LiDAR Application in Forest Fuel Measurements for Bushfire Hazard Mitigation

by

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Master of Science (Monash University)

This thesis is presented for the degree of Doctor of Philosophy at Monash University

Statement: the thesis is submitted in total fulfilment of the requirements for the degree

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January 2017

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I hereby declare that this thesis contains no material which has been accepted for the award of any other degree or diploma at any university or equivalent institution and that, to the best of my knowledge and belief, this thesis contains no material previously published or written by another person, except where due reference is made in the text of the thesis.

The thesis includes three original papers: 'Strata-based forest fuel classification for wild fire hazard assessment using terrestrial LiDAR', 'Development of a predictive model for estimating forest surface fuel load in Australian eucalypt forests with LiDAR data', and 'Stratifying eucalypt forest structures using airborne LiDAR indices to map litter-bed fuel load and hazards'. The core aim of the thesis is the development of efficient and accurate methods to quantify forest properties in terms of litter-bed fuel load and fuel structural characteristics at landscape scales through the integration of remote sensing, geographic information system (GIS), and statistical modelling for fire risk mitigation. The ideas, development and writing of all the papers in the thesis were the principal responsibility of myself, the candidate, working within the School of Earth, Atmosphere and Environmental under the joint supervision of Dr Xuan Zhu, Dr Marta Yebra (Australian National University), Dr Sarah Harris and Prof Nigel Tapper. These three papers are considered as the main content of this study, and are presented in the third, fourth and fifth chapters.

With regard to Chapter 3, 4, and 5, my contribution to the work involved the following:

Thesis Chapter	**Publication Title**	**Status** *(published, in press, accepted or returned for revision, submitted)*	**Nature and % of student contribution**	**Co-author name(s) Nature and % of Co-author's contribution***	**Co-author(s), Monash student Y/N***
3	*Strata-based forest fuel classification for wild fire hazard assessment using terrestrial LiDAR.*	*Published in Journal of Applied Remote Sensing.*	*Concept, collecting data, and writing first draft. Student contribution: 80%.*	*1) Xuan Zhu, input into manuscript and 5% of contribution.*	*No*
				2) Marta Yebra, input into manuscript and 5% of contribution.	*No*
				3) Sarah Harris, input into manuscript and 5% of contribution.	*No*
				4) Nigel Tapper, input into manuscript and 5% of contribution.	*No*
4	*Development of a predictive model for estimating forest surface fuel load in Australian eucalypt forests with LiDAR data.*	*Submitted to Journal of Environmental Modelling and Software.*	*Concept, collecting data, and writing first draft. Student contribution: 80%.*	*1) Xuan Zhu, input into manuscript and 5% of contribution.*	*No*
				2) Marta Yebra, input into manuscript and 5% of contribution.	*No*
				3) Sarah Harris, input into manuscript and 5% of contribution.	*No*
				4) Nigel Tapper, input into manuscript and 5% of contribution.	*No*
5	*Stratifying eucalypt forest structures using airborne LiDAR indices to map litter-bed fuel load and hazards.*	*Submitted to Journal of Remote Sensing of Environment.*	*Concept, collecting data, and writing first draft. Student contribution: 80%.*	*1) Xuan Zhu, input into manuscript and 5% of contribution.*	*No*
				2) Marta Yebra, input into manuscript and 5% of contribution.	*No*
				3) Sarah Harris, input into manuscript and 5% of contribution.	*No*
				4) Nigel Tapper, input into manuscript and 5% of contribution.	*No*

I have not renumbered sections of submitted or published papers in order to generate a consistent presentation within the thesis.

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ACKNOWLEDGEMENTS

This thesis would not have been possible without the following people and institutions who provided their expertise and support throughout my PhD candidature. I would like to express my sincere gratitude to them for their efforts.

First, and foremost, I would like to thank my supervisors **Dr Xuan Zhu, Dr Marta Yebra, Dr Sarah Harris,** and **Prof Nigel Tapper**, without whom this project would not have been possible. Their support and feedback throughout my PhD candidature have not only been invaluable in the preparation of this thesis, but have also made the learning process enjoyable and interesting.

I am particularly grateful to **Dr Xuan Zhu** for his kind guidance throughout my PhD study. I knew him since I commenced my Masters in 2011. He is very much like a father who is very supportive and generous with his time, and I felt touched every time I read his emails commenting on my work that were written at midnight or on weekends.

I would like to express my special thanks to **Dr Marta Yebra** for having kindly agreed to take the adviser's role since 2015. She has also been always very thoughtful and generous with her time. When I travelled to Canberra for training courses or workshops, she graciously provided me food and accommodation at her home. She is not only a supervisor but a good friend.

I am very grateful for having **Prof Nigel Tapper** as my supervisor throughout my PhD study. Without his support I would not have access to a powerful laptop for work. His warm advice always reassured me when I was worried about my work and future. I would also like to express my sincere thanks to him for his assistance in the application of access to the Upper Yarra catchment area.

I would also like to extend my special gratitude to **Dr Sarah Harris**. I worked for her as a research assistant prior to my PhD study. She is just like an older sister for me. Without her enthusiastic encouragement I would not be able to conduct a bushfire-related project and would not have developed my personal interest in bushfires.

For assistance with finding research questions and building contacts, I would also like to thank **Dr Musa Kilinc** who provided guidance in the early phase of the project.

I would like to express my gratitude to **Francis Hines** and **Nick Bauer** (from Fire and Emergency Management Division, Department of Environment, Land, Water and Planning - DELWP) for his assistance with identifying research problems.

For assistance with mathematical modelling, I would like to express my special thanks to **Dr Aidan Sudbury** (from School of Mathematical Sciences, Monash University), without his guidance the fuel load models would not have been developed.

I would like to thank **Dr Robert Zlot** (from Queensland Centre for Advanced Technologies, CSIRO) for assistance with the terrestrial LiDAR device training.

For assistance with fieldwork, I would like to extend my special gratitude to **Jithya Nanayakkara**, **Dr Adam Leavesley**, **Thomas Jovanovic**, **Dr Senthuran Arunthavanathan**, **Dr Dean Yulindra Affandi**, **Yang Di**, **Dr Zhan Wang**, **Dr Saadia Majeed**, **Yingying Qiao**, **and Darren Hocking**, without whom the data collection would not have been possible.

For assistance with my academic writing, I would like to thank my writing group members **Dr Lynette Pretorius, Dr Charlie Lam, Dr Ricky Lau, Dr Cuong Hoang, Dr Qiaoqiao Tan, Dr Basil De Caux, and Dr Trang Danng.** Without their feedback and support, I would not have been able to finish my thesis quickly. My special thanks to **Dr Lynette Pretorius** for leading our regular meetings and providing us a fun learning environment. It is not only a writing group for improving HDR students' academic writing, but also a big family that brings us a sense of belonging.

I would like to thank **Monash University** and **Bushfire and Natural Hazards CRC** for assisting this research through providing PhD scholarships; **CSIRO** Australia for providing the Zebedee three-dimensional Mapping System; **DELWP** for providing the airborne LiDAR data; **Parks Victoria** and **Melbourne Water** for supporting the fieldwork in Upper Yarra Reservoir Park.

Finally, and most importantly, I would like to thank **my parents, Wenhui Chen and Mingxia Yang** for their love and support throughout my candidature and my life overseas. Without their trust and support, this thesis would not have been possible.

PRIZES AND PUBLICATIONS DURING PHD CANDIDATURE

AWARDS

Royal Society of Victoria's Young Scientists Research Prize 2016;

Society for Optics and Photonics Technology, Remote Sensing's Best Student Paper Award 2016;

China Scholarship Council's Merit Overseas Student Prize 2016.

JOURNAL, REPORT AND CONFERENCE PUBLICATIONS

Chen, Y., Zhu, X., Yebra, M., Harris, S. and Tapper, N., 2016. Strata-based forest fuel classification for wild fire hazard assessment using terrestrial LiDAR. Journal of Applied Remote Sensing, 10(4): 046025-046025.

Chen, Y., Zhu, X., Yebra, M., Harris, S. and Tapper, N., 2016. Estimation of forest surface fuel load using airborne LiDAR data. In: SPIE Remote Sensing. International Society for Optics and Photonics, Edinburgh, UK: pp: 100050H-100050H-100057.

Chen, Y., Zhu, X., Yebra, M., Harris, S. and Tapper, N., 2016. Surface fuel load modelling with LiDAR data: A case study of upper Yarra reservoir area, Victoria, Australia. In: 5th International Fire Behaviour & Fuels Conference 2016. International Association of Wildland Fire, Melbourne, Australia.

Yebra, M., Marselis, S., Van Dijk, A., Cary, G.J. and Chen, Y., 2015. Using LiDAR for forest and fuel structure mapping: Options, benefits, requirements and costs. Bushfire and Natural Hazards CRC Report. Melbourne, Australia.

CONFERENCE POSTERS

Chen, Y., Zhu, X., Yebra, M., Harris, S. and Tapper, N., 2016. Estimation of forest litter-bed fuel load using airborne LiDAR data. In: Australasian Fire Authorities Council. Brisbane, Australia.

Chen, Y., Zhu, X., Yebra, M., Harris, S. and Tapper, N., 2015. Modelling forest fuel temporal change using LiDAR. In: Australasian Fire Authorities Council 2015. Adelaide, Australia.

Yebra, M., Van Dijk, A., Cary, G.J., Leavesley, A., Garlapati, N. and Chen, Y., 2015. Mapping bushfire hazard and impact. In: Australasian Fire Authorities Council 2015. Adelaide, Australia.

PRESENTATIONS

'LiDAR Application in Forest Fuel Measurements for Bushfire Hazard Mitigation', Research Advisory Forum, 17-19 Oct 2016, Canberra, Australia.

'Modelling forest litter-bed fuel load with LiDAR', Royal Society of Victoria Young Scientist Research Prizes in the Biological Sciences (non-Human) category, 11 Aug 2016, Melbourne, Australia.

'Estimation of forest surface fuel load using airborne LiDAR data', Society for Optics and Photonics Technology, Remote Sensing Conference, Earth Resources and Environmental Remote Sensing/GIS Applications, 26-29 Sept 2016, Edinburgh, the UK.

'Surface fuel load modelling with LiDAR data: a case study of Upper Yarra Reservoir area, Victoria, Australia'. 5th International Fire Behaviour & Fuels Conference, 11-15 April 2016, Melbourne, Australia.

'Modelling forest fuel hazard change over time using LiDAR technology', Environmental Sensing Activities Workshop, 13 Feb 2015, Canberra, Australia.

Abbreviations

A: aspect (degree)

AIC: Akaike information criterion

ALS: airborne LiDAR scanning

ASTER: Advanced Spaceborne Thermal Emission and Reflection Radiometer

BT: Burn type (wildfire or fuel hazard-reduction burns)

CBERS: China–Brazil Earth Resources Satellite

CD: canopy density (%)

CFFDRS: Canadian Forest Fire Danger Rating System

CV: Leave-one-out cross-validation

DBH: diameter of breast height

DEM: digital elevation model

DW: dry weight of forest fuel load (g)

E: elevation (m)

EVI: Enhanced Vegetation Index

FD: surface or litter-bed fuel depth (mm)

FFBTs: forest fire behaviour tables

FFDI: forest fire danger index

FFDM: forest fire danger meters

FT: Forest fuel type (dry or damp)

GAMLSS: Generalised Additive Model for Location, Scale and Shape

GFDI: grassland fire danger index

GFDM: grass fire danger meters

GIS: Geographic Information Systems

GVMI: Global Vegetation Moisture Index

KBDI: Keetch-Byram Drought Index

LAD: leaf area density

LiDAR: Light Detection and Ranging

LOWESS: Locally Weighted Scatterplot Smoothing

NDVI: Normalized Difference Vegetation Index

NFDRS: National Fire Danger Rating System

NPP: normal probability plot

PC: surface fuel percentage cover (%)

Radar: radio detection and ranging

RMSE: root mean square error

S: slope (degree)

SAVI: Soil-Adjusted Vegetation Index

SPOT: Satellite for observation of Earth

TLS: terrestrial LiDAR scanning

VARI: Visible Atmospherically Resistant Index

WI: Water Index

YSF: years since last fire

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Abstract

Australia's native Eucalypt forests are the most fire-prone in the world due to high rates of fuel accumulation, high flammability of fuel, and seasonally hot and dry weather conditions. Projected changes in the frequency and intensity of extreme climate and weather could increase the occurrence of 'mega-fires', extreme fire events with catastrophic impacts on people and the environment. Current methods for fire risk mitigation and prediction such as fire danger rating systems, fire behaviour models, and hazard reduction treatments require an accurate description of forest fuel. However, fire management authorities share a common challenge to efficiently and accurately quantify forest fuel properties (e.g. fuel load and fuel structure) at a landscape scale. A landscape includes the physical elements of geo-physically defined landforms, such as forests, grasslands, and lakes. This thesis investigates the application of the Light Detection and Ranging (LiDAR) technique in quantifying forest fuel properties, including fuel structural characteristics and litter-bed fuel load at a landscape scale.

