0.85. However, using the best calibrated parameters to the
soil moisture on the first layer to simulate the $LE$ and $H$ gave $NS-LE$ and $NS-H$ values of 0.29 and 0.50, respectively, while the $NS-F_c$ values were negative. The reason for lower $NS-LE$ and $NS-H$ values despite higher $NS-SWS$ value might be related to calibration of top layer soil moisture and not including deeper layer soil moisture.

As discussed, the single-response model calibration focused on one single model output and maximized the $NS$ value only for that single variable. Therefore, the outcome was biased to best fitting the calibrated variable. Naseem et al. (2015) reached a similar conclusion when they evaluated a merged conceptual ecohydrological model using the single-objective calibration approach with either streamflow or LAI data. McCabe et al. (2005) calibrated the TOPUP SVAT model against either latent or sensible heat flux measurements in a site located on the mid-north coast of New South Wales and they found different cumulative evapotranspiration totals using different single-objective calibrated parameters.

Table 9. Best parameters set in single-response model calibration

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Objective function</th>
<th>max values</th>
<th>Sim NO.</th>
<th>$m$ - mol m$^{-2}$s$^{-1}$</th>
<th>$b$ MPa$^{-1}$</th>
<th>$\psi_f$ MPa</th>
<th>$R_p$ MPa s m$^{-1}$</th>
<th>$K_{rad}$ s$^{-1}$</th>
<th>$K_{acs}$ mm s$^{-1}$</th>
<th>$Q_{10}$</th>
<th>$R_o$ µmol m$^{-2}$s$^{-1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1</td>
<td>NS-LE</td>
<td>0.49</td>
<td>331</td>
<td>9.76</td>
<td>0.006</td>
<td>0.78</td>
<td>-4.9</td>
<td>2.27</td>
<td>4.48E-07</td>
<td>9.45E-02</td>
<td>0.27</td>
</tr>
<tr>
<td>L2</td>
<td>NS-LE</td>
<td>0.49</td>
<td>315</td>
<td>9.68</td>
<td>0.007</td>
<td>7.08</td>
<td>-3.9</td>
<td>2.81</td>
<td>7.35E-09</td>
<td>4.33E-03</td>
<td>0.59</td>
</tr>
<tr>
<td>L3</td>
<td>NS-LE</td>
<td>0.49</td>
<td>1940</td>
<td>9.49</td>
<td>0.007</td>
<td>2.42</td>
<td>-8.7</td>
<td>19.27</td>
<td>4.30E-07</td>
<td>2.71E-03</td>
<td>0.40</td>
</tr>
<tr>
<td>L4</td>
<td>NS-LE</td>
<td>0.49</td>
<td>328</td>
<td>9.71</td>
<td>0.007</td>
<td>7.71</td>
<td>-5.4</td>
<td>15.74</td>
<td>1.59E-08</td>
<td>5.98E-03</td>
<td>1.56</td>
</tr>
<tr>
<td>L5</td>
<td>NS-LE</td>
<td>0.49</td>
<td>133</td>
<td>10.24</td>
<td>0.005</td>
<td>6.47</td>
<td>-3.0</td>
<td>6.28</td>
<td>1.54E-07</td>
<td>7.15E-03</td>
<td>0.04</td>
</tr>
<tr>
<td>H1</td>
<td>NS-H</td>
<td>0.76</td>
<td>1320</td>
<td>9.73</td>
<td>0.009</td>
<td>7.55</td>
<td>-3.5</td>
<td>9.93</td>
<td>3.50E-09</td>
<td>2.44E-02</td>
<td>0.78</td>
</tr>
<tr>
<td>H2</td>
<td>NS-H</td>
<td>0.76</td>
<td>1613</td>
<td>9.29</td>
<td>0.011</td>
<td>0.73</td>
<td>-6.5</td>
<td>2.56</td>
<td>6.86E-08</td>
<td>1.48E-03</td>
<td>0.67</td>
</tr>
<tr>
<td>H3</td>
<td>NS-H</td>
<td>0.76</td>
<td>328</td>
<td>9.71</td>
<td>0.007</td>
<td>7.71</td>
<td>-5.4</td>
<td>15.74</td>
<td>1.59E-08</td>
<td>5.98E-03</td>
<td>1.56</td>
</tr>
<tr>
<td>H4</td>
<td>NS-H</td>
<td>0.76</td>
<td>315</td>
<td>9.68</td>
<td>0.007</td>
<td>7.08</td>
<td>-3.9</td>
<td>2.81</td>
<td>7.35E-09</td>
<td>4.33E-03</td>
<td>0.59</td>
</tr>
<tr>
<td>H5</td>
<td>NS-H</td>
<td>0.76</td>
<td>890</td>
<td>9.96</td>
<td>0.007</td>
<td>1.86</td>
<td>-4.6</td>
<td>15.83</td>
<td>3.00E-07</td>
<td>7.49E-03</td>
<td>0.68</td>
</tr>
<tr>
<td>F1</td>
<td>NS-Fc</td>
<td>0.53</td>
<td>1892</td>
<td>7.11</td>
<td>0.030</td>
<td>0.88</td>
<td>-2.6</td>
<td>15.69</td>
<td>2.66E-07</td>
<td>9.35E-01</td>
<td>1.61</td>
</tr>
<tr>
<td>F2</td>
<td>NS-Fc</td>
<td>0.53</td>
<td>1380</td>
<td>1.04</td>
<td>0.064</td>
<td>9.23</td>
<td>-0.4</td>
<td>16.15</td>
<td>6.57E-07</td>
<td>6.90E-03</td>
<td>1.83</td>
</tr>
<tr>
<td>F3</td>
<td>NS-Fc</td>
<td>0.53</td>
<td>1804</td>
<td>11.67</td>
<td>0.008</td>
<td>0.11</td>
<td>-8.7</td>
<td>13.61</td>
<td>4.22E-08</td>
<td>1.66E-04</td>
<td>1.35</td>
</tr>
<tr>
<td>F4</td>
<td>NS-Fc</td>
<td>0.53</td>
<td>596</td>
<td>10.57</td>
<td>0.009</td>
<td>6.47</td>
<td>-2.5</td>
<td>5.62</td>
<td>4.29E-09</td>
<td>9.53E-03</td>
<td>1.46</td>
</tr>
<tr>
<td>F5</td>
<td>NS-Fc</td>
<td>0.53</td>
<td>218</td>
<td>13.31</td>
<td>0.0003</td>
<td>1.90</td>
<td>-2.7</td>
<td>15.29</td>
<td>3.59E-08</td>
<td>6.48E-01</td>
<td>1.62</td>
</tr>
<tr>
<td>S1</td>
<td>NS-SWS</td>
<td>0.85</td>
<td>1616</td>
<td>19.90</td>
<td>0.002</td>
<td>5.28</td>
<td>-1.2</td>
<td>9.56</td>
<td>2.63E-09</td>
<td>6.82E-04</td>
<td>1.04</td>
</tr>
<tr>
<td>S2</td>
<td>NS-SWS</td>
<td>0.85</td>
<td>1975</td>
<td>19.10</td>
<td>0.0003</td>
<td>5.83</td>
<td>-0.6</td>
<td>15.38</td>
<td>4.13E-09</td>
<td>1.85E-04</td>
<td>1.38</td>
</tr>
<tr>
<td>S3</td>
<td>NS-SWS</td>
<td>0.85</td>
<td>1312</td>
<td>15.10</td>
<td>0.001</td>
<td>2.03</td>
<td>-0.1</td>
<td>18.03</td>
<td>7.20E-09</td>
<td>1.12E-04</td>
<td>1.62</td>
</tr>
<tr>
<td>S4</td>
<td>NS-SWS</td>
<td>0.84</td>
<td>1505</td>
<td>15.69</td>
<td>0.004</td>
<td>6.21</td>
<td>-0.5</td>
<td>9.10</td>
<td>2.04E-08</td>
<td>3.13E-04</td>
<td>0.83</td>
</tr>
<tr>
<td>S5</td>
<td>NS-SWS</td>
<td>0.84</td>
<td>990</td>
<td>15.92</td>
<td>0.013</td>
<td>9.47</td>
<td>-0.4</td>
<td>19.40</td>
<td>1.09E-08</td>
<td>1.88E-04</td>
<td>1.44</td>
</tr>
</tbody>
</table>

Table 9 shows the single-response calibrated parameters corresponding to the simulations in Table 8. As seen in Table 9, when the model was calibrated against the $LE$ or $H$ observations ($L1$, $L2$, ..., $L5$ and $H1$, $H2$, ..., $H5$, respectively), the stomatal conductance parameters, $m$ and $b$, were around 10 and 0.007 [mol m$^{-2}$s$^{-1}$], respectively. These values were consistent with the sensitive ranges obtained using the dotty plots assessment in Figure 18, Section 4.1. These values are also close to the values reported
by Medlyn et al. (2007). It was shown that when these sets of calibrated parameters for $LE$ or $H$ were used to estimate the soil moisture or CO$_2$ flux, poor results were achieved, especially for the CO$_2$ flux. It is interesting to note that in the sensitivity analysis in Section 4.1, the $LE$ and $H$ estimations did not show sensitivities to the $K_{rad}$ and $K_{axs}$ parameter values. However, here the results showed that for the best five sets of parameters, the $K_{rad}$ and $K_{axs}$ values tended to be around $10^{-8}$ [s$^{-1}$] and $10^{-3}$ [mm s$^{-1}$], respectively, when the model was only fitted to the $LE$ or $H$ estimations. Moreover, the $Q_{10}$ values were mostly below 1, and the other parameters did not show sensitivities to the $LE$ or $H$ estimations, and their values varied over their entire ranges.

The calibrated parameters fitted for the best CO$_2$ flux estimation in Table 9 (simulations $F1$, $F2$,..,$F5$) show that the stomatal conductance parameters ($m$ and $b$) were different from those fitted to the $LE$ or $H$ estimations and they varied within their entire ranges. For example, simulations $F3$ to $F5$ appeared to have reasonably good $LE$ and $H$ estimates, with larger $m$ values. However, simulation $F2$ had the smallest $m$ value and poor $LE$ and $H$ estimates. This behaviour shows that for CO$_2$ flux estimations, the model is more sensitive to soil respiration than canopy assimilation. However, the soil respiration observations is not available for the site to further investigate this behaviour. Furthermore, this behaviour shows that the stomatal conductance parameters are not important for CO$_2$ flux estimations. According to Table 9, the soil surface CO$_2$ flux parameters, $R_o$ and $Q_{10}$, were around 0.7 [$\mu$mol m$^{-2}$ s$^{-1}$] and 1.5, respectively. As shown in Section 4.1, the $R_o$ parameter (Figure 20) was the most sensitive parameter for CO$_2$ flux estimations.

Table 9 also shows the single-response calibrated parameters to the first-layer observed soil moisture with maximum NS-SWS values (simulations $S1$, $S2$,..,$S5$). The table reveals that for the best soil moisture estimation, the $m$ parameter values were higher than those for the $LE$ and $H$ estimations. Based on this analysis, the best fit $m$ values ranged between 15 and 20. A pattern can be seen between the $m$ and $b$ values, in which greater $m$ values are associated with lower $b$ values, and vice versa. The results for the best soil moisture estimation suggested that the $m$ and $b$ values to be 15 and 0.006 [mol m$^{-2}$ s$^{-1}$] or 19 and 0.003 [mol m$^{-2}$ s$^{-1}$]. The $\psi_f$ values varied between -1.5 and 0 [MPa]. The $K_{rad}$ and $K_{axs}$ values tended to be in the order of $10^{-9}$ [s$^{-1}$] and $10^{-4}$ [mm s$^{-1}$], respectively. However, when the calibrated parameters to the first-layer soil moisture were used to estimate the $LE$ or $H$, they did not produce good results.
It was concluded that poor \( LE \) estimations are associated with very low or very high \( m \) values and \( b \) values outside the 0.001 to 0.01 range. Moreover, the best \( F_c \) estimation was associated with small \( R_o \) values of below 1 [\( \mu \text{mol m}^{-2} \text{ s}^{-1} \)] and \( Q_{10} \) values above 1. To have the best \( LE \) or \( H \) estimations, the model needs greater root conductivity values than when the model was calibrated to the best soil moisture estimations.

The results showed that the single-response calibrated parameters could not simulate more than one model output efficiently. Therefore, a multi-response calibration that takes into account the multiple model outputs is needed. The multi-response model calibration is discussed in Section 4.2.2.

### 4.2.1.2 Visual assessment of simulations with single-response calibrated parameters

In the previous section, the quantitative assessments of the \( LE, H, F_c \) and \( SWS \) estimations using MLCan were presented when the model was calibrated to a single model output. This section presents the seasonal variations of the four key model outputs simulated with the single-response calibrated parameters. Figures 22 to 24 show the five best average daily \( LE, H \) and \( F_c \) estimations for the year 2005 calibrated with the corresponding parameter sets, named as \( L1,L2,...,L5, H1,H2,...,H5, F1,F2,...,F5 \), respectively, as shown in Table 9.