Currently, fire fighters and land managers still rely on empirical knowledge to visually assess forest fuel characteristics of distinct fuel layers. The visual assessment method provides a subjective description of fuel properties that can lead to unreliable fire behaviour prediction and hazard estimation. This study developed a novel method to classify understorey fuel layers in order to quantify fuel structural characteristics more accurately and efficiently by integrating terrestrial LiDAR data and Geographic Information Systems (GIS). The GIS-based analysis and processing procedures allow more objective descriptions of fuel covers and depths for individual fuel layers. The more accurate forest fuel structural information derived from terrestrial LiDAR data can be used to prescribe fire hazard-reduction burns, predict fire behaviour potentials, monitor fuel growth, and conserve forest habitats and ecosystems in multilayered Eucalypt forests.

Traditionally, litter-bed fuel load is directly measured through destructive sampling, sorting, and immediate weighing after oven drying for 24 hours at 105 °C. This direct measurement of fuel load on a landscape scale requires extensive field sampling, post laboratory work and statistical analysis, which is labour intensive and time consuming. This study found new relationships among forest litter-bed fuel load, surface fuel depth, fire history and environmental factors through multiple regressions with airborne and terrestrial LiDAR data. The fuel load models established in this study indicate that litter-bed depth and fire history are the primary predictors in estimating litter-bed fuel load, while canopy density and terrain features are secondary predictors.

Current fuel models are constrained to estimate spatial variations in fuel load within homogeneous vegetation that previously experienced the same fire events. This study developed a predictive model through multiple regression to estimate the spatial distribution of litter-bed fuel load in multilayered eucalypt forests with various fire histories and forest fuel types. This model uses forest structural indices and terrain features derived from airborne LiDAR data as predictors, which can be applied when data on forest fuel types and previous fire disturbances are absent. It can be used to map the litter-bed fuel load distribution at a landscape scale to support regional wildland fire management and planning.

This study indicates that LiDAR allows a more efficient and accurate description of fuel structural characteristics and estimation of litter-bed fuel load. The results from this study can assist fire hazard assessment, fuel reduction treatment, and fire behaviour prediction, and therefore may reduce the impact to communities and environment.

Chapter 1. Introduction

1.1 Background

Australian natural ecosystems have evolved with fires and their biological diversity has been shaped by both historical and recent patterns of fires (Gill *et al.*, 1981; Bradstock *et al.*, 2002). Except for limited areas of rainforest, cypress pine and acacia associations, Eucalypt forests dominate Australian forests as they have developed extraordinary adaptations to relatively frequent fire events (McArthur, 1967). The highly flammable eucalypt-studded Australian landscape and seasonally hot, dry environment requires mitigation of fire threats due to potential damage to land, human property, environment, and even mortality (Bradstock *et al.*, 2012). Studies indicate that bushfire behaviour and effects are mainly determined by fuel condition (e.g. type, moisture content, load, and structure), weather, and topography (Andrews, 1986; Cheney *et al.*, 2012). For humans, the primary option available to reduce fire threats is through a modification of fuel availability (Fuller, 1991; Chatto, 1996). Therefore, sound fire mitigation requires accurate description of fuel properties to support fire hazard-reduction activities.

In Australia bushfire risk management is underpinned by a whole range of activities. One of the core themes relate to increasing the level of bushfire resistance through fuel management (McLennan and Handmer, 2012). Prescribed burning practices are fundamentally important land management tools for Australia’s stakeholders to achieve specific objectives (e.g. ecological, fuel reduction and traditional burning) (Adams and Attiwill, 2011). Global warming increases the dryness of forest fuels and ultimately increases the frequency and severity of bushfires (Flannigan *et al.*, 2013). The increase in occurrence of extreme weather narrows the window of prescribed burns (Clarke *et al.*, 2013). These impacts of climate change on fire regimes increase the difficulties of wildland fire management. Land managers and fire authorities also share a common challenge to efficiently and accurately quantify landscape-scale fuel properties including litter-bed fuel load (also known as surface fuel load) and fuel structures (Gould *et al.*, 2011).

Distribution of litter fuel varies across the landscape even within homogeneous vegetation communities due to the complexity of forest composition of overstorey and understorey vegetation, intensity and severity of previous fire disturbances, changes in annual and seasonal precipitation, radiation, wind direction and speed, aspect, slope and elevation (Brown and Bevins, 1986). Therefore, quantifying forest litter fuel on a landscape scale is challenging. Forest litter-bed fuel load is typically determined by field sampling, which is error prone when extrapolating to a larger scale (Brown and Bevins, 1986). Forest fuel hazard assessments as well as fire behaviour models require accurate descriptions of the horizontal continuity and vertical distribution of fuel at distinct fuel strata (Agee *et al.*, 1973; Gould *et al.*, 2008). However, current fuel hazard assessment relies on subjective scores given by the observers in the field survey (Hines *et al.*, 2010). Therefore, an accurate and efficient approach to quantify fuel properties including litter fuel load and fuel structural characteristics must be developed to support fire authorities in fire hazard mitigation (McLennan and Handmer, 2012).

Remote sensing technologies allow a spatially and temporally accurate description of fuel conditions across a landscape, and have been used to map forest fuel types, fuel moisture content and also have the potential to estimate spatial variations in canopy fuel structure and crown fuel load (Rollins *et al.*, 2004; Saatchi *et al.*, 2007; Thenkabail *et al.*, 2012). However, remote sensing application in litter-bed fuel load estimates and understorey fuel strata classification is not well understood. Understorey fuel structural characteristics and litter-bed fuel load are significant components of fire ecology, which provide accurate information of ecological restoration for fuel treatment activities (Covington and Moore, 1994; Agee and Skinner, 2005).

Many studies indicate that LiDAR (Light Detection and Ranging) data can be used to efficiently and accurately quantify crown fuel characteristics (Lefsky *et al.*, 1999; Lovell *et al.*, 2003; Andersen *et al.*, 2005). LiDAR waveforms are sensitive to forest structural changes (Andersen *et al.*, 2005; Erdody and Moskal, 2010; Jakubowksi *et al.*, 2013; Kramer *et al.*, 2014; Rowell *et al.*, 2016), which might have the potential to detect understorey fuel.

This study proposes to develop efficient and accurate methods to quantify forest physical properties in terms of litter-bed fuel load and fuel structure. The expected results ultimately benefit forest resource management, bushfire suppression, and framing bushfire-related policies. The best potential approaches to accomplish this purpose involve the integration of remote sensing, GIS and statistical modelling (Falkowski *et al.*, 2005). Quantification of grass fuel is relatively easier compared with forest fuel (Cheney and Sullivan, 1997); therefore, this study focuses on the forest fuel in order to support forest fire behaviour modelling and mitigation.

1.2 Research Questions and Objectives

This project aims to improve fuel structure and load measurement for the benefit of fire agencies. The core objective is to develop effective and efficient methods to quantify forest fuel properties, including fuel structural characteristics and litter-bed fuel load at a landscape scale. The expected results will support forest fire authorities and land management agencies for mitigation of fire threats to the community and environment in fire prone areas in Australia.

This study is going to answer the following questions:

- How to classify forest fuel strata using remote sensing technologies in order to quantify fuel structural characteristics efficiently and consistently (e.g. fuel depth, height, and cover) for forest fuel hazard assessment?

- How does forest litter-bed fuel load relate to fuel characteristics (e.g. litter-bed or surface fuel depth and fuel type), fire history (e.g. time since last fire, fire intensity, extent and severity) and terrain features?
- How to estimate spatial variations in forest litter-bed fuel load at a landscape scale using remote sensing technologies?

Corresponding to the research questions, this study has the subsequent objectives:

- To stratify understorey fuel strata using terrestrial LiDAR data.
- To develop a statistical model using fuel characteristics, previous fire events, and terrain features combined with field surveyed litter-bed fuel load.
- To develop a litter-bed fuel load model using stratified fuel structural characteristics derived from airborne LiDAR indices for mapping the spatial distribution of litter-bed fuel load across landscape.

1.3 Research Significance

The research significance can be described from the following forest fire management and fire behaviour modelling perspectives. First, forest fuel hazard assessment requires accurate description of understorey fuel structural characteristics, but it currently relies on subjective and inconsistent descriptions given by observers based on their trained knowledge and empirical experience (McCarthy, 1996; Hines *et al.*, 2010). This project aims to develop a more accurate and efficient method to quantify forest fuel structural characteristics using LiDAR data. The expected results will assist fire agencies in guiding forest fuel hazard-reduction treatments and monitoring ecological restoration after previous fires. Second, forest litter-bed fuel load is traditionally determined by field sampling and immediately weighing after oven drying fuel samples, which is labour intensive, expensive and time consuming (Brown and Bevins, 1986). McArthur's depth-to-load relationships indicate that forest litter-bed fuel depth is one of the key indicators to litter fuel load estimation (McArthur, 1967). It has been used by fire authorities to roughly estimate fuel load during fuel hazard assessment (McCarthy, 1996).

Other studies developed fuel accumulation models that take years since fire as an indicator to predict fuel regrowth after previous fire events for specific fuel types at specific locations (Peet, 1971; Fox *et al.*, 1979; Schaub *et al.*, 2008). This project will explore relationships among litter fuel load, forest fuel type, litter-bed depth, and fire history. Current fire behaviour modelling shares a common challenge in accurately quantifying litter-bed fuel load. The projected results will benefit fire authorities in predicting fire behaviour potential more accurately and efficiently. Last, the development of a litter-bed fuel load model using airborne LiDAR scanning (ALS) data reveals ALS's potential in estimating spatial distribution of litter fuel load across landscape. This novel method will be beneficial in fire spread modelling and danger rating system development for eucalypt forests with various terrain features, fire histories, and fuel types. In summary, the expected results will provide more efficient, less labour intensive and cost effective methods for better protection of communities and the environment in fire prone areas.

1.4 Thesis Outline

This thesis is comprised of six chapters, including an introduction, literature review, three main findings, and a general conclusion. The three major findings consist of a terrestrial LiDAR scanning (TLS)-derived fuel classification, development of a depth-based surface fuel load model using both ALS and TLS data, and an ALS-derived litter-bed fuel estimation at a landscape scale. These chapters are either published or submitted work, structured and presented in this thesis following the original journal formatting. More details regarding these works are referred to the declarations before each individual chapter.

Chapter 1 introduces the current knowledge gaps in forest fuel measurements. The section 1.2 and 1.3 define project questions, objectives, and significance. Research rationale, approach, and innovation are outlined in section 1.4.

The first section of Chapter 2 reviews forest fuel characteristics as important components of fire behaviour and danger rating models in North America, South Europe, and Australia (section 2.1.). It also summarises the limitation of traditional methods in forest fuel measurements. The following section (2.2) reviews the remote sensing application in forest fuel management. It identifies the knowledge gaps in current literature concluding that remote sensing-based understorey fuel strata classification and landscape-scale litter fuel load estimates in multilayered forests are not well understood. This section also highlights the potential of LiDAR data to overcome these issues.

Chapter 3 to 5 correspond to the original contributions of this thesis. Each of these three chapters correspond to published or submitted work to international journals. Chapter 3 is a published paper that describes strata-based forest fuel classification for wildfire hazard assessment using TLS data. In this study, LiDAR point cloud data were applied to reconstruct three-dimensional forest structures for forest fuel strata classification and fuel load estimation. This study firstly investigated the efficiency and accuracy of TLS - derived fuel characteristics for fuel hazard assessment. An automatic tool for forest fuel strata classification was then developed to assess fuel hazards based on integration between GIS and TLS data. It provides a consistent and accurate alternative to visual assessing techniques described in the Victoria forest fuel hazard assessment guide (Hines *et al.*, 2010) and the fire behaviour model (project Vesta) (Gould *et al.*, 2008).

Chapter 4 is a submitted manuscript regarding the development of a predictive model for estimating forest litter-bed fuel load in Australian eucalypt forests with LiDAR data. McArthur's depth-to-load models have been widely used as a rapid alternative to estimate litter-bed fuel load in order to support Australia's bushfire-related activities (Fernandes and Botelho, 2003). This study found a strong and positive correlation between forest litter-bed fuel load and litter-bed depth derived from TLS data. It led to a development of a new depth-to-load model for litter-bed fuel load estimates through a multiple regression analysis. The model predictors and coefficients indicate how the spatial variation in surface fuel load relates to litter-bed fuel depth, forest fuel type, fuel characteristics, topography, and previous fire disturbance. The calibrated model can be used to consistently and accurately predict forest surface fuel load and therefore assist forest fuel treatment activities.

Chapter 5 describes eucalypt forest vertical structure stratification using ALS data. It is also a submitted manuscript that indicates that an ALS indices-derived litter-bed fuel load model can be successfully used to map spatial variation in litter-bed fuel load efficiently and accurately. In order to assist Australian fire authorities for regional decision-making, this study also developed a novel fuel load model for landscape-scale litter-bed fuel load estimates using ALS-derived stratified height indices and topography. Forest vertical structure reflects understorey and overstorey vegetation species composition, microclimate, soil (e.g. type, moisture content, and productivity) as well as terrain features (e.g. topography, aspect and slope), which determines forest fuel productivity and decomposition (Dubayah *et al.*, 1997; Dubayah and Drake, 2000). Therefore, ALS indices relating to crown height, canopy density, depth and closure of both understorey and overstorey layers, as well as topography, are useful for quantifying litter-bed fuel. This project established a predictive model that described accurate spatial variation in surface fuel load using forest understorey and overstorey vegetation structural characteristics, and topography through multiple regressions with ALS data. The accurate information derived from this model can be used to assist forest fuel management, assess suppression difficulties, predict ongoing fires for operational activities, and assess potential fire hazards in the study area.