![Figure 22. Average daily latent heat flux estimations for the five best \( LE \) fits versus the observed data for year 2005](image-url)
Figure 23. Average daily sensible heat flux estimations for the five best $H$ fits versus the observed data for year 2005

Figure 24. Average daily CO2 flux estimations for the five best $F_c$ fits versus the observed data for year 2005

Figure 22 shows that the $LE$ estimations were reasonably good for the first half of the year but not for the second half. Figure 23 also shows a good fit between the observed and the estimated sensible heat flux ($NS-H = 0.76$) for the entire range. Figure 24 shows that the model did not reproduce well the fluctuations of the CO2 fluxes, especially during the winter.
Figure 25 shows the five best average daily estimated soil moisture values for the first layer (10 cm depth) for the year 2005, with the best calibrated parameter sets named $S1, S2, ..., S5$ in Table 9. As mentioned, the soil moisture data for the first layer has been used for the parameter calibrations in this study.

Figure 25. Average daily soil moisture estimations at the first layer for the five best $SWS$ fits versus the observed data for year 2005

Figure 26. Daily soil moisture profile for the best $SWS$ parameter set at year 2005
Figure 25 shows a sudden rise in the estimated and observed soil moisture after DOY 160, which coincided with consecutive precipitation events, as was shown in Figure 5a. The figure also shows that the model estimations agree well with the observations during the first half of the year, however the soil moisture was overestimated during the wet winter after DOY 160. The larger soil moisture estimated from the model is consistent with the modelled lower transpiration. Figure 26 shows the soil moisture profile for the best soil moisture estimation (S1). As seen in the soil moisture profile, the total 3 m soil profile was wet during the wet months in the second half of the year.

Figures 27 and 28 show the average daily stomatal conductance and the average daily latent heat flux, respectively, for the S1, S2,..., S5 simulations in Table 9. As seen in Figure 27, simulation S5 had an almost constant $g_s$ value of close to zero during the dry season in the first half of the year. However, the soil moisture estimation for the first layer for this simulation (S5) was similar to the other simulations (S1 to S4) and it correlated well with the observations during this time. According to Table 8, the NS-LE values for simulations S1 to S5 varied between 0.24 and 0.29. As seen in Figure 28, simulations S1 to S5 had very low LE estimations during the dry period in the first half of the year. This probably resulted from the higher $m$ and lower $b$, $K_{rad}$ and $K_{ass}$ values in the single-response calibration of the SWS (Table 9) compared to the corresponding parameter values in the single-response calibration of the LE. The above figures imply that, for the best soil moisture estimation, the model does not necessarily depend on the stomatal conductance simulation. This shows that the model can almost shut down the stomata (the horizontal line appeared in Figure 27) and reduces the transpiration during the dry season to keep the soil moisture at a reasonable level.

As seen in both Figure 22 and Figure 28, the model underestimated the latent heat flux during the wet season in the second half of the year. However, the soil moisture is available for transpiration (wet soil profile during the precipitation events) and was overestimated. This behaviour might suggest that the stomatal conductance model is not properly coupled to the soil water availability and transpiration process. Several studies have highlighted the regulation of the transpiration rate with the soil water content in the top 50 cm of a soil profile where the majority of the root density exists (Schenk & Jackson, 2002b). However, M. Zeppel et al. (2008), in a sensitivity study of the sap flux to soil and plant variables using the SPA model in Australian
woodland dominated by *Eucalyptus sclerophylla* in Cumberland Plains over 115 study days, found contrasting behaviours, in which the tree water use was not coupled to the soil water content in the top 80 cm of soil. Instead, they concluded that the soil water storage in deep clay layers (80 cm – 3 m) contributed to stand water use.

Figure 27. Average daily stomatal conductance estimations for the five best *SWS* fits for year 2005

Figure 28. Average daily latent heat flux estimations for the best *SWS* fits for year 2005
4.2.2 Multi-response model calibration

4.2.2.1 Quantitative assessment

The ecohydrology and land surface models typically have large numbers of outputs. Generally, little attention is given to the multiple-output nature of the ecohydrology models when a single-objective calibration is considered and, therefore, the results are biased to best fit the calibrated variable (McCabe et al., 2005). In contrast, the multi-objective model calibration fits the model parameters to multiple model outputs at the same time. The idea of using multiple sources of data for model calibrations have been used in many studies and have been shown to reproduce more realistic results (Houser et al., 2001; McCabe et al., 2005; Schulz et al., 2001).

In this section, the multi-response model calibration with the GLUE method is performed using the four key model outputs, including the latent heat flux \((LE)\), sensible heat flux \((H)\), CO\(_2\) flux \((Fc)\) and the soil moisture at the first layer \((SWS)\) simultaneously. This model calibration aims to find the set of parameters which best fit the multiple model outputs to the observations. To do so, we implemented an equal weight to each objective function and maximised the averages of the \(NS-LE\), \(NS-H\), \(NS-Fc\), \(NS-SWS\) values, named \(NS-all\). The five maximum \(NS-all\) values, abbreviated as \(a1, a2, ..., a5\), and their corresponding parameters, are assessed in this section.

Table 10 shows the five maximum \(NS-all\) values and the corresponding \(NS-LE\), \(NS-H\), \(NS-Fc\) and \(NS-SWS\) values for each of the five best simulations. The five maximum \(NS-all\) values varied between 0.59 and 0.61. It can be seen that when the model was fitted to multiple outputs simultaneously, the \(NS-LE\), \(NS-H\), \(NS-Fc\), \(NS-SWS\) for the five maximum \(NS-all\) simulations were around 0.45, 0.71, 0.52 and 0.72, respectively. The single-response calibration results in the previous section showed the bias in the \(NS\) value for the calibrated output and degraded the \(NS\) values for other uncalibrated outputs. However, the multi-response model calibration gives a compromise optimal solution for the multiple outputs. According to Table 10, the \(NS\) values for \(LE\), \(H\) and \(Fc\) in the multi-response calibration tended to be slightly smaller compared to the single-response calibration, however the \(NS\) value for the \(SWS\) showed a bigger reduction.

Naseem et al. (2015) compared the single-objective and multi-objective calibrations of a merged conceptual ecohydrology model and predicted the catchment scale streamflow and LAI in the Murray-Darling basin in Australia. They found that
the independently calibrated model outputs in the single-objective model calibration correlate well with the observations but the cross-validation with the single-objective calibrated parameters did not produce good results. In their study, the multi-objective calibration produced compromised estimations of the streamflow and LAI.

Table 10. Multi-response model calibration results

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Objective function</th>
<th>max $NS$-$all$ values</th>
<th>Sim NO.</th>
<th>$NS$-$LE$ for sim NO</th>
<th>$NS$-$H$ for sim NO</th>
<th>$NS$-$F_c$ for sim NO</th>
<th>$NS$-$SWS$ for sim NO</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a1$</td>
<td>$NS$-$all$</td>
<td>0.61</td>
<td>640</td>
<td>0.45</td>
<td>0.70</td>
<td>0.52</td>
<td>0.77</td>
</tr>
<tr>
<td>$a2$</td>
<td>$NS$-$all$</td>
<td>0.61</td>
<td>596</td>
<td>0.46</td>
<td>0.74</td>
<td>0.53</td>
<td>0.71</td>
</tr>
<tr>
<td>$a3$</td>
<td>$NS$-$all$</td>
<td>0.59</td>
<td>755</td>
<td>0.45</td>
<td>0.72</td>
<td>0.52</td>
<td>0.69</td>
</tr>
<tr>
<td>$a4$</td>
<td>$NS$-$all$</td>
<td>0.59</td>
<td>521</td>
<td>0.44</td>
<td>0.70</td>
<td>0.52</td>
<td>0.70</td>
</tr>
<tr>
<td>$a5$</td>
<td>$NS$-$all$</td>
<td>0.59</td>
<td>1834</td>
<td>0.43</td>
<td>0.70</td>
<td>0.52</td>
<td>0.70</td>
</tr>
</tbody>
</table>

Table 11 shows the calibrated parameters for the multiple outputs corresponding to the simulations with maximum $NS$-$all$ values. It is interesting to note that the first two simulations were both equally good, however simulation $a1$ had a higher $NS$-$SWS$ and a lower $NS$-$H$ than simulation $a2$. As there was no significant difference between the two simulations in the $NS$-$LE$ and $NS$-$F_c$, this comparison shows that the best soil moisture estimation was compensated with a worse sensible heat flux estimation.

Comparing the corresponding parameters in Table 11 shows that simulation $a1$ had the highest $m$ and $K_{axs}$ parameter values. However, simulation $a2$ had almost the lowest $m$ and $K_{axs}$ values. As the $m$ and $K_{axs}$ parameters are associated with the stomatal conductance and axial root conductivity, respectively, it was concluded that to have the best fit for soil moisture ($NS$-$SWS$) and energy flux estimations ($NS$-$LE$ and $NS$-$H$) the stomatal conductance and the axial root conductivity must change in the same manner.

In Table 11, the $m$ values varied from 10 to 15 and were close to 13 on average. The $b$ values are very small and they were 0.003 [mol m$^{-2}$ s$^{-1}$] on average. The $\psi_f$ values varied between -0.3 and -7.4 [MPa], which is around -4 [MPa] on average. The $K_{rad}$ and $K_{axs}$ were in the order of $10^{-9}$ [s$^{-1}$] and $10^{-1}$ [mm s$^{-1}$], respectively. The $Q_{10}$ values were around 1.5 and the $R_o$ values were less than 1 [\mu mol m$^{-2}$ s$^{-1}$], and nearly equal to
0.5 [µmol m\(^{-2}\) s\(^{-1}\)] on average. The \(S_f\), \(\psi_f\) and \(R_p\) values varied across the entire ranges, suggesting that there was no sensitivity to these parameters.

Table 11. Best parameters set in multi-response model calibrations

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Objective function</th>
<th>max NS-all values</th>
<th>Sim NO.</th>
<th>(m)</th>
<th>(b)</th>
<th>(S_f)</th>
<th>(\psi_f)</th>
<th>(R_p)</th>
<th>(K_{rad})</th>
<th>(K_{trans})</th>
<th>(Q_{10})</th>
<th>(R_o)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a1</td>
<td>NS-all</td>
<td>0.61</td>
<td>640</td>
<td>15.74</td>
<td>0.001</td>
<td>0.48</td>
<td>-0.3</td>
<td>7.37</td>
<td>3.06E-09</td>
<td>9.54E-01</td>
<td>0.57</td>
<td>0.50</td>
</tr>
<tr>
<td>a2</td>
<td>NS-all</td>
<td>0.61</td>
<td>596</td>
<td>10.57</td>
<td>0.009</td>
<td>6.47</td>
<td>-2.5</td>
<td>5.62</td>
<td>4.29E-09</td>
<td>9.53E-03</td>
<td>1.46</td>
<td>0.68</td>
</tr>
<tr>
<td>a3</td>
<td>NS-all</td>
<td>0.59</td>
<td>755</td>
<td>12.59</td>
<td>0.0004</td>
<td>6.83</td>
<td>-7.4</td>
<td>11.36</td>
<td>1.33E-09</td>
<td>2.47E-01</td>
<td>1.91</td>
<td>0.92</td>
</tr>
<tr>
<td>a4</td>
<td>NS-all</td>
<td>0.59</td>
<td>521</td>
<td>10.19</td>
<td>0.002</td>
<td>1.27</td>
<td>-2.9</td>
<td>1.31</td>
<td>2.47E-09</td>
<td>1.65E-01</td>
<td>1.21</td>
<td>0.62</td>
</tr>
<tr>
<td>a5</td>
<td>NS-all</td>
<td>0.59</td>
<td>1834</td>
<td>13.48</td>
<td>0.0002</td>
<td>1.27</td>
<td>-6.3</td>
<td>10.00</td>
<td>2.14E-09</td>
<td>1.25E-01</td>
<td>1.40</td>
<td>0.10</td>
</tr>
</tbody>
</table>

4.2.2.2 Visual assessment of simulations with multi-response calibrated parameters

This section assesses the seasonal variations of the four model outputs estimated with the multi-response calibrated parameters. Figures 29 to 31 show the five best average daily estimated \(LE\), \(H\) and \(Fc\) values for the year 2005 with the multi-response calibrated parameters (\(a1\) to \(a5\) parameter sets in Table 11), as well as the observed data for that year. As shown in Figure 29, all five simulations had similar underestimations of the \(LE\) during the second half of the year, especially during winter. However, simulations \(a3\) and \(a5\) slightly overestimated the \(LE\) during the summer. Figure 30 shows that the model slightly overestimated the sensible heat flux during the summer; however, it correlated well with the observed data. According to Table 10 and Figure 31, the best five simulations of the CO\(_2\) flux performed similarly and showed reasonable agreement with the observed data during the winter, but they underestimated during the summer and autumn.