Chapter 6 presents the general conclusion of this PhD study focusing on the potential utility of LIDAR technology for forest fuel measurements. The significance of this project’s contribution in terms of scientific innovations and practical implications to research community and wider society is also summarised. The study limitations as well as recommendations for future studies are highlighted in the last sections of this chapter.

Chapter 2. Literature review

2.1 Wildland Fire and Fuel Assessment

2.1.1 Introduction

Natural forest fuel is vegetation biomass with multiple sizes, states (e.g. alive or dead), arrangements and orientations (Anderson, 1970). For the smallest elementary unit, fuel is considered as a particle arranged into structural forms normally called the fuel bed or fuel strata (McCaw, 1991). Fuel is typically characterized by type, size, quantity, and structural arrangement. Therefore, forest fuel can be described in numerical terms by dry fuel load, fuel depth, fuel particle density, and coverage. These fuel characteristics have different contributions to fire behaviour. Research has used quantities of fuel and forest structural information described by fuel depth, particle density, and coverage to predict the rate of surface fire spread, flammability, and also to estimate fire danger ratings (Anderson, 1982; Gould *et al.*, 2008). The following sections describe the concepts of forest fuel load and fuel structure, and their significance in predicting fire behaviour and assessing fuel hazards.

2.1.2 Fire behaviour models and danger rating systems

Sound forest fire management (e.g. fire danger rating, prescribed burning and wildfire control) can benefit from an accurate and efficient description of forest fuel properties as one of the fire behaviour predictors (Burrows, 1999). Fire danger and behaviour models use fuel properties as inputs to derive fire danger indices or fire behaviour potentials. Fuel models describe fuel properties that are used as inputs to various fire danger ratings and mathematical surface fire spread models. Fire danger is determined by the combination of both constant and variable factors that impact the initiation, spread and difficulty to control a wildfire on a specific geographic area (Deeming and Brown, 1975). A fire spread model characterizes the fire's rate of spread, fire shape, direction, rate of energy release, mode of propagation, flame height, flame geometry, and fire transitions (from a surface fire to a crown fire) (Bradstock *et al.*, 2012). Fire danger and behaviour models vary across the globe due to the high-degree of variation in vegetation communities (fuel models) and climate.

2.1.2.1 North American and Mediterranean models

A National Fire Danger Rating System (NFDRS) was proposed in America in 1972 (Deeming *et al.*, 1972). It is a standardized set of equations to determine the relative seriousness of burning conditions and threat of fire in a specific area on a landscape using local observations of current or predicted conditions of fuel, weather, and topographic variables. The NFDRS has been used widely in the America as the main fuel model.

The NFDRS uses Rothermel's (1972) spread model as its core, and also integrates the impacts of existing and expected states of selected fire danger factors into qualitative indices for planning and operational purposes. The various factors of fuel characteristics, weather, topography, and risk are combined to assess the day-to-day fire protection programs on a fire danger rating area that has similar climate, fuel, and topography. This rating area should be sufficiently small that similar fire danger is preserved, but large enough such that fire protection operations and fire suppression can function efficiently (Fosberg and Furman, 1971). All fuel beds are categorized into six general classes (lichens and mosses, marsh grasses and reeds, grasses and forbs, shrubs and tree reproduction, trees, and slash) according to the predominant surface fuel (Deeming *et al.*, 1977). A total of twenty fuel models are developed based on the general classes of surface fuel and relative loading of different fuel components (Deeming *et al.*, 1977). Each individual fuel model uses fuel properties (e.g. surface fuel type, depth, weight, size, volume, and surface to volume ratio) of a fire danger rating area to determine the fire potential (Schlobohm and Brain, 2002). Therefore, accurate description of fuel properties is significant for predicting fire behaviour potential and assessing fire effects.

Climatic influences on fire danger are also involved in the NFDRS, as vegetation adapts to the general climate in a fire danger rating area, and the seasonal fuel and climate characteristics determine seasonal fire dangers. Adaption to various climate classes typically occurred across America, and the system grouped climate characteristics into four climate classes, numbered one through four: class one represents arid, semiarid desert or steppe country; class two is semi-humid climate where summertime moisture is deficient; class three is defined as semi-humid climate where summertime precipitation is adequate to sustain plant growth most of the season; class four represents the wet coastal areas where summertime precipitation and fog are common (Schlobohm and Brain, 2002). The climate classes are judged adequate for the purpose of rating fire danger in order to define the different linear drying rates for annuals, perennials, and woody plants. A climate class determines the seasonal response of fuel moisture content to environmental conditions.

Annual precipitation was introduced to the NFDRS system in 1988 along with the Keetch-Byram Drought Index (KBDI) for the system modification to address the impacts of long term drying or drought on forest soils and duff layer in the southeast part of America (Burgan, 1988). The correlation between air temperature and the daily drought factors varies with different levels of annual precipitation (Schlobohm and Brain, 2002). The annual precipitation in a fire danger rating area can be derived from local meteorological data or precipitation maps when estimating the daily drought factors.

Albini (1976) introduced thirteen fuel models that were developed to be interchangeable with the twenty NFDRS fuel models. These fuel models were also used with Rothermel's (1972) fire spread models. These thirteen fuel models quantitatively describe the same fuel loading components and are sorted into four classes: grass, shrub, timber, and slash (Anderson, 1982). Short grass, timber grass and understory, and tall grass were grouped into the class of grass; chaparral, brush, dormant brush, and southern rough were classified as the shrub group; the timber group included compact timber litter, hardwood litter, and timber understory; light slash, medium slash, and heavy slash were sorted into the slash group. They are also used for the severe period of the fire season when wildfires pose greater control problems during the dry season, and when the fuel bed becomes more uniform (Anderson, 1976; Scott and Burgan, 2005). These thirteen stylised fuel models were then used as inputs to the BEHAVE fire behavior prediction system that predicted wildland fire behaviour for fire management purposes nationwide in America (Andrews, 1986). This system has been modified and updated as a Windows-based program known as the BehavePlus fire modelling system, which is adaptable to various fire weather and fuel conditions (Andrews and Bevins, 2003). Its further technological development allows users to build and test their customized fuel models to describe wildland fire behaviour and impacts for specific fuel types and complexes (Heinsch and Andrews, 2010).

The Canadian Forest Fire Danger Rating System (CFFDRS) was developed to adapt to Canadian fuel complexes for fire management and planning used in prevention and mitigation of wildland fire disasters (Van Wagner, 1987). Similar to the NFDRS, the CFFDRS also requires a series of numerical ratings of fire weather and fuel conditions to predict wildland fire behaviour and effects for individual fuel types. It consists of seven components, including the litter and fine fuel moisture code, the duff moisture code, the drought code, the initial spread index, the build-up index, the fire weather index, and the forest fire behavior prediction system (Stocks *et al.*, 1989). The build-up index for one fuel type is a numeric rating of the total amount of fuel available for combustion or fuel load. The build-up index, the codes of fine fuel moisture, duff moisture, and drought determine fuel conditions, which are combined with initial spread index derived from daily weather data (e.g. air temperature, relative humidity, wind speed, and 24-hours rainfall) to predict the fire weather index. The forest fire behavior prediction system is applied to estimate various fire behavior parameters for sixteen distinct fuel types depending on the inputs from the fire weather observations, fuel moisture content, as well as topography. These fuel types are initially grouped into five general vegetation classes, including coniferous, deciduous, mixed woodland, slash, and open grass. The further classification depends on forest floor cover and organic layer, surface and ladder (above litter-bed layer) fuels, and stand structure and composition (Van Wagner *et al.*, 1992).

North American models were generated in an attempt to establish one national fire behaviour prediction system that could be adapted to various climate classes and multiple domestic fuel types across the country. The abundance of fuel loads, dryness, duff thickness and slash accumulation determine that North American fuel models are different in structure and emphasis from the fuel models generated in the Mediterranean climate and harsh dry eucalypt studded Australian landscape. Compared to the Australian fire behaviour studies, North American studies assume that the weather and fuel moisture determine a basic burning index (e.g. rate of spread) and then a fuel type is incorporated later during the prediction.

Fire behaviour and fuel models are not well documented in the Mediterranean area. Vegetation types in southern Europe are often assigned among the thirteen stylised fuel models in order to use the Rothermel's (1972) spread model in the Mediterranean area for their regional wildland fire management and planning (Allgöwer *et al.*, 1998; Loureiro *et al.*, 2002; Fernandes and Botelho, 2004). The Greek Mediterranean vegetation types (e.g. grasslands, phrygana, maquis, and closed-forest litter of pine species) are classified into seven standardised fuel models according to their dominant vegetation species, fuel load categories and vegetation structural parameters in order to use the BEHAVE simulations (Dimitrakopoulos, 2002). In Portugal, twenty two forest fuel models were developed based on the forest fuel types defined by the species composition and vertical structures (e.g. open or closed, and tall or low) from the Portuguese National Forest Inventory (Fernandes *et al.*, 2006). The Mediterranean studies share a common finding that forest fire behavior is primarily driven by stand structure rather than species composition of the stand by using the American fire behavior and danger rating models (Dimitrakopoulos, 2002; Fernandes *et al.*, 2006). However, the lack of litter-bed fuel load and depth data that are required as the inputs for estimation of fire behaviour potential and impacts constrains the application of the American fire models.

2.1.2.2 Australian models

In contrast to North American fire models, Australian fire models were developed based on several laboratory experiments and empirical data. Australian bushfire studies commenced in the early 1930s. Fire danger and fire behaviour models have been gradually developed and evolved to meet local circumstances, including vegetation communities and weather conditions. These models are concerned with the numerical simulation of wildland fires to present a systematic method for evaluating the risk of bushfires and predicting fire behaviour, many of which have become progressively more accurate and sophisticated.

McArthur first introduced grass fire danger meters (GFDM) for the grasslands - Mark 3 (1966). The grassland fire danger index (GFDI) is estimated based on one fuel variable (degree of curing), air temperature (°C), relative humidity (%), and wind speed (km/h). This fire danger rating system has been used by fire authorities across Australia to provide public warnings and indication of the difficulty of fire suppression over a wider range of fires burning conditions in grassland.

McArthur (1967) also proposed the forest fire danger meters (FFDM) for eucalypt forests - Mark 4. It was updated to the metric version - MK 5 in 1973. The forest fire danger index (FFDI) is determined by weather variables, including previous rainfall (mm), number of days since last rainfall, drought factor (ranging from 1 to 10), air temperature (°C), relative humidity (%), and wind speed (km/h) (Luke and McArthur, 1978). These indices were expressed by algorithms based on mathematical equations of best fit for easy computation and use (Noble *et al.*, 1980). However, the power function nature of the algorithm and accuracy in measuring the input variables (e.g. wind speed and temperature) may result in a large range of uncertainty (e.g. ± 20%) in the estimated FFDI values.

The FFDI is then converted to a fire danger rating category ranging from low to catastrophic (Table 1) by the responsible fire agency in each jurisdiction, based on information of weather and fuel, in order to define suppression difficulties (Noble *et al.*, 1980). In addition, likelihood of lightning ignitions and the severity of wind changes are also considered by the agencies in conducting a fire risk assessment. Furthermore, the rate of spread is estimated by the FFDI, fuel load, and slope of forest ground. The litter fuel load is expressed in tonnes per hectare of combustible material less than 6 mm on the forest floor.

Table 1. McArthur forest and grassland fire danger rating indices (Luke and McArthur, 1978).

	Fire Danger Index	
Category	**Forest**	**Grassland**
Catastrophic	100 +	150 +
Extreme	75–99	100–149
Severe	50–74	50–99
Very High	25–49	25–49
High	12–24	12–24
Low–Moderate	0–11	0–11

The MK5 model is simple to use and derived from the historical data in southeastern Australia (Noble *et al.*, 1980). It has been the most widely used fire danger and behaviour model by fire authorities and land management agencies in southeastern Australia to issue fire danger warnings, predict fire behaviour, suppress fire propagation to reduce risk and better protect communities in bushfire prone areas. Burrows (1999) evaluated the FFDM in Jarrah forests, Western Australia. The rate of spread could be overestimated by the FFDM, during conditions of high (surface litter) fuel quantities, low fuel moisture contents, and low wind speeds. However, during conditions of high wind speeds and low (surface litter) fuel quantities, the FFDM under predicted the rate of spread (Burrows, 1999). The under estimation could be explained by that the model assumed a direct relationship between fuel quantity and the rate of spread (Burrows, 1999). In addition, the impacts of the variation in understorey fuel structures and composition of overstorey and understorey vegetation on fire behaviour were not considered by the model, leading to underestimation of the rate of spread in the forests with shrubs (Gould *et al.*, 2008).

Since 1968, the Western Australian Forest Department has been supporting Peet's model, which provides forest fire behaviour tables (FFBTs) in Western Australia (Peet, 1965). Similar to the MK5, the Peet's model also uses historical weather records, actual weather, slope, moisture contents and quantities of surface fuel for fire-danger forecasting, interpolation of fire behaviour, and guiding prescribed burns (Sneeuwjagt and Peet, 1985). It has been applied to prescribe burning conditions in Western Australian forests, including Jarrah (*Eucalyptus marginata*) forests, Pine forests (*Pinus Radiata*), Karri forests (*Eucalyptus diversicolor*), and Wandoo forests (*Eucalyptus wandoo*).

However, this model could underestimate the rate of spread of fires spreading faster than about 50 – 60 m/h, and overestimate the rate of spread of slower fires burning under light winds (Burrows, 1999). It also overestimates the influence of low fuel moisture content on the rate of spread at wind speeds lower than 3.5 m/h. Unlike FFDI MK5, the Peet's model suggestes that most of variations in the rate of spread could be explained by wind speed and fuel moisture content, rather than fuel load. The head-fire rate of spread was found to be independent of litter fuel load providing there was sufficient fuel to sustain a spreading fire (e.g. more than about 4 t/ha). In addition, the modified Peet's model was developed based on non-linear regression that incorporated a power function in wind and a power function in fuel moisture content. On extrapolation to higher wind speeds (>10 km/h at 1.5 m in the forests or > 30km/h tower wind speed), this model tended to overestimate especially in dry fuel conditions (< 6% moisture content) (Burrows, 1999). Until the development of the Vesta model, quantities and moisture contents of fuel were the fuel characteristics used in southeastern Australian forest fire behaviour and danger rating models (Gould *et al.*, 2008).

The development of more efficient burning guidelines requires a sound understanding of fire behaviour and suppression difficulty in different forest fuel structure and vegetation composition. The project Vesta was conducted in dry eucalypt forests with different fuel ages and understorey vegetation structures (Gould *et al.*, 2008). It introduced an empirical model named the Vesta fire behaviour model that describes the relationship between a series of quantifiable fuel hazard criteria, wind speed, slope, and fuel moisture contents (related to temperature and relative humidity). Different to its predecessors, this model developed a new concept of fuel characteristic for the estimation of fire behaviour potential, and also emphasized the importance of fuel structure as well as the age-related changes in fuel attributes for modeling fire behaviour in dry eucalypt forests. Consequently, accurate and efficient methods to quantify fuel load and fuel structure are significantly useful for understanding forest fire behaviour and mitigating the frequency and intensity of catastrophic fires in Australia's fire prone areas.

2.1.3 Fuel measurements

2.1.3.1 Fuel load

Fuel load is defined as the surface fuel or litter-bed fuel (fine leaf and twig materials that are less than 6 mm in diameter), and quantified as tonnes per hectare. It has significant impacts on fire ignition, rate of spread, and propagation (Rothermel and Anderson, 1966). Research has found that the quantity of fuel is strongly correlated with the head-fire rate of spread as well as the residence time of flame (Byram *et al.*, 1966; Cheney, 1981). Therefore, quantifying forest fuel load is essential for bushfire behaviour and effects models that require fuel load as one of the significant inputs for estimation of potential and ongoing fire behaviour and effects. Modeling fire behaviour is significant for predicting the area and perimeter growth forecasts, as well as assessing potential damage and difficulty of suppression (e.g. equipment needed to control ongoing fires).

Traditionally forest fuel load is measured directly by field sampling, oven drying for 24 hours at 105 °C (Loomis and Main, 1980; Pook, 1993; Pook and Gill, 1993; Cheney and Sullivan, 1997), and immediately weighing (Gould *et al.*, 2011). Directly measuring fuel load on a landscape scale requires extensive field inventories with samplings, post laboratory work and statistical inference, which can be labour intensive and time consuming (Brown and Bevins, 1986; Burgan *et al.*, 1998).

McArthur (1962) found a positive correlation between the depth of surface litter-bed and the dry weight of surface fuel, known as the depth-to-load relationship. This relationship has been used as a rapid alternative to the direct measurement of litter-bed fuel load for fuel hazard assessment in eucalypt forests (McCarthy, 2004). The litter-bed fuel depth is directly measured in areas where near-surface fuels do not obscure the litter using a simple depth gauge – a 15 cm circular disk with a ruler through a slot in the centre (McCarthy *et al.*, 1998; McCarthy, 2004). To use this gauge, a small gap is made in the litter bed down to mineral soil, and then the end of the ruler is placed resting on the mineral soil surface. The disk is pushed down with light pressure until its whole perimeter is in contact with the fuel. Five measurements of litter-bed depth are carried out at each site sized 10 m in radius (Wilson, 1992; Wilson, 1992; 1993). The average value of the five measurements is one of the attributes that can be used to determine the surface fine fuel hazard. However, the number of measurements taken in an area influences its accuracy, since large variations in surface fuel depth could be found at a site within a homogeneous vegetation community (McArthur, 1962; McCarthy, 1996; Gould *et al.*, 2014). In addition, the fuel depth-to-load relationship varies with sites due to the high-degree of natural variability of overstorey and understorey vegetation species, environmental conditions, as well as previous fire severity and intensity (McArthur, 1962; Birk and Simpson, 1980).

Fuel accumulates over time depending on the productivity of fuel and environmental conditions. Forest fuel accumulation models describe a simplification of the difference between rates of fuel accession and decomposition (Agee *et al.*, 1973). These model curves follow a general form of an exponential distribution (Peet, 1971; Birk and Simpson, 1980; Raison *et al.*, 1983; 1986; Gould *et al.*, 2011):

$$\mathrm{w_t} = \mathrm{w_{ss}}(1 - \mathrm{e^{kt}}) \qquad (1)$$

where $\mathrm{w_t}$ is defined as the dry weight of litter-bed fuel accumulated at time *t* (years since the last fire); $\mathrm{w_{ss}}$ is the dry weight of the fuel accumulated under steady state conditions; *k* is defined as the decomposition constant. The shape of this accumulation curve is determined by climatic conditions, vegetation species, and time since last fire.

Australian fire authorities also rely on fuel accumulation models for specific forest vegetation species to roughly estimate the amount of surface or litter-bed fuel growth after previous fire events to provide fire danger indices and also guide prescribed burns. Current forest fuel accumulation models are listed in Table 2. The application of fuel accumulation models is constrained by specific vegetation species and locations. Fire authorities and current bushfire studies have a common challenge in quantifying forest fuel load across landscape due to the extreme high variations in vegetation species, microclimate, and terrains (Gould *et al.*, 2008). Therefore, the development of more efficient, accurate and consistent methods to quantify forest fuel is an ongoing requirement of the Australian government for fire-hazard mitigation and forest ecosystem conservation.

Table 2. Summary of forest fuel accumulation models in Eucalypt communities Australia.

Dominant Vegetation Species	Location	Model	Rainfall (mm)	Studies
E. Pilularis	Seal Rocks, NSW	$X_t = 1.67\ (1\text{-}e^{-0.31t})$	1400	(Fox *et al.*, 1979)
E. radiata / E. rubida	Wombat State Forest, VIC	$X_t = 8.28\ (1.47\text{-}e^{-0.506t})$	-	(Tolhurst and Kelly, 2003)
E. obliqua / E. radiata	VIC	$X_t = 1.69\ (1\text{-}e^{-0.44t})$	700	(Simmons and Adams, 1986)
E. pauciflora / E. dives	Subalpine region	$X_t = 11.1\ (1\text{-}e^{0.11t})$	-	(Raison *et al.*, 1983)
E. delegatensis	Subalpine region	$X_t = 29.4\ (1\text{-}e^{0.31t})$	-	(Raison *et al.*, 1983)
E. crebra	Chilten, VIC	$X_t = 7.15\ (1\text{-}e^{-0.876t})$	685	(Chatto, 1996)
E. moluccana / E. macrophnra / E. signata	Cooloola, QLD	$X_t = 7.4\ (1\text{-}e^{-0.64t})$	-	(Sandercoe, 1986)

2.1.3.2 Fuel structure

Fuel structure is defined by horizontal continuity and vertical arrangement (Figure 1). Horizontal continuity of fuel load describes the arrangement of fuel across the surface; the vertical arrangement refers to the upward distribution of fuel in a vertical dimension. Compared to fuel load, forest fuel structure has different impacts on fire behaviour, including fire intensity, flame height, flame structure and duration, due to changing fuel vertical arrangement. Tightly packed fuel is less likely to burn and smolder due to the lack of oxygen, whereas loosely arranged fuel burns quickly with a higher flame as more aspects of fuel are exposed to oxygen. Consequently, quantifying both forest fuel load and fuel structure is important for studying bushfire behaviour and impacts.

Figure 1: Forest structure and vertical fuel layers. Adapted from (Gould *et al.*, 2008).

Australian bushfire studies (Cheney *et al.*, 1992; McCaw *et al.*, 2003) have developed a system to quantify fuel structure with a numerical index that can be used as a fuel predictor variable to replace fuel load. The rating system that assesses the relative hazard of fuel factors that affect fire behaviour and suppression difficulty represents a new approach in forest fuel assessment (McCarthy *et al.*, 1998). The fuel hazard rating system developed by Wilson (1992; 1993) and McCarthy et al (McCarthy *et al.*, 1998) assesses fuel hazards for distinct fuel layers including eucalypt bark, elevated shrub fuel, near-surface fuel and surface fuel in order to estimate an overall fuel hazard rating, which provides a simple, easy-to-use method for operational assessment of the hazard presented by forest fuel structures. This assessment highlighted the fuel complex by combining a hazard rating for each of the different fuel layers (Figure 1), by visualizing fuel characteristics and providing subjective scores to evaluate the potential hazards that each fuel layer may contribute to fire behaviour and its main effects (McCarthy *et al.*, 1998; Gould *et al.*, 2008).

The fuel hazard rating (low, moderate, high, very high, and extreme) is calculated for each structural layer of forest fuel in a plot from 10 - 20 m in radius based on key attributes, such as how bark is attached, quantity of combustible bark, percentage of plant cover, percentage of dead fuel, vertical continuity, horizontal connectivity, vegetation density, and thickness of fuel pieces (McCarthy *et al.*, 1998). Project Vesta also adapts the hazard scores to estimate the potential fire behaviour. The overall forest fuel hazard rating is determined by the assessed levels of bark, elevated and combined surface and near-surface fuel hazards (Gould *et al.*, 2011). However, the canopy fuel or overstorey fuel is not incorporated in the fuel hazard assessment, as the canopy fuel affects fire intensity and energy output, but has minor impacts on fire spread (Tolhurst *et al.*, 1996). In addition, the rapid fuel hazard assessment is designed for trained fire fighters and land managers to use in guiding prescribed burns rather than predicting fire hazard in actual fire events (Hines *et al.*, 2010). This visual-based technique for a rapid visual assessment of fuel characteristics has a broad range of applications in wildland fire management and research (Gould *et al.*, 2011), which is inconsistent and subjective (Brown *et al.*, 2011). The development of accurate and consistent methods to quantify forest fuel structural characteristics has significant implication in both fuel hazard assessment and fire behaviour modelling.

Our study aims to improve the consistency and efficiency of forest fuel measurements in terms of fuel structure and fuel load, in southeastern Australian eucalypt forests. As discussed in the introduction, fuel is the only contributor to fire behaviour that can be modified by humans. This study develops a more accurate and efficient approach to quantify forest fuel structures using remote sensing technologies, which can be used as an accurate alternative to the current methods to assess fuel hazards. It also evaluates how the forest fuel load relates to the fuel characteristics and environmental factors in the study area. In addition, it develops a predictive model to estimate fuel spatial variation in forest litter-bed fuel load on a landscape scale. The outcomes of the study are expected to have multiple applications, including better guidance of fire hazard-reduction burns, prediction of fire behaviour potential, improved surveillance of fuel growth, forest habitats and ecosystems. For instance, a landscape-fuel load map is beneficial for fire authorities to guide fire-related operational activities to reduce fire threats, as it may accurately and efficiently locate the specific area that requires fuel-reduction burns. The following chapter reviews the application of remote sensing technology in forestry.

2.2 Remote Sensing of Forest Fuels

2.2.1 Introduction

Accurate description of spatial variations in fuel conditions (e.g. fuel type, load, structure, size, moisture content and previous fire disturbance) is essential to the development of wildland fire management strategies at local, regional, and national scales (Chuvieco and Congalton, 1989; North *et al.*, 2009). Traditionally, forest fuel characteristics, for example fuel types and load were mapped through extensive field inventory with sampling and statistical inference, which was expensive, inefficient and error prone when extrapolated to a greater scale (Arroyo *et al.*, 2008). It has been considered as an impractical approach for land managers and government agencies (Falkowski *et al*., 2005). The limitation of the traditional method in terms of accuracy, cost and coverage results to a development of more efficient methods to map fuel types using remote sensing technologies (Arroyo *et al.*, 2008).

Remote sensing technologies, including passive and active systems, provide information with spatial continuity and varying scales. They potentially reduce the cost and time required to map forest vegetation and post fire effects (Skowronski *et al.*, 2007). Remote sensing is the acquisition of information about objects or areas from a considerable distance without physical contact with the objects, typically from satellites, aircraft and ground stations (Sabins Jr, 1978). It has been used to map topography, fuel types, fuel moisture content and also has the potential to map spatial variations in fuel composition and fuel load across a landscape (Rollins *et al.*, 2004; Saatchi *et al.*, 2007; Thenkabail *et al.*, 2012). Consequently, remote sensing application in forest fuel measurements assists fire behaviour modelling and fire danger rating, forest fuel management, and fire-related activates. This section reviews the existing literature on the application of both remote sensing systems in forest fuel measurements, and also evaluates their potentials and limitations in quantifying fuel load and structural characteristics.