Figure 32 shows the five best average daily soil moisture estimations for the first layer for year 2005 which were estimated with the multi-response calibrated parameters (\(a1\) to \(a5\) parameter sets in Table 11). This figure shows that the model was overestimating during the second half of the year and underestimating during the first half of the year. It can be noted that all of the simulations were exactly the same during the second half of the year but they were different in the first half of the year. Figure 33 shows the average daily stomatal conductance for the best \(NS\)-all simulations. Figure 33 shows that the stomatal conductances resemble the seasonal pattern of the \(LE\) and \(H\) when the model was fitted to the multi-response model calibration.
Figure 29. Average daily latent heat flux estimations for the five best $NS$-$all$ parameter sets versus the observed data for year 2005

Figure 30. Average daily sensible heat flux estimations for the five best $NS$-$all$ parameter sets versus the observed data for year 2005
Figure 31. Average daily CO₂ flux estimations for the five best *NS-all* parameter sets versus the observed data for year 2005

Figure 32. Average daily soil moisture estimations at first layer for the five best *NS-all* parameter sets versus the observed data for year 2005
4.2.3 Single-response versus multi-response calibrations

The previous sections presented the results of the single-response and multi-response model calibrations. In the single-response model calibrations, the NS values for the four key model outputs (NS-LE, NS-H, NS-FC and NS-SWS) were separately maximised to best fit the estimations to the observations. In the multi-response model calibrations, the NS-LE, NS-H, NS-FC and NS-SWS were simultaneously maximised to best fit the four key model outputs to the observations. In other words, we looked for the maximum NS-all value, which is the average of the four NS values.

The single-response model calibrations produced different parameters, depending on whether the energy fluxes (latent and sensible heat), CO2 flux or soil moisture estimations were the focus of the calibration. These parameters produced outcomes biased by being fitted to the calibrated outputs and degraded the results to the uncalibrated outputs. Therefore, the single-response calibrated parameters could not be considered for efficiently simulating more than one model output. The multi-response model calibrations produced compromised results for the multiple outputs. The NS values for the LE, H and FC in the multi-response calibrations tended to be slightly smaller, compared to the single-response calibrations, however the NS value for the SWS showed a bigger relative reduction.
To explore the model’s behaviours further, the average daily $LE$, $H$, $Fc$ and $SWS$ estimations with the single-response and the multi-response calibrations were presented and compared with the corresponding observed data for the year 2005. The $LE$ estimations from the single-response calibrations (Figure 22) had less overestimations during the summer months and the first half of the year. A similar pattern was shown for the sensible heat flux estimations when comparing Figure 23 and Figure 30. The CO$_2$ flux estimations were very similar in the multi-response and single-response model calibrations. In general, comparing Table 8 and Table 10 shows that when one single flux estimation ($LE$, $H$ and $Fc$) was the focus of the calibration, the outcome was nearly the same as the outcome resulting from the multi-response calibration. However, the soil moisture estimations were different. The $NS$-$SWS$ value for the single-response soil moisture estimation ($S1$ simulation) was 0.85, however the $NS$-$SWS$ value for the best multi-response simulation ($a1$ simulation, as shown in Figure 32) was 0.77.

4.3 MODEL VALIDATION ON INDEPENDENT DATA

This section describes the independent model validation results for the eucalyptus forest in Tumbarumba for 2001 to 2008. The best parameter set in the multi-response calibration for 2005 (simulation $a1$) was used for the model validation. For the initial condition, the measured first layer soil moisture and soil temperature at the beginning of the 2001 was used. As there was no access to the soil moisture and temperature measurements at different depths, we considered depth-constant initial conditions equal to the first layer for the simulation, as shown in Table 12. The Nash-Sutcliffe ($NS$) objective function was used to evaluate the model’s performances on the estimations of the four model outputs ($LE$, $H$, $Fc$, $SWS$). Similar to the sensitivity analysis and model calibrations, hourly values of the model’s input and output data were used to run the model and to estimate the $NS$ values, respectively. Figure 34 shows the monthly precipitation in Tumbarumba for 2001 to 2008.
Table 12. Initial conditions at the beginning of 2001 for model validation

<table>
<thead>
<tr>
<th>Soil depth (m)</th>
<th>Soil temperature (°C)</th>
<th>Soil moisture (m³/m³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.10</td>
<td>12.36</td>
<td>0.22</td>
</tr>
<tr>
<td>0.27</td>
<td>12.36</td>
<td>0.22</td>
</tr>
<tr>
<td>0.58</td>
<td>12.36</td>
<td>0.22</td>
</tr>
<tr>
<td>1.18</td>
<td>12.36</td>
<td>0.22</td>
</tr>
<tr>
<td>2.28</td>
<td>12.36</td>
<td>0.22</td>
</tr>
<tr>
<td>3.72</td>
<td>12.36</td>
<td>0.22</td>
</tr>
</tbody>
</table>

Figure 34. Monthly precipitation between 2001 and 2008 in Tumbarumba

Table 13 shows the NS values for LE, H, Fc and SWS, and the annual rainfall for the years 2001 to 2008, as well as each year separately. Annual rainfall values are also reported to easily identify wet and dry years. The NS values were calculated based on the hourly values of the observed and estimated data. In this analysis, the soil moisture data available in the OzFlux (available for the first layer only) was used for NS-SWS calculations. As seen in Table 13, the NS values for 2005 were slightly different to the NS values calculated during the multi-response model calibrations for year 2005 in Table 10 (with the a1 parameter set). The difference was attributed to the effects of the initial conditions at the beginning of 2005. The effects of the initial conditions on the model’s estimations, particularly on the soil moisture estimations, will be thoroughly examined in Chapter 5.
The model showed good agreement in its estimations of the $LE$, $H$ and $Fc$ in 2001, but very poor agreement in its soil moisture estimations. The $NS-LE$ and $NS-H$ values for all the validation years were similar to the $NS$ values for 2005, which is the calibration year. The $NS-LE$ for 2003 was smaller than the other years, which will be evaluated visually later in this section. The $NS-Fc$ values for most of the years were similar to that of 2005, except for the years 2002 and 2003. The $NS-SWS$ values were negative for 2002 and 2008. These values may have resulted from high fluctuations in the hourly values. As seen in Table 13, the year 2006 was a dry year, with 428 mm precipitation. The $NS$ values for 2006 and 2007 showed that the model had good validation results for the dry year and the year following the drought period.

Table 13. $NS$ values for independent model validations for years between 2001 and 2008 using the best parameter sets ($a1$) from multi-response calibration for 2005

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$NS-LE$</td>
<td>0.54</td>
<td>0.56</td>
<td>0.33</td>
<td>0.62</td>
<td>0.46</td>
<td>0.52</td>
<td>0.56</td>
<td>0.65</td>
<td>0.54</td>
</tr>
<tr>
<td>$NS-H$</td>
<td>0.53</td>
<td>0.74</td>
<td>0.69</td>
<td>0.76</td>
<td>0.72</td>
<td>0.75</td>
<td>0.74</td>
<td>0.74</td>
<td>0.71</td>
</tr>
<tr>
<td>$NS-Fc$</td>
<td>0.64</td>
<td>0.32</td>
<td>0.06</td>
<td>0.48</td>
<td>0.51</td>
<td>0.66</td>
<td>0.58</td>
<td>0.60</td>
<td>0.46</td>
</tr>
<tr>
<td>$NS-SWS$</td>
<td>-5.50</td>
<td>-2.33</td>
<td>0.46</td>
<td>0.39</td>
<td>0.62</td>
<td>0.68</td>
<td>0.78</td>
<td>-0.09</td>
<td>0.38</td>
</tr>
<tr>
<td>Annual Rainfall (mm)</td>
<td>1048</td>
<td>986</td>
<td>1073</td>
<td>1037</td>
<td>1043</td>
<td>428</td>
<td>1014</td>
<td>610</td>
<td>-</td>
</tr>
</tbody>
</table>

Figures 35 to 38 show the hourly observed and estimated X-Y plots for the four key model outputs of $LE$, $H$, $Fc$ and $SWS$ during the validation years. The bottom plot in each figure shows the average monthly observed and estimated data. As shown in these figures, the X-Y plots for 2005 were not noticeably better than for other years, so it highlighted that the model validation using independent data was equally as good as the year that the model was calibrated for.

The model captured the hourly variations of $LE$, $H$ and $SWS$ reasonably well during the validation period, however it did not show a good performance in simulating $Fc$. The poor performance in the $Fc$ estimation might have been caused by errors in the photosynthesis estimation and/or soil CO$_2$ flux estimation. Drewry et al. (2010a) evaluated the performance of the MLCCan model in capturing the canopy responses of maize and soybean crops to environmental variability in the USA and found similar
discrepancies for $F_c$. They discussed the disagreements between the CO$_2$ flux estimations and observations in their study, and linked them to the assumptions of the fixed photosynthetic capacity parameters ($V_{cmax}$, $J_{max}$) in the photosynthesis estimations over the simulation periods. There has been evidence of seasonal changes in photosynthetic parameters (Misson et al., 2006; Quijano et al., 2012; Wilson et al., 2000; Xu & Baldocchi, 2003) and soil respiration parameters (Janssens & Pilegaard, 2003), however in this study it was assumed that the parameters were constant. Moreover, Teodosio (2017) concluded that considering more factors, such as soil moisture, air temperature, net radiation and soil heat flux, when simulating soil surface CO$_2$ fluxes might result in more accurate estimations than the common simplified equation based on the soil temperatures which have been used in MLCan. Further exploration of this area is for future work.
Figure 35. Observed-estimated X-Y plots for (a-d) hourly latent heat fluxes ($LE$) for individual years between 2001 and 2008 and (e) monthly $LE$ during the eight years.
Figure 36. Observed-estimated X-Y plots for (a-d) hourly sensible heat fluxes ($H$) for individual years between 2001 and 2008 and (e) monthly $H$ during the eight years.
Figure 37. Observed-estimated X-Y plots for (a-d) hourly CO$_2$ fluxes ($F_c$) for individual years between 2001 and 2008 and (e) monthly CO$_2$ during the eight years
Figure 38. Observed-estimated X-Y plots for (a-d) hourly soil moisture ($SWS$) at first layer for individual years between 2001 and 2008 and (e) monthly $SWS$ during the eight years.
Figures 39 and 40 show the average monthly simulated latent and sensible heat fluxes for the complete period and the observed data from OzFlux. In both figures, the model showed reasonable good agreements with the observed data. Figure 39 shows that the model underestimated the $LE$ during the winter in all simulation years and overestimated the peaks during the summers of 2003-2004, 2004-2005, 2005-2006 and 2007-2008. Similarly, in Figure 40, the model underestimated the $H$ during the summer in 2002-2003, 2004, 2005 and 2008.

As mentioned previously, the study site experienced the lowest rainfall in the summer of 2006-2007, however the observations did not show any reduction in the $LE$ fluxes and the model underestimated the peak of summer 2006-2007.

![Figure 39. Average monthly latent heat flux estimations versus observations for validations years (2001-2008). Dashed line shows January to December 2005 which was the calibration year](image-url)
Figure 40. Average monthly sensible heat flux estimations versus observations for validation years (2001-2008). Dashed line shows January to December 2005 which was the calibration year.

Figure 41. Average monthly CO₂ flux estimations versus observations for validation years (2001-2008). Dashed line shows January to December 2005 which was the calibration year.

Figure 41 shows the average monthly CO₂ fluxes for the years between 2001 and 2008 versus the observed data from OzFlux. The figure shows that the model did not
correlate well with the observed data at a monthly resolution. It can be noted that there was a reduction in the CO₂ flux observations during the dry year in 2006 which shows the lower growth during that year. However, the modelling results could not capture it. Leuning et al. (2005) predicted a larger reduction in forest production than in evapotranspiration during future drought periods in Tumbarumba. Li et al. (2012) discussed the NEE (Net Ecosystem Exchange) simulations in Tumbarumba during 2002-2006 modelled using the CABLE model, while including both the hydraulic redistribution function and alternative root water uptake (Scenario S4 in their paper). They found improvements in the NEE estimations in Scenario S4 compared to other scenarios without hydraulic redistribution or with a default root water uptake. However, it still did not match very well with the observed data. They attributed the disagreements between the NEE estimations and the observations to errors in the TER (Terrestrial Ecosystem Respiration) estimations.

Figure 42 shows the average monthly soil moisture estimations for the period 2001-2008 against the available observed data for depths where observations were available. Access to the observed soil moisture data at different depths was made available by the site investigator, and was not obtained from the OzFlux site. Nevertheless, the data had some gaps in it. Figure 42 shows that the model’s estimations agreed reasonably well with the observed data at all depths, especially in the two first layers near the surface. In the deeper layers, the model’s estimations agreed reasonably well with the observed data, especially after 2005.
4.4 COMPARISON WITH PREVIOUS MODELLING IN TUMBARUMBA

As discussed in Chapter 1, the eucalyptus forest at Tumbarumba has been studied using other land surface models such as CABLE (Kowalczyk et al., 2006; Li et al., 2012). In this section, the results from the MLCan model are compared with previous work using the CABLE model for the estimation of latent heat flux and soil moisture in Tumbarumba.

As mentioned in Sections 1.2.2, 1.3 and 4.3, Li et al. (2012) analysed the responses of the CABLE model to seasonal drought in Tumbarumba by comparing four different scenarios (namely $S1$ to $S4$) which were defined by the inclusion of two different water uptake functions in tandem with, or without, the hydraulic redistribution function. Their results showed that Scenario $S4$, which included the root water uptake function of Lai and Katul (2000) as well as the hydraulic redistribution function (Ryle et al., 2002), improved the estimations of the latent heat flux and soil moisture in Tumbarumba in comparison to the other alternative simulations ($S1$ to $S3$). Therefore, for this section, the estimated latent heat flux and soil moisture have been digitised in Scenario $S4$ using the CABLE model as well as the corresponding observed data in Tumbarumba (as reported by Li et al. (2012)).
The average monthly latent heat fluxes ($LE$) for the years 2002 to 2006, as estimated by the MLCan and CABLE (Scenario $S4$) models, as well as the observed $LE$ data reported in Li et al. (2012) and the data available on the OzFlux website are shown in Figure 43. It can be noticed that the observed data reported by Li et al. was not consistent with the observed data available from OzFlux, especially for the low values during the wintertime. As explained in Section 2.3.2, this study used the data from the $L6$ processing level, which had been uploaded to the OzFlux website in 2014. The differences between the observed data reported by Li et al., and the $L6$ data, suggests that the researchers used different gap-filling techniques.