2.2.2 Passive Remote Sensing

Passive sensors known as optical sensors do not emit radiation but detect natural energy that is reflected or emitted from the observed scene (Sabins Jr, 1978). Reflected sunlight is the most common external source of radiation sensed by passive sensors (Robert, 2007). The most common passive remote sensing imageries, for example Landsat, MODIS (Moderate Resolution Imaging Spectroradiometer), ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer), SPOT (Satellite for observation of Earth), CBERS (China–Brazil Earth Resources Satellite), Quickbird and RapidEye have been widely used in multiple forest applications. Current studies map fuel types and fuel moisture content using various passive remote sensing imageries (Riaño *et al.*, 2007; Arroyo *et al.*, 2008; Yebra *et al.*, 2013). Their lack of significant information about canopy heights and understorey vegetation leads to the integration with active remote sensing data or field-surveyed data to overcome this limitation.

2.2.2.1 Forest fuel type

Forest fuel types can be classified and mapped using various passive remote sensing data including multispectral and hyperspectral data through four primary methods. The initial approach is vegetation classification using either supervised classification, unsupervised classification or principal components (Kourtz, 1977). Fuel types are assigned according to the vegetation categories. This method produces accuracies of fuel type classification ranging from 65% to 80% (Chuvieco *et al.*, 1999). A more accurate method to classify fuel types was proposed by Cohen (1989), which used the tasselled cap transformation of Landsat TM multispectral data (Kauth and Thomas, 1976). The obtained accuracy of this method is 65% (Van Wagtendonk and Root, 2003), which can be increased to 86% by combining the Landsat TM data with ancillary data (e.g. Normalized Difference Vegetation Index - NDVI, slope, texture, illumination) (Riaño *et al.*, 2002; Fernandes *et al.*, 2006). Recent studies applied these two methods using very high resolution multispectral data (e.g. ASTAR, Quickbird, and IKONOS) (Andrews and Queen, 2001; Lasaponara and Lanorte, 2007) and hyperspectral data (e.g. AVIRIS and MIVIS) to increase the accuracy of fuel classification. Additionally, the object-oriented classification method is also adapted to map multispectral imagery-based fuel types (Giakoumakis *et al.*, 2002; Arroyo *et al.*, 2006; Gitas *et al.*, 2006). The hyperspectral imagery-derived forest fuel characteristics (e.g. fuel types, canopy closure, ratio of dead to live fuel materials, and fuel moisture content) can be estimated through Spectral Mixture Analysis (Roberts *et al.*, 1997; Cheng *et al.*, 2006). These passive remote sensing data are unable to reveal understorey vegetation and derive height information (Van Leeuwen and Nieuwenhuis, 2010). The reflectance of individual fuel types is not directly related to heights of overstorey and understorey vegetation (Riaño *et al.*, 2007); vegetation heights however are critical information to discriminate forest fuel types (Arroyo *et al.*, 2008). Therefore current studies fuse passive remotes sensing data with heights of understorey and overstorey vegetation derived from active remote sensing data sources (e.g. LiDAR data) to improve fuel type mapping (Riaño *et al.*, 2007; Mutlu *et al.*, 2008).

2.2.2.2 Forest fuel moisture content

Forest fuel moisture content is the mass of water contained within vegetation. It is one of the important components of fire danger rating systems and behaviour models, as it significantly impacts on the flammability of the fuel, combustion, the amount of available fuel and the rate of spread of a fire (Danson and Bowyer, 2004). Moisture content of dead fuel is highly correlated to temperature, humidity and wind speed, which can be easily estimated from weather danger indices (Saatchi *et al.*, 2007). However, the moisture content of live fuel for a specific fuel type varies spatially and temporally due to the interaction of plant physiology with soil moisture conditions as well as plant adaptations to longer term climate events (e.g. drought) (Chuvieco *et al.*, 2002). Traditionally, live fuel moisture content is determined by field sampling, which is time consuming and expensive (Pook and Gill, 1993). Studies found positive correlations between leaf water content and remote sensing vegetation indices (e.g. NDVI, Soil-Adjusted Vegetation Index - SAVI, Enhanced Vegetation Index - EVI, Visible Atmospherically Resistant Index - VARI, Water Index - WI and Global Vegetation Moisture Index - GVMI), as liquid water has strong absorption features in the near and shortwave infrared spectral regions (Ceccato *et al.*, 2001; Danson and Bowyer, 2004; Yebra *et al.*, 2008). Therefore, the passive remote sensing data has the advantage of efficiently estimating the spatial distribution of live fuel moisture content at a fairly greater scale compared with the traditional method.

2.2.3 Active Remote Sensing

Although forest fuel types and moisture content of fuel could be interpreted based on the reflectance using passive remote sensing data, current studies share a common challenge in accurately describing physical properties of forest fuel (e.g. fuel load, sizes and structure) (Pyne *et al.*, 1996). Forest vegetation biomass as well as horizontal and vertical position are among the key predictors to forest fire intensity, flame height and burn severity (Gould *et al.*, 2011). The technology development in active remote sensing allows more accurate and efficient description of forest fuel structural characteristics and estimation of crown fuel load over a large area with a fine spatial resolution.

In contrast to the passive sensors, active sensors emit radiation towards the target to be detected, which require a large amount of energy for illumination (Campbell and Wynne, 2011), such as radio detection and ranging (radar) and light detection and ranging (LiDAR) technologies. A radar sensor uses a transmitter to emit electromagnetic radiation to distant objects at either radio or microwave frequencies (Waring *et al.*, 1995). A directional antenna is applied to measure the time of arrival of the reflected or backscattered pulses of radiation to calculate the distance to the objects using the speed of light (Skolnik, 1962). Airborne radar data can be used to estimate forest stand height, canopy fuel load, crown closure, and canopy bulk density (Waring *et al.*, 1995; Saatchi *et al.*, 2007). Similarly, a LiDAR sensor uses a laser to transmit a light pulse and a receiver with sensitive detectors to measure the backscattered or reflected light from a target (Sampath and Shan, 2007). The distance to the target is determined by the time between the transmitted and backscattered pulses at the speed of light (Dubayah *et al.*, 1997). Studies found airborne LiDAR data could be useful for forest inventory, including canopy height measurements (Næsset and Bjerknes, 2001), estimation of diameter of breast height (DBH) and basal area (Simonse *et al.*, 2003; Næsset, 2004; Maas *et al.*, 2008; Hyyppä *et al.*, 2009; Moskal and Zheng, 2011), as well as delineation of individual trees for tree height measurements (Brandtberg *et al.*, 2003; Popescu *et al.*, 2003; Koukoulas and Blackburn, 2005; Chen *et al.*, 2006; Popescu, 2007), which provide a potential opportunity to quantify three-dimensional forest fuel structure more efficiently and accurately.

LiDAR application in forestry is usually categorised as either discrete return or fuel waveform systems depending on how they vertically (e.g. the number of range samples recorded for each individual emitted laser pulse) and horizontally (e.g. footprint sizes and number footprint/hits per unit area) sample forest structure (Lim *et al.*, 2003). A discrete return LiDAR system known as multi echo airborne LiDAR system allows for one or more returns to be recorded for each laser pulse during a measurement; the number of the returns determines the amount of detail about forest vegetation that is present in a laser footprint (Dubayah and Drake, 2000). A single return system is useful for canopy height estimates; a multi echo LiDAR system provides point cloud data, and captures understorey vegetation and terrain features (Dubayah and Drake, 2000). In contrast, a full waveform airborne LiDAR system records the amount of energy returned to the sensor for a series of equal time intervals; the amplitude-against-time waveform is constructed from each time interval and is representative of forest vertical interception

(Chauve *et al.*, 2007). The following sections describe the current studies that use the radar and LiDAR data to quantify crown fuel characteristics and forest vertical structure.

2.2.3.1 Crown fuel

In general, forest fires are classified as two main types of wildland fires including surface fire and crown fire (Scott and Reinhardt, 2001). Surface fire is defined as the combustion of the fuel above the ground surface and within understorey fuel layers (Brown *et al.*, 1982); crown fire is more difficult to control due to the extension of the combustion to overstorey fuel layers (Wagner, 1977). Crown fuel can be quantified in numeric terms of canopy fuel weight, canopy closure, canopy bulk density, canopy cover, foliage moisture content, canopy height and canopy base height (Scott and Reinhardt, 2001). Although radar sensors have not been widely applied in fire-related operational activities globally, studies have found the potential of providing quantitative information about the forest overstorey vegetation biomass and structure that can be used to estimate live fuel moisture content and crown fuel when operating at microwave frequencies (Saatchi and Moghaddam, 2000). Radar backscatter signals at linear polarizations (horizontal and horizontal, horizontal and vertical, and vertical and vertical for transmit and receive configurations, respectively) are sensitive to the three-dimensional canopy profile, which can resonate with the radar wavelength at low frequencies ranging from 400 to 1500 MHz (Saatchi *et al.*, 2007).

Crown fuel load is the total dry weight of crown biomass including foliage and thin branchwood, which is traditionally calculated based on empirical allometric equations for specific forest fuel types (Brown, 1978). Passive remote sensing and radar provide efficient alternative approaches to the field measurement-based equations through leaf area index measurements (Fassnacht *et al.*, 1994) and biomass estimates (Saatchi and Moghaddam, 2000), respectively. Radar-derived biomass can be estimated from the statistical correlation of radar backscatter measurements at different frequencies and polarizations with forest biomass acquired from field measurements (Dobson *et al.*, 1995).

Crown structural characteristics can be described as tree size, canopy bulk density, canopy height and canopy base height, and canopy closure, which mainly affect flame height, intensity and spread of crown fire (Wagner, 1977). Canopy height can be identified by the inversion of physically based backscatter models derived from airborne radar or LiDAR data (McGaughey *et al.*, 2004). Crown base height is considered as the vertical distance between the ground and the base of the live crown, which determines the threshold for transition from surface fire to crown fire (Dean *et al.*, 2009). The estimation of crown base height using radar or LiDAR techniques could be performed either by analyzing the waveform of backscatter signal or by regression models (Riaño *et al.*, 2003; Andrews *et al.*, 2005; Ferraz *et al.*, 2009).

Current studies indicate the potential use of airborne full waveform LiDAR data to estimate forest vertical profile (Lefsky *et al.*, 2002; Persson *et al.*, 2005; Wagner *et al.*, 2006; Hermosilla *et al.*, 2014); however, it is restrictive in representing crown fuel characteristics, including canopy closure and crown bulk density (Coops *et al.*, 2007). Canopy closure is defined as the progressive reduction of space between crowns, which influences the fire behavior by affecting the amount of fuel available for a crown fire, as well as changing fuel moisture content and wind speed below the canopy ultimately influencing a surface fire (Ferraz *et al.*, 2009). Canopy closure of single layered forests could be obtained from optical data, while the underlying shrubs and grass may increase the difficulty of estimation (Means *et al.*, 1999; Chuvieco, 2003). Multi echo LiDAR-derived canopy closure is typically determined by the number of canopy reflections divided by all reflections from overstorey, understorey and ground over a unit area (Means *et al.*, 1999; Chuvieco, 2003; Riaño *et al.*, 2003). Canopy bulk density is the mass of available fuel per unit canopy volume that can be computed as crown biomass divided by canopy height. The spatial accuracy and efficiency of crown fuel load and structure estimates derived from radar data can be increased by LiDAR point cloud data (Drake *et al.*, 2002; Andrews *et al.*, 2005; Hyde *et al.*, 2005; Persson *et al.*, 2005).

2.2.3.2 Understorey fuel

Understorey fuel including elevated, near-surface and surface or litter-bed fuel layers significantly affect the surface fire intensity, flame height, flame structure and duration, due to changing vertical continuity of fuel availability (Gould *et al.*, 2008). Understorey fuel structural characteristics are the key criteria to assess eucalypt forest fuel hazards in Australia (McCarthy, 1996). Currently, the structural characteristics (e.g. plant height and cover at individual fuel layers) are described in numeric terms by field observers based on visual assessment in order to determine the overall fuel hazard in a forest (Watson *et al.*, 2012). This visual assessment is acceptable when roughly predicting fuel hazards over a landscape scale; however, it can be bias prone when used as an input to fire behaviour models, such as Vesta (Gould *et al.*, 2008). Therefore, an innovation of accurate quantification of understorey fuel structural characteristics is needed for a sound forest fuel management.

In multilayered forests, forest understorey fuel layers are shadowed by the overstorey vegetation, which increases the difficulty in quantitatively describing these fuel layers using remote sensing data. Optical remote sensors fail to distinguish understorey vegetation from canopy due to the two dimensional description of forest vegetation (Waring *et al.*, 1995; Carlson and Ripley, 1997; Turner *et al.*, 1999). A radar sensor provides three-dimensional information on forest vertical structure, but its sensitivity and spatial accuracy to structural changes through forest vertical succession decrease with increasing canopy density and understorey vegetation biomass (Dubayah and Drake, 2000; Lefsky *et al.*, 2002). The new generation of active remote sensing systems – LiDAR has higher spatial accuracy and frequency that allows a complete representation of forest vertical structure (Van Leeuwen and Nieuwenhuis, 2010).

The extraction of understorey fuel characteristics derived by remote sensing technologies is not well understood in current literature. Fine fuel loading with fuel particles sized 0 - 6 cm requires small footprint and high resolution of LiDAR data (Hermosilla *et al.*, 2014). Large footprint LiDAR has significant difficulties to detect low vegetation biomass cover, as the signal disparities between low fuels and the ground are difficult to separate (Næsset and Bjerknes, 2001; Chauve *et al.*, 2007). Full waveform small footprint LiDAR technologies permit extraction of low vegetation signal within the understorey, the waveform detection however allows an accurate determination of the peaks of overlaid pulses down to a target separation of about 0.5 m (Hug *et al.*, 2004; Persson *et al.*, 2005). Therefore, a full waveform LiDAR sensor has difficulty in separating understorey fuel layers, and fails to estimate plant cover and depth of understorey fuel at distinct fuel layers.

In the USA, ladder fuels (above the litter-bed layer and under the crown fuel layer) are typically estimated by empirical equations that are developed based on stand canopy base height for a specific forest fuel type as a substitute of the direct measurement (Andrews, 1986). The canopy base height can be computed through either intensive sampling in the field or airborne LiDAR measurement of canopy heights (Scott and Reinhardt, 2001); however, the empirical equations are restricted by forest fuel types and locations (McAlpine and Hobbs, 2014). In practice, the canopy based height has not been well defined (Mitsopoulos and Dimitrakopoulos, 2014). Current studies found that height metrics derived from airborne LiDAR point clouds (vertically ranging from 1 m to 4 m with 1 m intervals) are strongly correlated to field measured shrubby ladder fuel height and cover within these individual height classes in mixed conifer forests (Skowronski *et al.*, 2007; Clark *et al.*, 2009; Wing *et al.*, 2012). These studies indicate that

LiDAR point cloud data allows accurate description about shrubby or elevated fuel height and cover.

A multi echo airborne LiDAR sensor allows a three dimensional forest structural measurement based on multiple pulse returns leading to a limitation in detecting forest surface or litter-bed fuel when fewer pulses reach the forest floor in a very dense forest. The litter-bed fuel load affects fire ignition and rates of fire spread, which are key information for fire danger rating and fuel hazard assessment. Terrestrial LiDAR sensors have the potential to overcome these limitations as they produce point clouds of higher density and higher laser ranging accuracy than airborne LiDAR systems (Simonse *et al.*, 2003). They can scan a full hemisphere from a point on the canopy floor to tree stem and foliage.

Terrestrial LiDAR application in forestry has focused on forest inventory estimates at a fine resolution but at smaller scales (Bellian *et al.*, 2005; Dassot *et al.*, 2011). Similar to airborne LiDAR overlapping flight lines, overlapped scans using the tripod-mounted devices are also often found in forest applications in order to increase the size of the scanning sites and improve the detection accuracy of vegetation further away from the scanning positions (Hopkinson *et al.*, 2004). Many mathematical morphology techniques, such as the Hough-transformation and circle approximation were tested for tree stem identification (Simonse *et al.*, 2003; Pfeifer and Winterhalder, 2004; Henning and Radtke, 2006; Maas *et al.*, 2008; Moskal and Zheng, 2011). A tree topology skeleton algorithm was developed to reconstruct a three-dimensional tree structure by fitting a sequence of overlapping cylinders in point clouds to model stem and some major branches of a tree for a wood volume estimation (Pfeifer and Winterhalder, 2004). Côté et al. (2009) applied the three-dimensional Monte Carlo ray-tracing model Rayspread (Widlowski *et al.*, 2006) to estimate the wood area and the leaf area. Hosoi and Omasa (2006) used the voxel-based three-dimensional model to estimate leaf area density. Although these studies did not use terrestrial LiDAR data to retrieve or reconstruct a forest structure, they demonstrated that terrestrial LiDAR has the potential to present understorey fuel structure more accurately on a very fine resolution (e.g. cm or mm).

For bushfire-related studies, using terrestrial LiDAR data to classify fuel structure and to quantify understorey forest fuel structural characteristics (e.g. depth, cover, and volume) is still an emerging field. Marselis et al. (2016) successfully separated forest fuel layers (canopy, tree trunks, elevated shrubs and near-surface vegetation) according to the vertical connection of a laser point's representation in eucalypt forest vegetation. They used a handheld LiDAR device (Zebedee). However, the litter-bed fuel layer could not be identified in their study, and the method was tested in a simple-structured young forest that has flat terrain and relatively low overstorey and understorey vegetation (Marselis *et al.*, 2016). In reality, dense and mature forests with steep slopes tend to have higher forest fire danger rates. Therefore, this method requires testing in forests with various fire history and complex terrain features. In conclusion, current bushfire fire-related studies and operational activities share common challenges in quantifying litter-bed fuel load as well as understorey fuel strata classification.

2.2.4 Conclusion

Remote sensing technologies allow forest fuel measurements to be more time effective, objective, and cheaper as they provide accurate and consistent information about forest fuel characteristics across a large area with a fine resolution. Active remote sensing derived forest fuel type classification and fuel moisture content estimates have been applied for fire danger rating and fire spread modelling. Many studies found that active remote sensing data including airborne radar and LiDAR data can be used to efficiently and accurately quantify crown fuel characteristics at a landscape scale. They also overcome the limitations of the passive remote sensing systems that only provide two-dimensional imagery of forest canopy and cannot penetrate the forest canopy to detect understorey vegetation. However, remote sensing application in understorey fuel structure measurements as well as litter-bed fuel load estimates have not been well studied.

Forest fuel reduction treatments (e.g. prescribed burns) require accurate information about understorey fuel growth after previous fire events. Results of an overall forest fuel hazard assessment are determined by an accurate description about understorey fuel cover and depth of distinct fuel layers including elevated, near-surface and litter-bed fuel layers. Litter-bed fuel load is one of the most significant forest fuel characteristics required by fire danger rating systems and surface fire spread models. In conclusion, an accurate and efficient approach to classify fuel layers and quantify understorey fuel characteristics including fuel load, depth and cover underpins sound forest fuel management to mitigate fire threats to our community and environment. Therefore, this project aims to develop a novel method to quantify understorey fuel more accurately and efficiently using LiDAR data. Improved fuel characterisation will be of benefit to the fire agencies and land managers in their fire risk planning and therefore potentially resulting in better fire management decision-making.

Chapter 3 statement

Chapter 3 has been published in the Journal of Applied Remote Sensing in 2016. This chapter describes forest fuel strata classification using TLS data. In this study, an automatic tool for forest fuel strata classification has been developed in order to accurately extract forest fuel structural characteristics based on integration between GIS and TLS data. It provides a consistent and accurate alternative to visual assessing techniques described in the current fuel hazard assessment guides and fire behaviour models. The accurate description of forest structural characteristics obtained by this method benefits bushfire-related operational activities and the development of fire behaviour models.

Chapter 3. Strata-based forest fuel classification for wild fire hazard assessment using terrestrial LiDAR data

Abstract

Fuel structural characteristics affect fire behaviour including fire intensity, spread rate, flame structure and duration, therefore quantifying forest fuel structure has significance in understanding fire behaviour as well as providing information for fire management activities (e.g. planned burns, suppression, fuel hazard assessment and fuel treatment). This paper presents a method of forest fuel strata classification with an integration between terrestrial light detection and ranging (LiDAR) data and Geographic Information System (GIS) for automatically assessing forest fuel structural characteristics (e.g. fuel horizontal continuity and vertical arrangement). The accuracy of fuel description derived from terrestrial LiDAR scanning (TLS) data were assessed by field measured surface fuel depth and fuel percentage covers at distinct vertical layers. The comparison of TLS-derived depth and percentage cover at surface fuel layer with the field measurements produced *RMSE* values of 1.1 cm and 5.4%, respectively. TLS-derived percentage cover explained 92% of the variation in percentage cover at all fuel layers of the entire dataset. The outcome indicated TLS-derived fuel characteristics is strongly consistent with field measured values. TLS can be used to efficiently and consistently classify forest vertical layers to provide more precise information for forest fuel hazard assessment and surface fuel load estimation in order to assist forest fuels management and fire-related operational activities. It can also be beneficial for mapping forest habitat, wildlife conservation and ecosystem management.

Keywords: TLS, GIS, canopy height, Eucalyptus spp.

3.1 Introduction

The development of accurate and reliable methods to quantify forest fuels is an ongoing requirement of government and fire authorities, due to continual need for improvement in fire resource management (Gould *et al.*, 2008). In Australia, fuel characteristics are usually assessed and described in numerical terms by fuel loading, fuel depth, and fuel particle density (McArthur, 1962; McCaw, 1991). Traditional fuel assessment relies on destructive measurement by directly measuring dry weight of total live and dead biomass per unit area, particularly fine litter fuel (Peet, 1971; Fox *et al.*, 1979; Raison *et al.*, 1983; Simmons and Adams, 1986), often defined in Australia as those fuel particles less than 6 mm in diameter. This is a required input to the McArthur empirical rate of spread model for eucalypt forests(Luke and McArthur, 1978; Watson *et al.*, 2012). However, these direct measurements are time and labor intensive (Keane *et al.*, 2001; Sandberg *et al.*, 2001; Maas *et al.*, 2008; Chen *et al.*, 2011; Gould and Cruz, 2013). An Australian bushfire study, Project Vesta, identified the importance of fuel structural characteristics in determining fire behaviour and ease of suppression, rather than fine fuel load (Gould *et al.*, 2008). Fuel structure is comprised of five layers based on their horizontal arrangement and vertical position in the forest profile, including canopy fuels, shrubby elevated fuels, near-surface fuels, litter fuels (surface fuels), and bark fuels (Gould *et al.*, 2008). Currently, guidelines for fuel structure measurement through visual assessment have been developed for southeastern Australia and Western Australia, through the Overall Victorian Fuel Hazard Assessment Guide and Project Vesta, respectively. The visual assessment of fuel structural characteristics (e.g. fuel depth, height, percentage cover, horizontal continuity and vertical arrangement) at distinct fuel layers are rapid; however it can be subjective, inconsistent and also be restricted by local complex terrain. Therefore, an efficient and accurate method to assess fuel structural characteristics is a significant need in bushfire-related studies and forest fuel resources management (Dubayah and Drake, 2000; Lim *et al.*, 2003; Andersen *et al.*, 2005; Gould *et al.*, 2011).

Light Detection and Ranging (LiDAR) can be used to reconstruct the vertical overstorey and understorey vegetation arrangement due to its capability of three-dimensional (3D) measurements with high accuracy (Lefsky *et al.*, 2002; Lim *et al.*, 2003; Popescu *et al.*, 2003; Andersen *et al.*, 2005). Airborne Laser Scanner (ALS)-derived canopy height models (CHMs) have been used to describe canopy height distribution (Naesset, 1997; Gaveau and Hill, 2003; Pitkänen *et al.*, 2004; Andersen *et al.*, 2005) and to identify individual tree heights (Popescu *et al.*, 2003; Pitkänen *et al.*, 2004; Suárez *et al.*, 2005; Koch *et al.*, 2006; Popescu, 2007). Moreover, LiDAR-derived vertical distribution of forest structures provides a new perspective to describe canopy profile. Recent studies, including for example that of Hermosilla et al. (2014) and Jakubowksi (2013), described vertical profile of forest vegetation using theoretical distribution functions of ALS-derived indices. In these studies, lower vegetation (< 3 m) were excluded in the vertical description of forest structure, the authors argued the complete vegetation profile including the removal points would not follow the theoretical distribution. However, the lower vegetation including elevated shrubs, near-surface grass and surface litter fuel are significant fuel structural components, which directly impact on fire ignition and its rate of spread. ALS has limitations in detecting understorey fuels in multilayered forests, since the emitted laser beams have difficulty in penetrating the upper canopy to hit the ground with the majority of the energy reflected back to the sensor from overstorey vegetation (Lefsky *et al.*, 2002; Zimble *et al.*, 2003; Devereux *et al.*, 2005; Liu, 2008). In this context, terrestrial LiDAR scanning (TLS) can be used as a substitution of ALS for description of shadowing effected understorey vegetation (Dassot *et al.*, 2011).

Several studies have evaluated the significant improvement of using TLS (e.g. static and mobile TLS) in reducing the shadowing effects of overstorey vegetation to detect understorey fuel.

TLS changes the scanning angles and positions from top of canopy to understorey, which allows the majority of energy from laser beams to directly reflect back to the laser sensor from the lower (live and dead) vegetation, it also improves the spatial accuracy up to millimetres (Thies and Spiecker, 2004). The survey sizes, however, can be restricted within the given scanning scales (vertical and horizontal) of the survey instruments (Bellian *et al.*, 2005; Dassot *et al.*, 2011). Overlapped scans using the static (e.g. tripod mounted) devices are also often found in forest applications in order to increase the size of the scanning sites and also to improve the accuracy of further vegetation away from the scanning positions (Hopkinson *et al.*, 2004). The overlapping scans are not necessary when using mobile TLS, since it utilises a navigation module to determine the position of each laser beam when the laser takes measurements of the environment (Ryding *et al.*, 2015). The vegetation measurements derived from TLS can be utilized as a basis for assessing biophysical tree parameters that include tree heights, diameter at breast height (DBH), woody volume and leaf area (Loudermilk *et al.*, 2009; Newnham *et al.*, 2015).