Figure 43 also shows that the $LE$ fluxes estimated by the MLCan model (the red dotted line) correlated better with the observed data reported by Li (the blue line with circle marker). The differences observed in the figure show that using different datasets for the calibrations yields different parameters and different results. This comparison highlights the importance of accurate data for the model calibration and validation. This discussion shows that the MLCan model could estimate the surface fluxes as well as the Australian land surface model (CABLE). When the reported observed $LE$ data was considered, the MLCan estimated $LE$ fluxes better matched with the observed data.

Figure 43. Comparison of monthly average latent heat fluxes; observed by (OzFlux, reported by Li et al. (2012) and estimated by the MLCan model and CABLE model
Figure 44 shows the average monthly soil moisture estimations using the MLCan model and the observed data from the OzFlux website during the years between 2002 and 2006 at different depths. Figure 44 also shows the soil moisture estimations by the CABLE model and the observed soil moisture data at similar depths during 2002 to 2006 that were reported in Li et al. (2012). Figures 44a and 44b show that the observed data reported by Li (digitised) and the observed data available in OzFlux were similar at depths of 15 and 30 cm, however they were different at 60 and 120cm. Comparing the soil moisture estimations by MLCan and CABLE in Figure 44 shows that both models better matched the observations for the surface layers (15 and 30 cm depths) than for the deeper layers. Both the MLCan and CABLE models similarly overestimated the soil moisture at all depths during 2001 to 2005. In 2006, however, both models underestimated at 15 cm depth and showed better estimations for the other depths.

The above comparison revealed that both models have similar performances in simulating the ecohydrology of the eucalyptus forest in Tumbarumba. However, for the MLCan model the calibrated parameters for the site were used, whereas for the CABLE model Li et al. used the default model parameters for the evergreen plant functional type. This result highlights the fact that the complexity of the model’s structure does not necessarily improve the model’s performance. Prentice et al. (2015) also underlined the fact that increasing the number of model parameters in a complex model can reduce the reliability and robustness of the land surface models despite representing realistic simulations.
Figure 44. Comparison of monthly observed and estimated soil moisture data at different depths a) 15 cm, b) 30 cm, c) 60 cm, d) 120 cm
4.5 SUMMARY AND CONCLUSION

All of the land surface models require a large number of parameters to run. This chapter has discussed the results of the parameter sensitivity analysis and the model calibration and validation for simulating the ecosystem exchange fluxes and soil moisture of the eucalyptus forest in Tumbarumba using the MLCan model and the GLUE method.

The parameter sensitivity analyses for the key model outputs of LE, H, Fc and SWS using dotty plots showed that some of these outputs in the model were not sensitive to some of the parameters. As a result, it was found that among the nine selected parameters, m and b, the Ball-Berry stomatal conductance parameters, were the most identifiable parameters for estimating the LE, H and SWS. However, their sensitivity ranges varied. For example, the results suggested that for the best LE and H estimations, the m values were between 9 and 11 and the b values were between 0.001 and 0.01 [mol m\(^{-2}\) s\(^{-1}\)]. However, the best estimates of the SWS were for m values greater than 10, with an unchanged range for b. Therefore, to produce the best estimations of LE, H and SWS, the multi-response calibration might be considered.

The sensitivity analysis also showed that the Ro parameter, soil respiration at 10 °C, was the only identifiable parameter for estimating Fc in which the best estimations have the Ro close to 1 [µmol m\(^2\) s\(^{-1}\)]. Therefore, as a result of this sensitivity analysis, the m, b, Ro parameters were identified as the most sensitive parameters in the MLCan model. Other parameters were non-identifiable across the parameter sampling ranges.

In the model calibration, the Nash-Sutcliffe objective functions for the estimations of the four key model outputs were compared in the single-response and multi-response approaches. The calibrated values for the parameters in these two calibration approaches were also discussed. In the single-response model calibrations, each NS value was separately maximised to best fit the model’s estimations to the observations. However, in the multi-response calibrations, the averages of the four NS values (named NS-all) were maximised. The analysis showed that the single-response approach produced biased results for the calibrated variables and degraded outcomes for the uncalibrated variables. However, the multi-response approach yielded compromised estimations with the multiple model outputs. The NS-LE, NS-H, NS-Fc and NS-SWS for the best multi-response calibrations were 0.45, 0.70, 0.52 and 0.77, respectively. However, in the single-response calibrations, the best NS-LE, NS-H, NS-
$F_c$ and $NS-SWS$ were 0.49, 0.76, 0.53 and 0.85, respectively. The $NS$ values for $LE$, $H$ and $F_c$ in the multi-response calibrations tended to be slightly smaller compared to the single-response calibrations, however the $NS$ value for $SWS$ showed a bigger reduction. Therefore, the single-response calibrated parameters could only be useful to simulate the calibrated output. Therefore, the best multi-response calibrated parameters were used to validate the model between 2001 and 2008.

Regarding the choice of the Ball-Berry stomatal conductance parameters, the single-response and multi-response calibrations produced different parameter sets. For the best $LE$ and $H$ estimations only, the results suggested 9.71 and 0.007 [mol m$^{-2}$ s$^{-1}$] for the $m$ and $b$ parameters, respectively. Moreover, the analysis for the best soil moisture estimations only suggested two sets of values for the $m$ and $b$ parameters which were equally good, and they were 15.1 and 0.001 [mol m$^{-2}$ s$^{-1}$] or 19.9 and 0.002 [mol m$^{-2}$ s$^{-1}$], respectively. However, for the best multi-response estimations, the results suggested $m = 15.74$ and $b = 0.001$ [mol m$^{-2}$ s$^{-1}$]. For the other parameters, a unique value for the parameter could not definitely be concluded. However, there was a discussion of the ranges that each parameter was limited to give the best results.

The results of the model validations on the independent data between the years 2001 and 2008 showed that the estimations of $LE$, $H$ and $SWS$ are in reasonable agreement with the observations. However, the model could not estimate the $F_c$ very well.

The comparison between the estimations of the $LE$ and $SWS$ using the MLCan model and the CABLE model in Tumbarumba showed that both models correlated well with the observed data. This result highlights the fact that the complexity of the model’s structure does not necessarily improve the model’s performance.
Chapter 5: The Influence of the Soil Initial Conditions

The MLCan model needs the initial soil moisture and temperature data down through the soil profile to run a simulation. Chapter 4 discussed the results of the simulations with depth-varying soil initial conditions (see Table 4) and showed the results of the parameter sensitivity analysis and model calibration. In some cases, the initial soil conditions might not be available or only available at or near the soil surface. Therefore, the effects of the soil initial conditions on the model’s simulations are discussed here. In this chapter, the effects of depth-constant soil initial conditions on the model’s simulations are investigated.

It is hypothesized that the initialisations of the soil moisture and temperature variables primarily affect their estimations. Moreover, these two variables might affect the estimations of the soil surface fluxes and the above-ground processes (Cosgrove et al., 2003; Rodell et al., 2005; Yang et al., 2011; Yang et al., 1995). Soil surface temperature can affect the soil respiration, through Equation (5) (Janssens & Pilegaard, 2003), and the soil surface fluxes (Drewry et al., 2010a; Hinzman et al., 1998). Depending on the memory of the soil processes, the effects of the initialisation of the soil moisture and temperature might last for a few weeks to months. Soil moisture and temperature are also coupled, and their estimations might have cross effects on each other. This topic is discussed in more detail at the end of this chapter (Section 5.2) to show that the initial soil temperature did not significantly affect the results.

In the following sections, the effects of the initial soil moisture on the model calibrations are first evaluated in Section 5.1. The cross effects of the initial soil temperature and soil moisture on the model’s results are investigated in Section 5.2. Section 5.3 summarizes the work performed in this chapter and highlights the concluding remarks.
5.1 EFFECTS OF INITIAL SOIL MOISTURE

In this section, the focus is on the effects of the initial soil moisture on the model’s simulations. In Section 5.1.1, the effects of the depth-constant initial soil moisture on the single-response and multi-response model calibrations are investigated and these outcomes are compared with the results from similar analyses performed in Chapter 4. It is hypothesized that the changes seen in this section are due to changing the initial soil moisture (not the initial soil temperature) which is suggested by the results at the end of the chapter. In Section 5.1.2, the effects of the different calibrated parameters, in tandem with different initial conditions, on the soil moisture estimations are investigated and the effects of the temporal memory of soil moisture are evaluated in the MLCan model.

5.1.1 Effects of initial soil moisture on model calibrations

This section discusses the effects of the initial soil moisture on the parameter calibrations by applying a similar methodology to that used in Chapter 4, by using the MLCan model and GLUE method with data from the year 2005.

In this analysis, 2600 model simulations were run for the eucalyptus forest in Tumbarumba for the year 2005, with the input data described in Sections 2.3 and 2.4. The input data included climate data ($R_g$, $LW_{in}$, $T_a$, $P_a$, $e_a$, $PPT$, $U$, $ustar$, $VPD$), the eucalyptus tree canopy and root structures (see Figures 6 and 7) and model parameters extracted from the literature (Table 5). The same nine parameters used in Chapter 4 for the GLUE analysis, with the same sampling ranges (Table 6), were also considered for the model calibrations in this chapter. These nine parameters were the stomatal conductance parameters ($m$, $b$, $S_f$, $\psi_f$), soil respiration parameters ($Q_{10}$, $R_o$), root conductivity parameters ($K_{rad}$, $K_{axs}$) and plant resistance parameter to flow ($R_p$). On the OzFlux website for the Tumbarumba site, the only available soil moisture and temperature data were at depths of 15 cm and 5 cm, respectively. It was thus assumed these data to be constant for all soil depths (the initial conditions as shown in Table 14). There were equivalent depth-varying soil initial conditions (shown in Table 4). The Nash-Sutcliffe ($NS$) objective functions were then calculated to evaluate the results of the model calibrations.
Table 14. Depth-constant soil initial conditions for 2005 considered for this analysis

<table>
<thead>
<tr>
<th>Soil depth (m)</th>
<th>Soil temperature (°C)</th>
<th>Soil moisture (m³/m³)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.10</td>
<td>14.02</td>
<td>0.15</td>
</tr>
<tr>
<td>0.27</td>
<td>14.02</td>
<td>0.15</td>
</tr>
<tr>
<td>0.58</td>
<td>14.02</td>
<td>0.15</td>
</tr>
<tr>
<td>1.18</td>
<td>14.02</td>
<td>0.15</td>
</tr>
<tr>
<td>2.28</td>
<td>14.02</td>
<td>0.15</td>
</tr>
<tr>
<td>3.72</td>
<td>14.02</td>
<td>0.15</td>
</tr>
</tbody>
</table>

5.1.1.1 Single-response model calibration

In this section, the single-response model calibration results with the depth-constant soil initial conditions are presented and are then compared with the results in Section 4.2.1 using the depth-varying soil initial conditions. A single-response model calibration is performed for each of the four key model outputs, including the latent heat flux ($LE$), sensible heat flux ($H$), CO₂ flux ($F_c$) and soil moisture at the first layer ($SWS$).

Table 15 shows the single-response model calibration results with the depth-constant initial soil conditions. This table shows five maximum $NS$ values for each variable (i.e., $LE$, $H$, $F_c$ or $SWS$) with the abbreviations $L_1, L_2,...,L_5$, $H_1,H_2,...,H_5$, $F_1,F_2,...,F_5$ and $S_1,S_2,...,S_5$, respectively. Table 15 also shows, in other columns: the corresponding simulation numbers, the $NS$ values for other uncalibrated model outputs and the $NS$-all values (the average of all $NS$ values similar to the multi-response calibration analysis).

According to Table 15, and similar to the discussion in Section 4.2.1, when the model is calibrated to $LE$ or $H$, the five maximum $NS$-$LE$ and $NS$-$H$ values were identical and were equal to 0.49 and 0.76, respectively. When the calibrated parameters for the $LE$ or $H$ were used to estimate the $F_c$ and $SWS$, the model showed poor correlations. Only simulations $L_1$ and $H_3$ (which were both simulation No. 2067) had acceptable $F_c$ and $SWS$ estimations. Simulation No. 2067 had maximum $NS$ values for the fluxes, and was one of the simulations calibrated to multiple outputs with maximum $NS$ values for every single variable which appeared in Table 15.
Table 15. Single-response model calibration results with depth-constant initial conditions

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Objective function</th>
<th>Max values</th>
<th>Sim NO.</th>
<th>NS-LE for sim NO</th>
<th>NS-H for sim NO</th>
<th>NS-Fc for sim NO</th>
<th>NS-SWS for sim NO</th>
<th>NS-all for sim NO</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1</td>
<td>NS-LE</td>
<td>0.49</td>
<td>2067</td>
<td>0.49</td>
<td>0.76</td>
<td>0.52</td>
<td>0.47</td>
<td>0.56</td>
</tr>
<tr>
<td>L2</td>
<td>NS-LE</td>
<td>0.49</td>
<td>1678</td>
<td>0.49</td>
<td>0.76</td>
<td>-3.63</td>
<td>-0.09</td>
<td>-0.62</td>
</tr>
<tr>
<td>L3</td>
<td>NS-LE</td>
<td>0.49</td>
<td>557</td>
<td>0.49</td>
<td>0.75</td>
<td>-1.15</td>
<td>-1.92</td>
<td>-0.46</td>
</tr>
<tr>
<td>L4</td>
<td>NS-LE</td>
<td>0.49</td>
<td>624</td>
<td>0.49</td>
<td>0.75</td>
<td>0.12</td>
<td>-1.95</td>
<td>-0.15</td>
</tr>
<tr>
<td>L5</td>
<td>NS-LE</td>
<td>0.49</td>
<td>762</td>
<td>0.49</td>
<td>0.75</td>
<td>-0.53</td>
<td>-1.96</td>
<td>-0.31</td>
</tr>
<tr>
<td>H1</td>
<td>NS-H</td>
<td>0.76</td>
<td>1678</td>
<td>0.49</td>
<td>0.76</td>
<td>-3.63</td>
<td>-0.09</td>
<td>-0.62</td>
</tr>
<tr>
<td>H2</td>
<td>NS-H</td>
<td>0.76</td>
<td>1701</td>
<td>0.48</td>
<td>0.76</td>
<td>-2.94</td>
<td>-2.09</td>
<td>-0.95</td>
</tr>
<tr>
<td>H3</td>
<td>NS-H</td>
<td>0.76</td>
<td>2067</td>
<td>0.49</td>
<td>0.76</td>
<td>0.52</td>
<td>0.47</td>
<td>0.56</td>
</tr>
<tr>
<td>H4</td>
<td>NS-H</td>
<td>0.76</td>
<td>1126</td>
<td>0.49</td>
<td>0.76</td>
<td>-6.61</td>
<td>0.45</td>
<td>-1.23</td>
</tr>
<tr>
<td>H5</td>
<td>NS-H</td>
<td>0.75</td>
<td>2067</td>
<td>0.49</td>
<td>0.75</td>
<td>0.12</td>
<td>-1.95</td>
<td>-0.15</td>
</tr>
<tr>
<td>F1</td>
<td>NS-Fc</td>
<td>0.53</td>
<td>2047</td>
<td>0.07</td>
<td>0.44</td>
<td>0.53</td>
<td>-2.85</td>
<td>-0.45</td>
</tr>
<tr>
<td>F2</td>
<td>NS-Fc</td>
<td>0.52</td>
<td>2067</td>
<td>0.49</td>
<td>0.76</td>
<td>0.52</td>
<td>0.47</td>
<td>0.56</td>
</tr>
<tr>
<td>F3</td>
<td>NS-Fc</td>
<td>0.52</td>
<td>2063</td>
<td>0.25</td>
<td>0.56</td>
<td>0.52</td>
<td>0.11</td>
<td>0.36</td>
</tr>
<tr>
<td>F4</td>
<td>NS-Fc</td>
<td>0.52</td>
<td>2034</td>
<td>0.45</td>
<td>0.74</td>
<td>0.52</td>
<td>-1.86</td>
<td>-0.04</td>
</tr>
<tr>
<td>F5</td>
<td>NS-Fc</td>
<td>0.52</td>
<td>398</td>
<td>-0.05</td>
<td>0.35</td>
<td>0.52</td>
<td>-0.74</td>
<td>0.02</td>
</tr>
<tr>
<td>S1</td>
<td>NS-SWS</td>
<td>0.86</td>
<td>2593</td>
<td>0.11</td>
<td>0.32</td>
<td>0.36</td>
<td>0.86</td>
<td>0.41</td>
</tr>
<tr>
<td>S2</td>
<td>NS-SWS</td>
<td>0.85</td>
<td>2426</td>
<td>0.06</td>
<td>0.25</td>
<td>0.36</td>
<td>0.85</td>
<td>0.38</td>
</tr>
<tr>
<td>S3</td>
<td>NS-SWS</td>
<td>0.84</td>
<td>2563</td>
<td>0.02</td>
<td>0.20</td>
<td>-3.15</td>
<td>0.84</td>
<td>-0.52</td>
</tr>
<tr>
<td>S4</td>
<td>NS-SWS</td>
<td>0.83</td>
<td>548</td>
<td>0.22</td>
<td>0.43</td>
<td>-0.57</td>
<td>0.83</td>
<td>0.23</td>
</tr>
<tr>
<td>S5</td>
<td>NS-SWS</td>
<td>0.82</td>
<td>1702</td>
<td>0.03</td>
<td>0.27</td>
<td>-0.90</td>
<td>0.82</td>
<td>0.06</td>
</tr>
</tbody>
</table>

When the model was calibrated to $F_c$, the five maximum $NS-F_c$ values were about 0.52, which was similar to the depth-varying soil initial conditions results in Chapter 4 ($NS-F_c = 0.53$). The $NS-LE$, $NS-H$ and $NS-SWS$ estimations using the calibrated parameters to $F_c$, however, showed variable behaviours. Except for simulation $F2$, which was similar to $L1$ and $H3$ (simulation No. 2067), the rest of the estimated $NS-LE$ and $NS-SWS$ values were mostly poor. The calibrated parameters for the $F_c$ showed better performances in estimating the sensible heat flux.

The $NS-SWS$ values of the single-response calibrations for the soil moisture at the first layer varied between 0.82 and 0.86. They were similar to the depth-varying soil initial condition results in Chapter 4 ($NS-SWS$ varied between 0.84 and 0.85). As before, the calibrated parameters for the soil moisture at the first layer did not produce good estimations of the $LE$, $H$ and $F_c$. 

Chapter 5: The Influence of the Soil Initial Conditions
As shown in Table 15 for the single-response model calibrations for the \( LE, H, F_c \) and \( SWS \) with depth-constant initial conditions, the maximum \( NS-LE, NS-H, NS-F_c, NS-SWS \) values were similar to the \( NS \) values in Table 8 with depth-varying initial conditions (see Chapter 4). The results in this section show that when the focus of the model calibration is only on one single variable (e.g., \( LE, H, F_c \) or \( SWS \)), the initial soil moisture does not affect the model’s performance, and the initial soil moisture can be simplified by assuming the depth-constant initial soil moisture.

Table 16. Best parameter sets in single-response model calibration

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Objective function</th>
<th>Max ( m )</th>
<th>( b ) ( \text{mol m}^{-2} \text{s}^{-1} )</th>
<th>( S_f ) ( \text{MPa}^{-1} )</th>
<th>( \psi_f ) ( \text{MPa} )</th>
<th>( R_p ) ( \text{MPa m}^{-2} \text{s}^{-1} )</th>
<th>( K_{\text{rad}} ) ( \text{mm s}^{-1} )</th>
<th>( Q_{10} ) ( - )</th>
<th>( R_o ) ( \mu\text{mol m}^{-2} \text{s}^{-1} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>L1</td>
<td>NS-LE</td>
<td>0.49</td>
<td>2067</td>
<td>11.69</td>
<td>0.006</td>
<td>0.06</td>
<td>-7.4</td>
<td>11.38</td>
<td>1.32E-09</td>
</tr>
<tr>
<td>L2</td>
<td>NS-LE</td>
<td>0.49</td>
<td>1678</td>
<td>9.50</td>
<td>0.007</td>
<td>6.98</td>
<td>-9.4</td>
<td>8.44</td>
<td>3.51E-09</td>
</tr>
<tr>
<td>L3</td>
<td>NS-LE</td>
<td>0.49</td>
<td>2577</td>
<td>10.35</td>
<td>0.003</td>
<td>7.26</td>
<td>-10.0</td>
<td>9.40</td>
<td>2.74E-07</td>
</tr>
<tr>
<td>L4</td>
<td>NS-LE</td>
<td>0.49</td>
<td>624</td>
<td>10.39</td>
<td>0.004</td>
<td>6.40</td>
<td>-9.2</td>
<td>10.35</td>
<td>1.84E-07</td>
</tr>
<tr>
<td>L5</td>
<td>NS-LE</td>
<td>0.49</td>
<td>762</td>
<td>10.35</td>
<td>0.003</td>
<td>7.93</td>
<td>-7.7</td>
<td>19.50</td>
<td>6.19E-07</td>
</tr>
<tr>
<td>H1</td>
<td>NS-H</td>
<td>0.76</td>
<td>1678</td>
<td>9.50</td>
<td>0.007</td>
<td>6.98</td>
<td>-9.4</td>
<td>8.44</td>
<td>3.51E-09</td>
</tr>
<tr>
<td>H2</td>
<td>NS-H</td>
<td>0.76</td>
<td>1701</td>
<td>10.79</td>
<td>0.005</td>
<td>8.13</td>
<td>-8.6</td>
<td>15.38</td>
<td>1.26E-07</td>
</tr>
<tr>
<td>H3</td>
<td>NS-H</td>
<td>0.76</td>
<td>2067</td>
<td>11.69</td>
<td>0.006</td>
<td>0.06</td>
<td>-7.4</td>
<td>11.38</td>
<td>1.32E-09</td>
</tr>
<tr>
<td>H4</td>
<td>NS-H</td>
<td>0.76</td>
<td>1126</td>
<td>10.11</td>
<td>0.007</td>
<td>5.35</td>
<td>-9.9</td>
<td>11.99</td>
<td>1.42E-07</td>
</tr>
<tr>
<td>H5</td>
<td>NS-H</td>
<td>0.75</td>
<td>624</td>
<td>10.39</td>
<td>0.004</td>
<td>6.40</td>
<td>-9.2</td>
<td>10.35</td>
<td>1.84E-07</td>
</tr>
<tr>
<td>F1</td>
<td>NS-Fc</td>
<td>0.53</td>
<td>2047</td>
<td>3.62</td>
<td>0.067</td>
<td>8.49</td>
<td>-3.2</td>
<td>16.80</td>
<td>2.25E-07</td>
</tr>
<tr>
<td>F2</td>
<td>NS-Fc</td>
<td>0.52</td>
<td>2067</td>
<td>11.69</td>
<td>0.006</td>
<td>0.06</td>
<td>-7.4</td>
<td>11.38</td>
<td>1.32E-09</td>
</tr>
<tr>
<td>F3</td>
<td>NS-Fc</td>
<td>0.52</td>
<td>2063</td>
<td>5.73</td>
<td>0.047</td>
<td>9.13</td>
<td>-6.7</td>
<td>13.18</td>
<td>1.53E-09</td>
</tr>
<tr>
<td>F4</td>
<td>NS-Fc</td>
<td>0.52</td>
<td>2034</td>
<td>7.26</td>
<td>0.020</td>
<td>8.35</td>
<td>-9.1</td>
<td>15.34</td>
<td>2.31E-07</td>
</tr>
<tr>
<td>F5</td>
<td>NS-Fc</td>
<td>0.52</td>
<td>398</td>
<td>2.73</td>
<td>0.076</td>
<td>3.43</td>
<td>-8.5</td>
<td>10.00</td>
<td>1.21E-09</td>
</tr>
<tr>
<td>S1</td>
<td>NS-SWS</td>
<td>0.86</td>
<td>2593</td>
<td>16.53</td>
<td>0.000</td>
<td>2.43</td>
<td>-1.2</td>
<td>19.04</td>
<td>2.84E-09</td>
</tr>
<tr>
<td>S2</td>
<td>NS-SWS</td>
<td>0.85</td>
<td>2426</td>
<td>17.50</td>
<td>0.001</td>
<td>3.33</td>
<td>-0.9</td>
<td>5.78</td>
<td>6.42E-09</td>
</tr>
<tr>
<td>S3</td>
<td>NS-SWS</td>
<td>0.84</td>
<td>2563</td>
<td>15.94</td>
<td>0.001</td>
<td>5.66</td>
<td>-0.1</td>
<td>14.37</td>
<td>2.85E-07</td>
</tr>
<tr>
<td>S4</td>
<td>NS-SWS</td>
<td>0.83</td>
<td>548</td>
<td>18.01</td>
<td>0.011</td>
<td>9.58</td>
<td>-1.6</td>
<td>18.45</td>
<td>1.08E-09</td>
</tr>
<tr>
<td>S5</td>
<td>NS-SWS</td>
<td>0.82</td>
<td>1702</td>
<td>19.59</td>
<td>0.001</td>
<td>4.69</td>
<td>-1.8</td>
<td>9.82</td>
<td>1.43E-09</td>
</tr>
</tbody>
</table>

Table 16 shows the corresponding parameter sets in Table 15. When compared to the results from the previous section using depth-varying initial conditions (Table 9), this table shows that the initial soil moisture did not significantly change the values of the sensitive parameters. From the sensitivity analysis to the parameters (Section 4.1), it was found that the stomatal conductance parameters \( m \) and \( b \) were sensitive for \( LE \) and \( H \) estimations. Most of the \( m \) values for the \( LE \) and \( H \) estimations were slightly above 10. However, most of the \( m \) values in Section 4.1 were slightly under 10. The \( b \) values varied between 0.003 and 0.007 [\text{mol m}^{-2} \text{s}^{-1}], and tended to be around 0.005 [\text{mol m}^{-2} \text{s}^{-1}] here. The \( \psi_f \) values varied between -7 and -10 [\text{MPa}]. The \( K_{\text{rad}} \) and \( K_{\text{axs}} \) parameter values were, on average, around \( 10^{-7} \left[ \text{s}^{-1} \right] \) and \( 10^{-3} \left[ \text{mm s}^{-1} \right] \), respectively, when the model was only fitted to the \( LE \) or \( H \) estimations. These values
were greater than the root conductivity values calibrated for the $LE$ and $H$ in the single-response approach with depth-varying initial conditions in Section 4.1 (the $K_{rad}$ and $K_{sys}$ values tended to be around $10^{-8}$ [s$^{-1}$] and $10^{-3}$ [mm s$^{-1}$], respectively). Moreover, nearly all of the $Q_{10}$ values were above 1, and they were, on average, around 1.25. It can be seen that a few simulations had $m$ values slightly higher or lower than 10, and also lower $K_{rad}$ values of the order of $10^{-9}$ [s$^{-1}$]. These simulations also tended to have higher $b$ values. So it can be seen that there was a pattern between the parameter values for the best $LE$ and $H$ estimations with the MLCan model.