Studies found that static TLS-derived mathematical morphology techniques (e.g. Hough-transformation, circle approximation, and locating arc centre algorithm) could be used to estimate DBH accurately and consistently (Besl and McKay, 1992; Simonse *et al.*, 2003; Aschoff and Spiecker, 2004; Pfeifer and Winterhalder, 2004; Henning and Radtke, 2006; Maas *et al.*, 2008; Côté *et al.*, 2009; Moskal and Zheng, 2011). A proof of concept test conducted by Ryding et al. (2015) demonstrated the ability of mobile TLS (including Zebedee and FARO) to extract DBH and stem position using circle approximation. The DBH and the stem position derived from Zebedee achieved a *RMSE* value of 1.5 cm and 2.1 cm, respectively. The maximum measurement error stated by the manufacturer is 3 cm at a range up to 10 m (Bosse *et al.*, 2012). Consequently, mobile TLS-representation of tree trunks can assist forest fuel strata classification.

Other studies have described estimating woody volume and leaf area by reconstructing tree structures using TLS-based 3D modelling. For instance, tree topology skeleton algorithms for estimating woody volume of main branches were proposed by Gorte and Pfeifer (2004). They fitted a sequence of overlapping cylinders in point clouds to model stem and some major branches of a tree. Côté et al. (2009) applied the 3D Monte Carlo ray-tracing model Rayspread (Widlowski *et al.*, 2006) reconstruction modelling to estimate the woody area and the leaf area. These methods, however, have yet not been validated with ground data (Thies and Spiecker, 2004; Moskal and Zheng, 2011). Hosoi and Omasa (2006) used a voxel-based 3D model to estimate leaf area density (LAD). In their study, the best LAD estimates showed errors of 17% at minimum horizontal layer thickness and 0.7% at the maximum thickness, respectively. Xu et al. (2007) represented tree trunks and main branches using polygonal meshes derived from TLS. This approach has only been tested by scanning of Elm, Ash, and Cottonwood trees (Xu *et al.*, 2007).

Consequently current methods developed to detect information of understorey vegetation have restrictions on operational use to assess forest fuel structures, because they are invalid for fuel strata-based classification, tree species or specific forest fuel types. For bushfire-related studies, using TLS to classify fuel structures and quantify understorey forest fuel structural characteristics (e.g. depth, cover, and volume) is still in an early stage. Litter-bed depth highly varies among plots; TLS is sensitive to height variation than traditional point intercept sampling (Loudermilk *et al.*, 2009). Loudermilk et al. (2009) also found TLS voxel-based fuel volume estimates were linear correlated with biomass and leaf area distribution for individual shrubs when influenced by species, size and plant section. A transition from grass clumps, low forbs, and shrubs to grass seed heads and taller shrubs was determined by a derivative function on the frequency values of the fuel height (< 0.5 m) distribution derived from TLS (Rowell *et al.*, 2016). Marselis et al. (2016) used the circle fitting method to identify the tree trunks from elevated shrubs in a young open eucalypt forest. Their study successfully separated distinct vertical fuel layers, including canopy, tree trunks, elevated shrubs and near-surface vegetation, according to vertical connection of laser point's representation in forest vegetation. This method, however, was only assessed in a simple-structured young forest that has flat terrain and relatively low overstorey and understorey vegetation. More tests are essential in dense and mature forests with complex terrain features.

Our study proposed an integrated method of TLS and GIS for an automatic classification of eucalypt forest fuel structures and quantification of understorey fuel structural characteristics, including surface fuel depth and percentage cover of fuel at individual fuel layers. This method provided an efficient and consistent alternative to visual assessment for fuel layer classification in multi-layered eucalypt forest with complex terrain features, in order to assist fuel hazard assessment, forest fuels management, and bushfire-related activities across study area.

3.2 Materials and Methods

3.2.1 Study Area and Data

The study area is located at Upper Yarra Reservoir, Victoria, in south-eastern Australia (37°34'32''S, 145°56'17''E) (Figure 1), which is a eucalyptus open forest with a shrubby understorey. It has a large range of indigenous eucalypt species which include, Manna Gum (e.g. *Eucalyptus viminalis*), Grey Gum (e.g. *Eucalyptus cypellocarpa*), Messmate (e.g. *Eucalyptus obliqua*), Peppermint (e.g. *Eucalyptus croajingolensis*, *Eucalyptus dives*, *Eucalyptus elata*, *Eucalyptus radiata*), Silvertop (e.g. *Eucalyptus sieberi*), Stringybark (e.g. *Eucalyptus baxteri*, *Eucalyptus cephalocarpa*, *Eucalyptus globoidea*), and Candlbark Gum (e.g. *Eucalyptus rubida*), and mixed understorey species (e.g. *Calochlaena dubia*, *Acacia dealbata*, *Acacia myrtifolia*, *Coprosma quadrifida*). The elevation ranges from 219 m to 1205 m; the slope ranges from 0 to 60 degree; the average annual rainfall is approximately 1122 mm and the main soil type is clay loam.

Our study sites consisted of six plots of 50 m by 50 m with different terrain features and fire histories. Controlled burns have been conducted as a typical fuel-management activity in this area, and wildfires also occurred over time after recovery from the Black Friday fires of 13th January 1939. Plot 1 and plot 2 and plot 3 experienced wildfires in February 2009; plot 4, plot 5, and plot 6 underwent controlled burns in March 2010, April 2008 and April 2007, respectively.

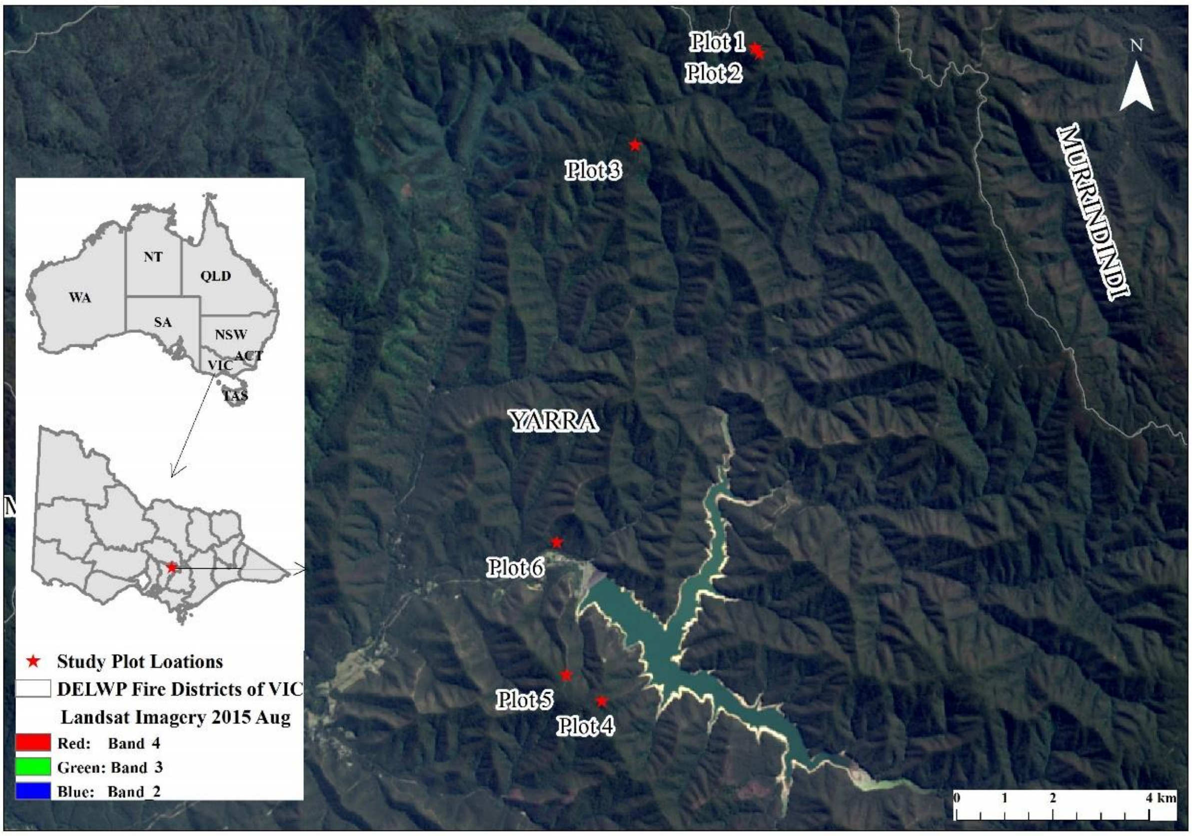


Figure 1. Study plot locations.

The TLS data covering these six plots were acquired from April to May 2015 using a Zebedee three-dimensional Mapping System developed by CSIRO Australia. The device consists of a lightweight laser scanner with a maximum 30 m scanning range, and a micro-electromechanical systems inertial measurement unit mounted on a simple spring mechanism (Bosse *et al.*, 2012). As an operator holding the device moves through the environment, the scanner loosely oscillates about the spring, therefore producing a rotational motion that converts the laser's inherent 2D scanning plane into a local 3D field of view. Walking slowly through each plot allows detailed, spatially extensive laser data to be collected. The scanning time is about 20 to 30 minutes for each plot depending on the accessibility and the local topography and the trajectory; point density can be increased by increasing scanning time.

Field data, including fuel depth (height) and percentage cover at surface fuel layer, near-surface fuel layer, and elevated fuel layer, were collected simultaneously with the TLS survey. For each plot, random samplings were chosen in order to validate the accuracy of fuel assessment derived from the TLS data. The sample size for each plot varies from 5 to 8 depending on the local environment and accessibility. The sampling fuels were directly measured and assessed within a 1 m by 1 m frame. The surface fuel depth (cm) was directly measured in areas where near-surface fuels did not obscure the litter using a simple depth gauge - a 15 cm circular disk with a ruler through a slot in the centre(Deeming *et al.*, 1977). The finalised depth was determined by averaging five measurements within the frame. The depth was determined by an average value of five measurements at each site and fuel coverage was assessed visually. Both fuel characteristics were collected based on the criteria from Victorian Overall Forest Fuel Hazard Assessment Guide.

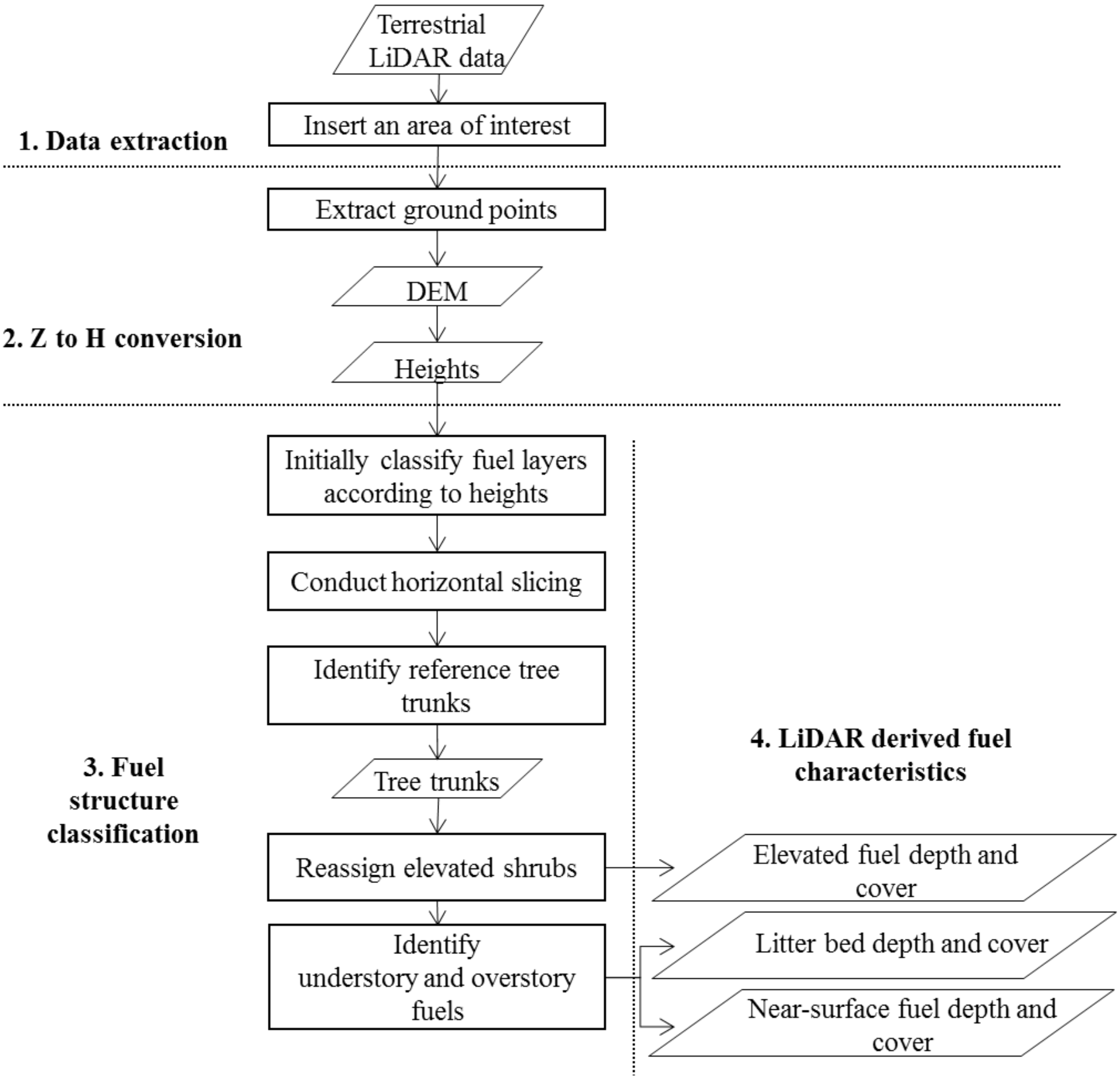


Figure 2. TLS-derived fuel strata classification.