For the $CO_2$ flux estimations, the $Q_{10}$ and $R_o$ parameters were found to be the most sensitive parameters. Therefore, in the single-response model calibrations for $CO_2$ flux, we looked at the sensitive parameters. The $Q_{10}$ values were between 1 and 2 and the $R_o$ values were below 1 [$\mu$mol m$^{-2}$ s$^{-1}$]. These values were similar to those obtained in Section 4.1.

For the single-response model calibrations for soil moisture, the $m$ values varied between 15 and 20, and the $\psi_f$ values varied between -2 and 0 [MPa]. These values were similar to the sensitive parameter values in Section 4.1.

In conclusion, the depth-constant initial soil moisture did not significantly affect the calibrations of the parameters. Table 16 shows the different sets of parameters that can result in the best estimations of $LE$, $H$, $F_c$ or $SWS$, similar to Section 4.2.1 with results from the depth-varying initial soil moisture. Since the results of this section are similar to the results in Section 4.2.1, the visual assessments of the results are not shown here.

### 5.1.1.2 Multi-response model calibration

In this section, the results of the multi-response model calibrations using the depth-constant soil initial conditions are discussed and then compared with the results from Section 4.2.2 using the depth-varying initial conditions.

In this section, the multi-response model calibrations using the four key model outputs are performed, including the latent heat flux ($LE$), sensible heat flux ($H$), $CO_2$ flux ($F_c$) and soil moisture at the first layer ($SWS$) simultaneously. To do so, the averages of the $NS-LE$, $NS-H$, $NS-F_c$, $NS-SWS$ values are maximised, and are named $NS$-$all$. The five maximum $NS$-$all$ values, abbreviated as $a1$, $a2$, ..., $a5$, and their corresponding parameters, are assessed in this section.
Table 17 shows the five maximum *NS-all* values and the corresponding *NS-LE*, *NS-H*, *NS-Fc* and *NS-SWS* values for each of the five best simulations. The *NS-all* values in this table ranged between 0.52 and 0.56, which was smaller than the *NS-all* values in Table 10 (see Section 4.2.2) with the depth-varying initial soil moisture (*NS-all* ranged between 0.59 and 0.61 in Table 10).

Table 17. Multi-response model calibration results with depth-constant initial soil moisture

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Objective function</th>
<th><em>Max NS-all values</em></th>
<th>Sim NO.</th>
<th><em>NS-LE</em> for sim NO</th>
<th><em>NS-H</em> for sim NO</th>
<th><em>NS-Fc</em> for sim NO</th>
<th><em>NS-SWS</em> for sim NO</th>
</tr>
</thead>
<tbody>
<tr>
<td>a1</td>
<td><em>NS-all</em></td>
<td>0.56</td>
<td>2067</td>
<td>0.49</td>
<td>0.76</td>
<td>0.52</td>
<td>0.47</td>
</tr>
<tr>
<td>a2</td>
<td><em>NS-all</em></td>
<td>0.55</td>
<td>1819</td>
<td>0.43</td>
<td>0.69</td>
<td>0.49</td>
<td>0.61</td>
</tr>
<tr>
<td>a3</td>
<td><em>NS-all</em></td>
<td>0.55</td>
<td>2257</td>
<td>0.45</td>
<td>0.73</td>
<td>0.49</td>
<td>0.53</td>
</tr>
<tr>
<td>a4</td>
<td><em>NS-all</em></td>
<td>0.53</td>
<td>1729</td>
<td>0.42</td>
<td>0.70</td>
<td>0.49</td>
<td>0.50</td>
</tr>
<tr>
<td>a5</td>
<td><em>NS-all</em></td>
<td>0.52</td>
<td>2065</td>
<td>0.40</td>
<td>0.66</td>
<td>0.52</td>
<td>0.52</td>
</tr>
</tbody>
</table>

Table 17 shows that the five best multi-response simulations with the depth-constant initial conditions resulted in wider ranges for the *NS-LE*, *NS-H*, *NS-Fc*, and *NS-SWS* values and, thus, a wider range for the *NS-all* values, compared to Section 4.2.2. For example, the *NS-LE*, *NS-H*, *NS-Fc*, and *NS-SWS* varied here in the intervals [0.40, 0.49], [0.66, 0.76], [0.49, 0.52] and [0.47, 0.61], respectively. However, the same values with the depth-varying soil initial conditions (Table 10) varied in the ranges of [0.43, 0.46], [0.70, 0.74], [0.52, 0.53] and [0.69, 0.77], respectively.

It can be seen that most of the *NS* values have generally been reduced, compared to Table 10, except for the simulation a1 (simulation No. 2067) in which the *NS-LE* and *NS-H* increased while having the worst soil moisture estimations among the five simulations. It was thought that this happened randomly since the general trend shows that the depth-constant initial soil moisture had decreased the model’s efficiency in multi-response calibrations compared to the depth-varying simulations.

The comparison of the multi-response calibration results in this chapter with those in Section 4.2.2 shows that the main component in the decrease of the *NS-all* values was the *NS-SWS* value as it had a significant reduction when the depth-constant initial soil moisture was considered down the soil profile. The effects of the various scenarios of initial soil moisture and parameters on estimating the soil moisture at different depths is further discussed in Section 5.1.2.
Table 18 shows the five best-fit parameter sets for the multi-response model calibrations with the depth-constant soil initial conditions. The parameter ranges in this table have changed in comparison to those in Section 4.2.2 with the depth-varying initial conditions (see Table 11). The $m$ values in Table 18 varied between 5 and 12 and decreased from an average of 13 (in Table 11) to around 10 in the overall sampling range [1, 20]. In Table 11, the $m$ values for the multi-response calibrations were all above 10, however here they were both above and below 10. Although the $m$ value is not the only effective parameter in an \textit{LE} estimation, the lower $m$ values in Table 18 corresponded to the lower \textit{NS-LE} values. Moreover, the occasional improvement in the \textit{NS-LE} and \textit{NS-H} values for simulation $a1$ (simulation No. 2067), contrary to the general trend, might be related to the parameter values. It was thought that an unusual parameter set, which had been randomly given to the model, resulted in this behaviour. The values for the $b$ parameter varied between the specified range [0.002, 0.015] [mol m$^{-2}$ s$^{-1}$]. The $\psi_f$ values decreased to around -8 [MPa] on average (compared to an average of -4 [MPa] in Table 11) in the sampling range [-10, 0] [MPa]. Compared to Table 11, the values for the $K_{rad}$, $Q_{10}$, $R_o$ parameters have slightly changed. The $K_{rad}$ values reduced to slightly smaller factors of $10^{-9}$ [s$^{-1}$] in the broader sampling range [$10^{-9}$, $10^{-6}$] [s$^{-1}$]. The $Q_{10}$ values decreased to values slightly smaller than 1 from an average of 1.5 within the sampling range [0, 2]. Finally, the $R_o$ values increased to values of slightly bigger than 1 [$\mu$mol m$^{-2}$ s$^{-1}$] compared to the previous values smaller than 1 within the sampling range [0, 20] [$\mu$mol m$^{-2}$ s$^{-1}$].

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|c|c|}
\hline
Symbol & Objective function & Max values & Sim NO. & $m$ & $b$ & $S_f$ & $\psi_f$ & $R_p$ & $K_{rad}$ & $K_{axs}$ & $Q_{10}$ & $R_o$ \\
& & & & & [mol m$^{-2}$ s$^{-1}$] & [MPa$^3$] & [MPa] & [MPa s m$^{-1}$] & [s$^{-1}$] & [mm s$^{-1}$] & & \\
\hline
$a1$ & NS-all & 0.56 & 2067 & 11.69 & 0.006 & 0.06 & -7.4 & 11.38 & 1.32E-09 & 4.69E-01 & 1.24 & 0.34 \\
$a2$ & NS-all & 0.55 & 1819 & 12.87 & 0.002 & 5.46 & -6.9 & 15.18 & 1.11E-09 & 7.68E-04 & 0.45 & 1.33 \\
$a3$ & NS-all & 0.55 & 2257 & 12.75 & 0.0002 & 4.71 & -8.5 & 16.43 & 1.25E-09 & 2.17E-02 & 0.55 & 1.89 \\
$a4$ & NS-all & 0.53 & 1729 & 5.89 & 0.015 & 7.12 & -10.0 & 12.61 & 1.31E-09 & 1.65E-02 & 0.37 & 1.70 \\
$a5$ & NS-all & 0.52 & 2065 & 8.63 & 0.004 & 0.71 & -7.4 & 2.38 & 2.53E-09 & 9.54E-04 & 1.58 & 0.07 \\
\hline
\end{tabular}
\caption{Best parameter sets in multi-response model calibration with depth-constant initial soil moisture}
\end{table}

The results of this section show that the depth-constant initial soil moisture affects the parameter values compared to those with depth-varying initial conditions. The effects of the soil initial conditions are particularly important for model validations with independent data and/or future estimations of the land surface processes where the field measured initial soil moisture might not be available. The results highlight...
the importance of the initial soil moisture on the parameter calibrations and the
model’s performance as it is usually one of the components of the uncertainty analysis
of land surface models (Dumedah & Walker, 2014; Pianosi et al., 2016).

5.1.1.3 Visual assessment of simulations with multi-response calibrated
parameters

Figures 45 and 46 show the average daily latent and sensible heat fluxes for the
five best multi-response calibrated parameter sets with the depth-constant initial soil
moisture for 2005. Figure 45 shows good agreement with the observed latent heat flux
data. In this figure, there was less overestimation during the first half of the year for
several of the simulations compared to Figure 29 (simulation with depth-varying initial
soil moisture). The overestimations in Figure 29 perhaps resulted from a combination
of higher estimated soil moisture down the soil profile and/or different parameter sets
when simulating with the depth-varying initial soil moisture. The differences shown
in the \( LE \) estimations when comparing Figure 29 and Figure 45 could be the effects of
the deep soil moisture on estimating the above-ground processes like \( LE \), and
underlines the coupling between the above-ground processes and the below-ground
processes. This coupling could be the result of hydraulic lift, in which water is
transferred from the deep wet soil layers to shallow dry layers through the root system
during dry periods. Therefore, the dense root fractions in the shallow layers can absorb
the transferred water. It might also be a result of a preferential water uptake, in which
plant roots selectively absorb water from the wetter part of the soil in deep layers.
Figure 46 also shows a good correlation between the estimated and observed sensible
heat flux data and shows no visible differences compared with Figure 30.

Figure 47 shows the average daily \( CO_2 \) fluxes for the five best parameter sets of
the multi-response model calibrations for year 2005 with the depth-constant initial soil
moisture. The figure shows a good correlation, however it shows greater
overestimations during winter compared to Figure 31.
Figure 45. Average daily estimated latent heat fluxes for the five best *NS-all* parameter sets versus the observed data for year 2005

Figure 46. Average daily estimated sensible heat fluxes for the five best *NS-all* parameter sets versus the observed data for year 2005
Figure 47. Average daily estimated CO₂ fluxes for the five best NS-all parameter sets versus the observed data for year 2005.

Figure 48. Average daily soil moisture estimations at first layer for the five best NS-all parameter sets versus the observed data for year 2005.

Figure 48 shows the soil moisture estimations at the first layer for the five best multi-response calibrated parameter sets with the depth-constant initial soil moisture for 2005. The figure shows a good correlation between the estimated and observed soil moisture values during the spring and early summer. However, it shows that the model
did not capture the fluctuations very well; the model shows less fluctuations during the autumn and higher fluctuations during the winter after a rainfall event and a sudden rise in soil moisture content.

The soil moisture estimations with the depth-constant initial soil moisture show that the soil moisture down the soil profile influenced the surface layer soil moisture estimations. This result suggests the impacts of the vegetation on the soil moisture estimation through the effect of hydraulic redistribution and the preference of roots to extract water from the deeper layers. In addition, the effects of the initial soil moisture lasted throughout the year, and did not only influence the beginning of the simulations. Therefore, it implies that the soil moisture memory appears to be at least one year. Comparing Figure 48 with Figure 32 highlights the importance of the initial soil moisture estimations of an ecohydrology model.

5.1.2 Effects of initial soil moisture and calibrated parameters

In this section, the results of an analysis conducted to compare the effects of two different initial soil moisture conditions and two different parameter sets on the daily soil moisture estimations for the year 2005 are presented.

Table 19 shows the four different scenarios considered for evaluating the effects of the initial soil moisture conditions and parameters. The two initial conditions were the depth-varying (Scenario 1 and 4) and the depth-constant (Scenario 2 and 3) initial soil moisture profiles. For each of the initial conditions, two different parameter sets were tested. For Scenarios 1 and 2, the best calibrated multi-response parameters with the depth-varying initial soil moisture conditions were used (simulation a1 in Table 11, Section 4.2.2) which is called in Table 19 “Calibrated with Depth-varying ICs” or, hereafter, the depth-varying parameters. For Scenarios 3 and 4, the second best calibrated multi-response parameters with the depth-constant initial soil moisture conditions were used (simulation a2 in Table 17, Section 5.1.1.2) which is called in Table 19 “Calibrated with Depth-constant ICs” or, hereafter, the depth-constant parameters. As previously explained, an anomaly was found in simulation a1 in the multi-response calibrations with an unusual pattern compared to the other simulations. Therefore, the parameters from simulation a2 were used for this comparison (please note that the main results discussed still hold for simulation a1).
Table 19. Different scenarios for evaluating the effects of the parameters and Initial Conditions (ICs)

<table>
<thead>
<tr>
<th>Scenario no.</th>
<th>Parameters</th>
<th>Initial soil moisture</th>
<th>Initial soil temperature</th>
<th>NS-SWS (multi-response)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Chapter 4)</td>
<td>Calibrated with Depth-varying ICs</td>
<td>Depth-varying</td>
<td></td>
<td>0.77</td>
</tr>
<tr>
<td>2</td>
<td>Calibrated with Depth-varying ICs</td>
<td>Depth-constant</td>
<td></td>
<td>0.66</td>
</tr>
<tr>
<td>3 (Chapter 5)</td>
<td>Calibrated with Depth-constant ICs</td>
<td>Depth-constant</td>
<td></td>
<td>0.61</td>
</tr>
<tr>
<td>4</td>
<td>Calibrated with Depth-constant ICs</td>
<td>Depth-varying</td>
<td></td>
<td>0.66</td>
</tr>
</tbody>
</table>

As shown in Table 19, the best soil moisture estimation at the first layer in the multi-response calibrations had both the depth-varying calibrated parameters and the initial soil moisture, and had $NS-SWS = 0.77$. This was the best outcome of the four scenarios. Considering the similar depth-varying initial soil moisture conditions in Scenarios 1 and 4, the comparison between the soil moisture estimations at the first layer shows the effects of the different parameter sets. It was also the same when comparing the similar depth-constant initial soil moisture conditions in Scenario 2 and 3. The worst first-layer soil moisture estimation resulted from both the depth-constant calibrated parameters and the depth-constant initial soil moisture ($NS-SWS = 0.61$). As seen, having one depth-varying item, either the depth-varying calibrated parameter or the depth-varying initial soil moisture, can improve the soil moisture estimations at the first layer.

By comparing Scenarios 1 and 2, or Scenarios 3 and 4, we can see that with either depth-varying or depth-constant calibrated parameters, the initial soil moisture affects the soil moisture estimations at the first layer. It is to be noted that the depth-varying initial soil moisture yields the better estimations. For example, with the depth-varying calibrated parameters, changing the initial soil moisture, from the depth-constant to the depth-varying, improved the $NS-SWS$ from 0.66 to 0.77. Similarly, with the depth-constant calibrated parameters, changing the initial soil moisture, from the depth-constant to the depth-varying, improved the results from 0.61 to 0.66. These results highlight the importance of the depth-profile initial soil moisture when
calibrating the model parameters. It also showed the importance of the depth variation initial soil moisture and calibrated parameters on the soil moisture estimations.

Figure 49 shows the average daily estimated soil moisture profiles (left) and the observed versus estimated first-layer soil moisture plots (right) for Scenarios 1 to 4. Comparing the $NS-SWS$ values in Table 19 for Scenarios 2 and 4, and the first-layer soil moisture plots in Figure 49 shows that these two simulations had the same goodness-of-fit values ($NS-SWS$), however their soil moisture patterns were different.

Comparing the soil moisture plots and profiles in Figure 49 shows that both the initial soil moisture and the calibrated parameters affected both the surface and deep layer soil moisture estimations. Regarding the effects of the parameters on the surface layers, comparing the soil moisture plots at Scenarios 1 and 4 shows that the soil moisture values for Scenario 1 were higher than for Scenario 4. The soil moisture plot of Scenario 1 also matched well with the observations during the dry period in the first half of the year. Moreover, the soil moisture profile for Scenario 1 shows that the upper part of the soil during the first half of the year was wetter than for Scenario 4 (it is orange rather than red).

Regarding the effects of the parameters on the deep layers, the comparison between the soil moisture profiles in Scenarios 1 and 4 shows that Scenario 1 was wetter than Scenario 4 in the deep layers during the second half of the year (it is blue rather than green). Similarly, for Scenarios 2 and 3, and regarding the effects of the parameters on the surface layers, it is seen that Scenario 2 was slightly wetter than Scenario 3 at the first layer and better matched with the observations during the dry season in the first half of the year, however both plots appeared to be similar at first sight. Scenario 2 also fluctuated more during the wet season, especially after rainfall. Regarding the effects of the parameters on the deep layers, the comparison between the soil moisture profiles in Scenarios 2 and 3 shows that Scenario 2 was wetter than Scenario 3 in the deep layers during the second half of the year (it is orange rather than red). The effects of the different parameters discussed above might be related to the stomatal conductance parameters that regulate the transference of water from the soil to the atmosphere, as both of the two parameter sets have similar root conductivities.

Regarding the effects of the initial soil moisture on the surface layer soil moisture estimations, comparing the soil moisture plots in Scenarios 1 and 2 shows that Scenario 1, with the depth-varying initial conditions, overestimated the first-layer soil moisture
values during the wet season in the second half of the year, especially after the rainfall events on DOY 165. However, Scenario 2, with the depth-constant initial conditions, fluctuated highly during this time and gradually matched with the observations. The same pattern was also seen when comparing Scenarios 3 and 4. Knowing that the soil moisture values are the same for the first layer for both initial conditions, it can be concluded that the soil moisture for the deep layers can affect the soil moisture estimations for the first layer. Regarding the effects of the initial soil moisture on the deep layer soil moisture estimations, the soil moisture profiles in Scenarios 1 and 4, with the depth-varying initial soil moisture, were always wetter and had higher soil moisture values in the deep layers than in Scenarios 2 and 3, with the depth-constant initial soil moisture throughout the year. The differences in the simulated soil moisture estimations at the deep layers implies that the model has a long memory, in the order of 12 months, in which the effect of the initial condition lasts till end of the year. This result is consistent with other studies of soil moisture memory over decades to a few months (Koster et al., 2004; Zhang, 2004). This finding is important, especially in climate change and weather forecast studies, as soil moisture is a slow-varying component of the land surface processes. The length of soil moisture memory is also controlled by climate, vegetation type and soil hydraulic properties. Therefore, the time scale of the soil moisture memory might be changed during wet or dry years. It is worthwhile to perform a similar analysis for longer period of time to investigate the effect of forcing data for future study.
Figure 49. Average daily soil moisture profiles (left) and estimated versus observed soil moisture plots at first layer (right) for Scenarios 1 to 4 in Table 19
Koster et al. (2004) highlighted the impact of soil moisture initialization on precipitation predictions using the Atmospheric General Circulation Model (AGCM) during the summer in the northern hemisphere. They showed that this slow-varying component affects weather forecasts by influencing the evaporation and surface energy fluxes. Zhang (2004) studied the length of soil moisture memory using 16 different models and evaluated the effects of soil moisture memory on the prediction of surface climate variability in the Australian continent. Zhang found that the soil moisture memories were different among the models, and that models with simple bucket type soil columns showed faster responses in soil moisture variations, which contributed to shorter soil moisture memories. However, the more complex and detailed models showed slower soil moisture variations with longer soil moisture memories, from 3 months to about several months.

### 5.2 CROSS EFFECTS OF SOIL TEMPERATURE AND SOIL MOISTURE

In soil physics, the thermal properties of water are dramatically different from the thermal properties of soil. As soil water changes, the soil thermal properties that affect the soil temperature also change. In other words, that means that the soil moisture and the soil temperature are coupled. Therefore, when the soil moisture changes, the soil temperature might change as well, and the reverse can also be true. In MLCan, soil temperature profile is calculated by numerically solving the soil heat transport model of Oleson et al. (2004), in which soil thermal conductivity and soil heat capacity depend on the soil moisture. Soil moisture is also modelled using Richards equation (8) as explained in Chapter 2. In this section, the cross effects of the soil moisture and soil temperature estimations are investigated under different scenarios of the initial conditions and calibrated parameters.

Following the scenarios in Table 19, this section defines a new scenario with the depth-constant soil temperature and depth-varying soil moisture, which is here called Scenario 5. Table 20 shows five different scenarios with different soil initial conditions and parameters. Similar to in Scenarios 4 and 5, Scenario 5 has been simulated with the same depth-constant parameters obtained in the multi-response calibrations in Chapter 5. Therefore, the last three scenarios have been simulated with the same parameters, but with different soil initial conditions.
Table 20. Different soil initial conditions and parameters for Scenarios 1 to 5

<table>
<thead>
<tr>
<th>Scenario no.</th>
<th>Parameters</th>
<th>Initial soil moisture</th>
<th>Initial soil temperature</th>
<th>NS-SWS (multi-response)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 (Chapter 4)</td>
<td>Depth-varying</td>
<td>Depth-varying</td>
<td></td>
<td>0.77</td>
</tr>
<tr>
<td>2</td>
<td>Depth-varying</td>
<td>Depth-constant</td>
<td></td>
<td>0.66</td>
</tr>
<tr>
<td>3 (Chapter 5)</td>
<td>Depth-constant</td>
<td>Depth-constant</td>
<td></td>
<td>0.61</td>
</tr>
<tr>
<td>4</td>
<td>Depth-constant</td>
<td>Depth-varying</td>
<td></td>
<td>0.66</td>
</tr>
<tr>
<td>5</td>
<td>Depth-constant</td>
<td>Depth-varying</td>
<td>Depth-constant</td>
<td>0.66</td>
</tr>
</tbody>
</table>

5.2.1 Effects of soil temperature on soil moisture

In this section, the effects of the initial soil temperature on the soil moisture estimations at different depths are investigated using the last two scenarios (Scenarios 4 and 5) in Table 20. Figure 50 shows the soil moisture estimations at different depths for the five different scenarios. As seen in Figure 50, the soil moisture estimations for Scenarios 4 and 5 were on top of each other at all depths. Comparing the two aforementioned scenarios with the same parameters and the same initial soil moisture, but with different initial soil temperatures, shows that the initial soil temperature did not significantly affect the soil moisture estimations.
Figure 50. Soil moisture estimations at different depths for different scenarios a) 10 cm, b) 27 cm, c) 58 cm
Figure 50. Soil moisture estimations at different depths for different scenarios d) 118 cm, e) 228 cm, f) 372 cm
5.2.2 Effects of soil moisture on soil temperature

Figure 51 shows the soil temperature estimations at different depths for the different scenarios in Table 20. The figure shows that the soil temperatures for the different scenarios were almost the same throughout the year in the top soil layers. It can be seen that the soil temperatures for Scenarios 1 and 4 and Scenarios 2, 3 and 5 were almost the same at all depths. As Scenarios 1 and 4 had the depth-varying initial conditions and Scenarios 2 and 3 had the depth-constant initial conditions, it can be concluded that the differently calibrated parameters did not affect the soil temperatures.

The figure also shows that for the shallow layers (10, 27 and 58 cm), the effects of the different soil initial conditions disappear after 3-4 weeks from the beginning of the simulations. However, for the deeper layers (118, 228 and 372 cm), the soil temperature estimations converged after a few months. Therefore, the soil temperatures during the second half of the year were the same for all of the scenarios at all soil depths. This figure implies that the model had a soil temperature memory of a few weeks in the surface layers and a few months in the deep layers, which could last up to six months at a depth of 372 cm. Due to small thermal inertia, soil temperature reaches equilibrium much faster than the soil moisture, which is consistent with our results. Yang and Zhang (2016) evaluated the soil temperature memories over China using soil temperature observations from 626 stations during 1981-2005. They found that soil temperature memory increased with soil depths, and it could be several months. They found that the soil temperature memory could last up to 12 months, or more at 320 cm depth.

Moreover, it can be seen that the soil temperature estimations for Scenarios 3 and 5 were almost the same. Having similar parameters and initial soil temperatures, but with different initial soil moistures, shows that the initial soil moisture did not significantly influence the soil temperature estimations.

Therefore, it can be concluded that changing the initial soil temperature did not affect the analysis performed at the beginning of this chapter, and that the results discussed in Section 5.2 were mainly influenced by the initial soil moisture as hypothesized.
Figure 51. Soil temperature estimations at different depths for different scenarios a) 10 cm, b) 27 cm, c) 58 cm
Figure 51. Soil temperature estimations at different depths for different scenarios d) 118 cm, e) 228 cm, f) 372 cm
5.3 SUMMARY AND CONCLUSION

In this chapter, the effects of depth-varying soil initial conditions on the MLCan model calibrations in the eucalyptus forest in Tumbarumba were evaluated. The results of both the soil moisture and the soil temperature initial conditions were analysed. It was hypothesized that the soil moisture initial conditions, not the soil temperature initial conditions, did significantly affect the results. Therefore, the effects of the initial soil moisture and the temporal memory of soil moisture on the model calibrations were investigated. The single-response and multi-response model calibrations with depth-constant initial conditions were performed using GLUE and the outcomes were compared with the results in Chapter 4. An analysis was also performed with two different initial soil moisture profiles and two different calibrated parameter sets on the estimations of soil moisture. The cross effects of the initial soil temperature and soil moisture on the estimations of these two variables were then examined using the MLCan model.

In the model calibrations, the Nash-Sutcliffe objective functions for the estimations of the four key model outputs (LE, H, Fc and SWS) in the single-response and multi-response approaches were compared. In the single-response model calibrations, each NS value was separately maximised to best fit the model estimations to the observations. However, in the multi-response calibrations the averages of the four NS values (named NS-all) were maximised.

The results of the single-response model calibrations with the depth-constant initial soil moisture showed that this approach produced results that were biased towards the calibrated variables. The NS-LE, NS-H and NS-Fc for the five best single-response calibrations were 0.49, 0.76 and 0.52, respectively. The NS-SWS ranged between 0.82 and 0.86. These values were similar to the NS values in the single-response calibrations in Chapter 4.

In contrast to the single-response calibrations, the multi-response calibrations yielded compromised estimations of the model outputs. The maximum NS-all value was 0.56 (for simulation No. 2067) and included the maximum NS values for the LE, H and Fc fluxes. Ignoring this simulation, the best multi-response model calibration had NS-all = 0.55, in which the NS-LE, NS-H, NS-Fc and NS-SWS were 0.43, 0.69, 0.49 and 0.61, respectively. These values tended to be slightly smaller, in comparison to the
single-response calibrations. This pattern was similar to the one found in Chapter 4 between the single-response and multi-response model calibrations.

Comparing the multi-response model calibration results in this chapter with those in Chapter 4 showed that the model’s performance (maximum $NS_{-all}$ value) in fitting simultaneously to the four key model outputs degraded, from 0.61 to 0.55. The results in this section revealed that the multi-response model’s performance was degraded, mainly due to the degradation in the soil moisture estimations, and that other estimations, such as the $LE$, $H$ and $F_c$, were not significantly affected. However, simulations with the best multi-response model calibration (simulation No. 2067) appeared in this section as an exception. Compared to the multi-response model calibrations in Chapter 4, this simulation showed an improvement in the $LE$ and $H$ estimations, while having the worst soil moisture estimations. This simulation was considered as an anomaly resulting from an unusual parameter set randomly being given to the model. Therefore, it did not interfere with the general conclusions that were made in this study.

Regarding the choice of parameter values, from the sensitivity analysis in Section 4.1, it was found that stomatal conductance parameters ($m$ and $b$) were the most identifiable for the $LE$, $H$ and $SWS$ estimations. In the single-response calibrations in this chapter, most of the $m$ values were found to be slightly above 10 for the $LE$ and $H$ estimations. The $b$ values varied between 0.003 and 0.007 [mol m$^{-2}$ s$^{-1}$], and tended to be around 0.005 [mol m$^{-2}$ s$^{-1}$]. For the $SWS$ simulations, the $m$ values varied between 15 and 20. Comparing the single-response calibrated parameters in this chapter with the corresponding parameters in Chapter 4 showed that the initial soil moisture conditions did not significantly change the values of the sensitive parameters. Comparing the results of the single-response calibrations in Chapters 4 and 5 highlighted the relations between the purpose of the modelling study and the effects of the initial conditions. When the study aims to simulate one single variable (e.g., $LE$ or $SWS$), rather than estimating all the variables simultaneously, the initial soil moisture does not affect the model’s performance and the initial soil moisture can be simplified by assuming the depth-constant initial soil moisture.

Moreover, for the best multi-response parameters, the results in this chapter showed that the $m$ values varied between 5 and 12, and the $b$ values varied between the specified range [0.002, 0.015] [mol m$^{-2}$ s$^{-1}$]. Comparing the multi-response
calibrated parameters in this chapter with those in Chapter 4 showed that the initial soil moisture changed the parameters’ calibrations. It was also discussed that the values for the $\psi_f$, $K_{rad}$, $Q_{10}$ and $R_o$ parameters also slightly changed. This result highlighted the importance of the initial conditions on the model calibration and was consistent with other studies that reported the initial conditions as one of the sources of error in uncertainty assessments of land surface models (Dumedah & Walker, 2014; Pianosi et al., 2016).

The results of the $LE$ estimations with the calibrated parameter set from the multi-response model calibrations with depth-constant initial conditions showed no overestimations during the first half of the year. This shows the effects of the soil moisture down the soil profile for estimating the above-ground processes like $LE$.

The results of the analysis of the soil moisture estimations under the four different scenarios with the MLCan model showed that the depth-varying initial soil moisture (with either of the two calibrated parameter sets) produced better soil moisture estimations at the first layer than the depth-constant initial soil moisture. The best soil moisture estimations at the first layer resulted from both the depth-varying initial soil moisture and the calibrated parameters, with $NS-SWS = 0.77$. Comparing the soil moisture profiles of these four scenarios also showed that both the initial soil moisture and the calibrated parameters can affect the soil moisture estimations at the surface, as well as in the deep layers. The discussion revealed that the model had a soil moisture memory in the order of 12 months. This result was consistent with the results of other studies on soil moisture memory (Koster et al., 2004; Zhang, 2004).

The cross effects of the soil moisture and soil temperature analyses showed that the soil moisture did not affect the soil temperature. Moreover, the analysis of the effects of the initial soil temperature on the estimations of soil moisture and other fluxes showed that the initial soil temperature profile did not affect the soil moisture and flux estimations. Therefore, the hypothesis at the beginning of this chapter was proven, in which the effects of the soil initial conditions are mainly driven by the initial soil moisture.
Chapter 6: Conclusions And Potential Future Works

This study analysed the ecohydrological modelling results for a eucalyptus forest in central New South Wales using the multilayer canopy-root-soil model, MLCan, based on observations from the Tumbarumba flux station. The project focused on the parameter sensitivity analysis to capture the dynamics of the land surface processes of the eucalyptus forest. Particular attention was paid to estimating the latent heat flux ($LE$), sensible heat flux ($H$), CO$_2$ flux ($F_c$) and soil moisture, as they are the key model outputs. The model calibrations and validation were carried out in the study area. Moreover, the sensitivity of the model to the soil initial conditions was investigated.

To accomplish the objectives of this study, the effects of multiple canopy layers on the model’s estimations were first examined in order to find the optimum number of canopy layers. As a result of the sensitivity analysis with different numbers of canopy layers conducted in Chapter 3, it was found that 12 canopy layers were the optimum number of layers which produced a total PAR absorption within 5% difference from the results of a 48-layer canopy model. The results were in agreement with the previous analysis of the sensitivities of different numbers of canopy layers and the suggestion, as a general rule, to limit the LAI at each layer to a maximum of 0.5 $[m^2 \cdot m^{-2}]$ (Baldocchi et al., 2002; Drewry et al., 2010a; Norman, 1979; Pyles et al., 2000).

The sensitivity analysis on the values of the root conductivities in Chapter 3, increased our knowledge of the importance of axial root conductivity. The results of the analysis showed that increasing the radial root conductivity did not significantly affect the average monthly latent heat flux ($LE$), however increasing the axial root conductivity enhanced the monthly average latent heat fluxes particularly during the summer and autumn. Results of evaluating the effects of the root conductivities and hydraulic redistribution on soil moisture estimations, supported the presence of the hydraulic lift and hydraulic descent phenomenon in the study area. The importance of the root conductivities, especially the axial root conductivities, on the water uptake, soil moisture, latent heat flux and hydraulic redistribution estimations were
highlighted, as a result of the manual sensitivity analysis in Chapter 3. Following the recommendations of Li et al. (2012) in their study of the Tumbarumba eucalyptus forest and the results of the sensitivity analysis in Chapter 3, subsequent simulations performed in Chapters 4 and 5, considered the effects of hydraulic redistribution.

As a result of the parameter sensitivity analysis using GLUE in Chapter 4, it was found that among the nine selected parameters, the slope \( m \) and intercept \( b \) of the Ball-Berry stomatal conductance model were the most sensitive parameters for estimating the latent heat flux \( LE \), sensible heat flux \( H \) and soil moisture at the first layer \( SWS \). The \( R_o \) parameter, soil respiration rate at 10 C°, was found to be the only sensitive parameter for estimating \( F_c \). The other parameters were non-identifiable (insensitive) across the parameter sampling ranges, which means that any parameter value could produce similar results. For the best multi-response estimations, the results suggested \( m = 15.74 \) and \( b = 0.001 \ [\text{mol m}^{-2} \text{s}^{-1}] \). These values were in general agreement with the values reported in the literature (Medlyn et al., 2007; Quijano et al., 2012).

The single-response and multi-response model calibrations using GLUE were performed and the effects of two different initial conditions for soil moisture and soil temperature, namely, depth-varying and depth-constant soil initial conditions, were investigated. The model calibrations were conducted with the depth-varying initial conditions in Chapter 4 and with the depth-constant initial conditions in Chapter 5. From the comparison between single-response and multi-response model calibrations on estimating the four key model outputs (i.e. \( LE \), \( H \), \( F_c \) and \( SWS \)), it was concluded that the multi-response calibration produced comparable results to the single-response. The single-response calibration showed considerable bias towards the calibrated variable. These conclusions were consistent with similar studies doing the same comparison with other ecohydrological models, or with soil-vegetation-atmosphere transfer (SVAT) models.

Comparing the single-response model calibrations in Chapters 4 and 5 showed that the profile of the initial soil moisture did not affect the model’s performance and the calibrated parameters for the estimations of the four key model outputs, including the soil moisture at surface layer. It was found that when a study aims to simulate one single variable (e.g., \( LE \) or \( SWS \)), rather than estimating all of the variables
simultaneously, the initial soil moisture can be simplified by assuming the depth-constant initial soil moisture.

Comparing the multi-response model calibrations in Chapters 4 and 5 showed that the depth-constant initial soil moisture degraded the model’s performance in simultaneously estimating the four key model outputs. The results of this comparison revealed that the multi-response model’s performance decreased (maximum $NS_{-all}$ value degraded from 0.61 to 0.56), mainly due to the degradation in the soil moisture estimation ($NS_{-SWS}$), while other estimations such as the $LE$, $H$ and $F_c$ were not significantly affected. This comparison also showed that the depth variations in the initial soil moisture changed the parameter’s calibration.

The results of this study highlighted the importance of the initial soil moisture depth profile on the parameter’s calibration, which is not usually paid much attention to in modelling studies. The results showed that the initial soil moisture profile has the potential to affect the parameters when the model is calibrated to multiple outputs (i.e., $LE$, $H$, $F_c$ and $SWS$). However, it did not significantly affect the parameters when calibrating to single model outputs (e.g., $LE$ or $SWS$).

The results of this study have implications for choosing the best dataset for model parameterisation when measured soil initial conditions are scarce. Our results suggest that simulating the soil moisture using an ecohydrological model is still acceptable in the absence of more detailed information for soil initial conditions profile when the model is calibrated to soil moisture observations only.

The study also sheds light on the soil memory. The MLCan model has a soil moisture memory of at least one year. This information could be useful in model initialisation when studying the future climate or when validation using independent data in the absence of the measured information. In addition, it was found that the soil temperature memory is about a few weeks in the shallow layers and about six months in the deeper layers.

The results of the model validations during 2001-2008 highlighted that the model validation using independent data was equally as good as the year that the model was calibrated for. The model captured the hourly variations of $LE$, $H$ and $SWS$ reasonably well during the validation period. However, the model could not estimate the $F_c$ very well. The poor performance in the $F_c$ estimation might have been attributed to errors in the
photosynthesis estimation and/or soil CO$_2$ flux estimation. Further exploration of this area is for future work.

Comparing the monthly latent heat flux and soil moisture simulations using MLCan with those from the recent study by Li et al., (2012) using the CABLE model revealed that both models have similar performances in simulating the ecohydrology of the eucalyptus forest in Tumbarumba. The results presented in this thesis demonstrate that the MLCan model can be used to adequately capture ecohydrologic fluxes in eucalyptus ecosystems in Australia.

In this project, the photosynthesis parameters were not studied as there were measured values for them. The behaviours of the model and the parameter sensitivity analysis while considering the photosynthesis parameters simultaneously with other parameters might provide interesting insights. It is recommended that this analysis be included in future research objectives.

Moreover, in this study, we had only access to the soil moisture observation up to 120 cm depth. However, we have studied a deep-rooted vegetation with up to 3 m root depth. It would be useful to consider observed soil moisture from deeper layers for model calibration in future studies and investigate the effects of deep layer calibrated soil moisture on estimating the forest-atmosphere exchange fluxes.


temperate Eucalyptus delegatensis forest using multiple constraints. *Agricultural and Forest Meteorology, 145*(1), 48-68.