3.2.2 Methods

The integration between LiDAR and GIS-based method for an automatic forest fuel strata classification can be described in the following processing steps: converting elevation data to height values (*Z* to *H* conversion), fuel structure classification, and LiDAR derived fuel characteristics (Figure 2). These processing procedures were scripted and automated in ArcGIS ModelBuilder. The algorithm is illustrated as below.

3.2.2.1 Z to H Conversion

After the LiDAR point clouds are extracted for the selected area, a digital elevation model (DEM) is generated which is used to convert the elevation value of each point (*Z*) to its height value above the bare earth (*H*). The DEM is generated through interpolation according to the lowest point within a 1 m by 1 m grid in order to keep consistency with the field measurements. The values of *H* are calculated by subtracting a smoothed DEM from the *Z* values for further fuel structure classification and assessment.

3.2.2.2 Fuel Structure Classification

Forest fuel layers are separated and grouped based on the spatial continuity of the forest bio-physical knowledge. As shown in Figure 2, the fuel structure classification method involves the following steps:

1) Classification of surface fuel and near surface fuel.

   Surface fuel is known as litter fuel, predominantly horizontal in orientation. Near-surface fuel, on the other hand, has a mixture of vertical and horizontal orientations. The frequency plot of TLS points against height ($h < 0.5$) (Rowell *et al.*, 2016) tends to follow a bimodal distribution. The division point of the bimodal curve is identified by derivative functions. These two fuel layers are then separated by the identified division point.

2) Initial classification of elevated shrub fuels (0.5 m - 2 m) and overstorey fuels (greater than 2 m).

   The fuel layer classification based on only the height information is illustrated in Figure 3. By applying the initial classification directly to the LiDAR points, tall shrub fuels may be incorrectly assigned as overstorey fuels; low shrub fuels may also be misclassified as near-surface fuels; trunks cannot be classified by this simple step which creates the difficulty of separating the trunks from overstorey fuels. These misclassified and unclassified points need to be reassigned according to their vertical and horizontal continuity.

3) Horizontal slicing the initially classified laser points into groups based on a height interval. Diameters of tree trunks do not change much within the 1 m interval of height (Gorte and Pfeifer, 2004). The smaller the interval requires longer processing time. For the processing efficiency, *1* m is chosen as the height interval; each sliced point layer (*l*) has 1 m height thickness. The sliced point layers will be used for the reference tree trunk identification where *li* (*i* = the number of height intervals) ranges from 0 to the maximum height of the canopy.

4) Identification of reference trunks through locating closest points between two of the discontinued slices as shown in Figures 4a, b and c.

   The two slices are selected from the initially classified overstorey fuels with the height range between 2 m (minimum height of the overstorey in the study area) and *h* (the minimum height of the tree branches). The *h* values can be estimated based on empirical information (e.g. the species and the forest age). We assume that trunks from the two sliced point layers have linear relationships when they are projected to two dimensions according to the x and y coordinates of the laser points. For example, in Plot 1, slice *l3* with the height range of 2 m to 3 m is shown in Figure 4a and slice *l9* with the height range from 8 m to 9 m is shown in Figure 4b. The reference tree trunks can be identified by searching for the closest points within a threshold, *r*. The threshold (*r*) is defined according to the footprint size of the laser system. We used a value of 0.02 m for r in our calculations. The laser points representing tree trunks from the discontinued slices as shown in Figure 4c, are then used as a reference to search for the trunks from each slice.

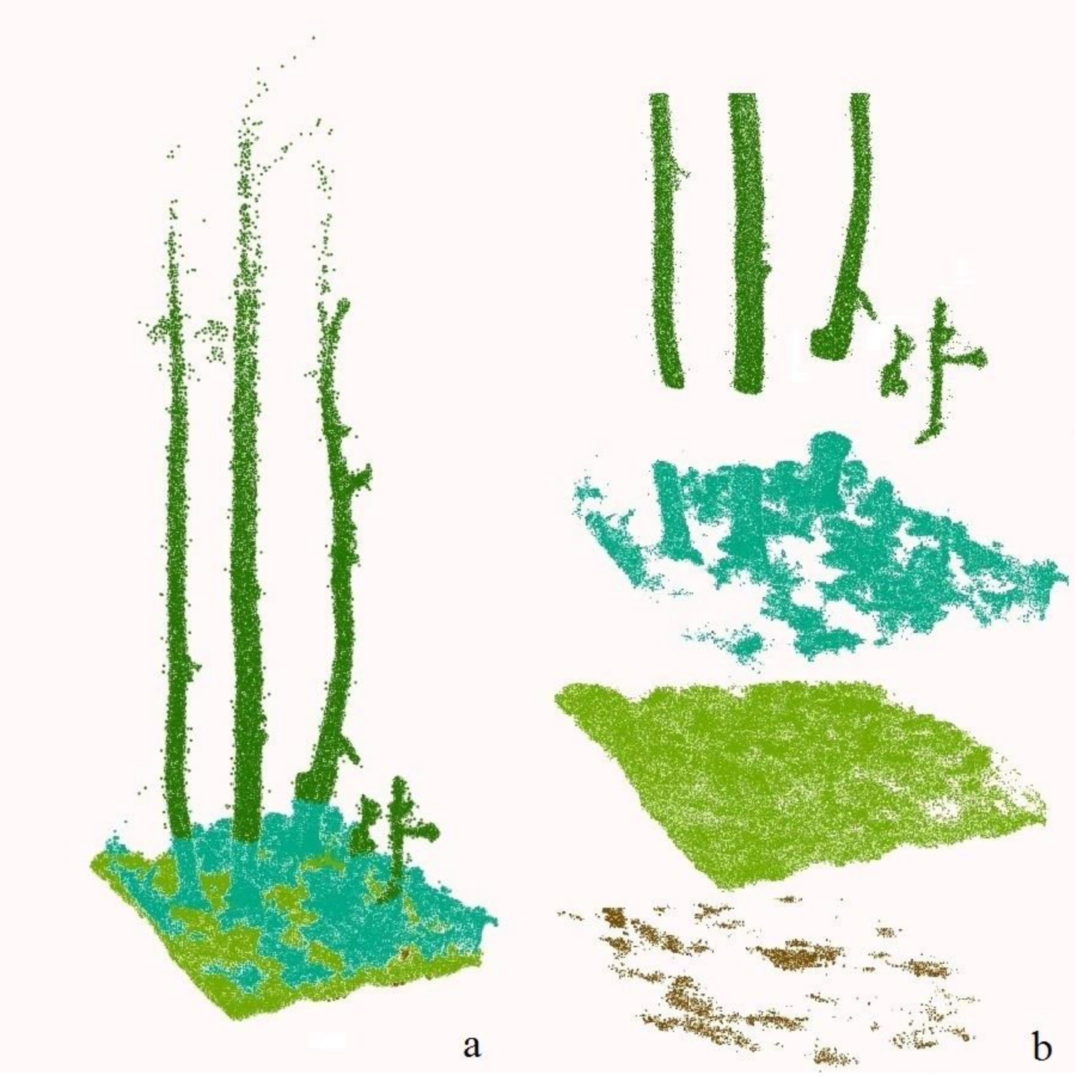


Figure 3. Fuel layer classification based on vertical height ranges. 3a. An overview of the initial classification based on height ranges; 3b. The initially classified fuel strata from top to bottom, including overstorey fuel, elevated fuel, near surface fuel, and surface fuel.

5) Searching tree trunks from other slices using the reference trunks.

Using the above example, the identified points from slice l_9 act as a reference trunk layer to determine other points from the neighbouring slices l_{10} and l_8 by searching their closest point upwards and downwards against slice l_9. The determined points from the neighbouring slices then are assigned and grouped into the reference layer to continue the searching procedure upwards and downwards, till no further trunks can be identified and assigned. The assigned trunks from these slices are then merged together for next classification step (Figure 4d).

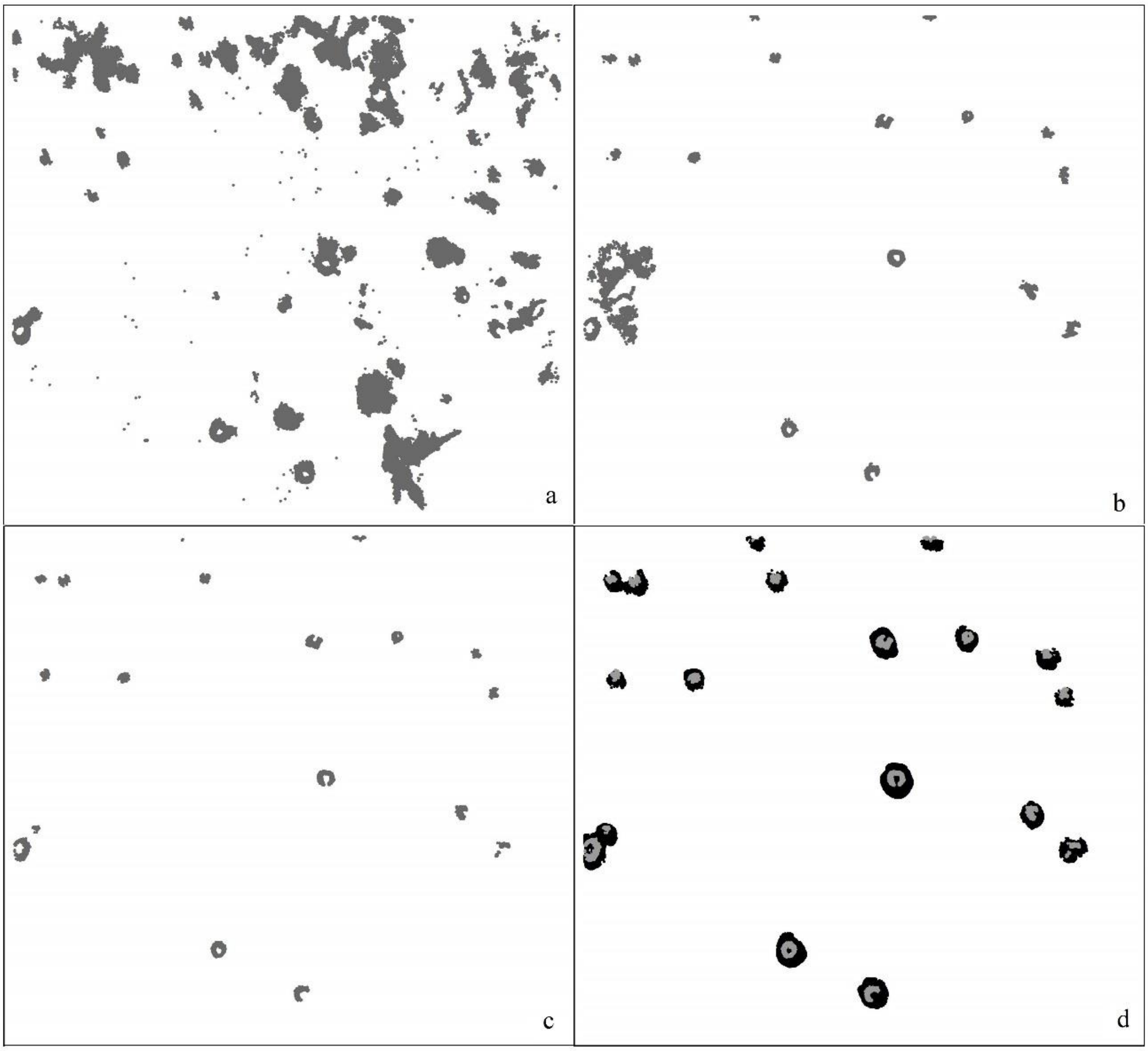


Figure 4. Reference trunks identification.4a and 4b show the sliced points from layers l3 and l9, respectively; 4c represents the reference trunks; 4d shows assigned tree trunks (black) according to the reference trunks (grey).

6) Elevated shrub reassignment from the incorrectly assigned overstorey.

   This is accomplished by a) subtracting laser points of trunks from the slices; b) searching shrubs at the subtracted slices from the height range between 2 m to *h'* (the maximum height of the shrubs), progressing upwards until no further point can be allocated, thus *h'* can be defined; c) reassigning the searched shrubs and merging them with the initial elevated fuel class to regroup the elevated fuels together.

7) Identifying tree branches and leaves by subtracting the reassigned elevated shrubs from the rest of the points above 2 m and assigning them as branches and leaves.

3.2.2.3 LiDAR Derived Fuel Structural Characteristics

After the fuel layer classification, TLS points are used to quantify forest fuel structural characteristics, such as surface fuel depth and percentage cover at distinct fuel layers.

1) A raster image of surface fuel depth is interpolated based on TLS points' height values (h) at surface fuel layer. The cell sizes vary depending on the spatial accuracy and the footprint of the laser scanning system.
2) Fuel cover is presented as a binary image with the same cell size by classifying the cells into two groups according to the presence (1) or absence (0) of TLS points. The percentage cover of fuel is estimated by calculating the proportion of presence of TLS points in individual fuel layers.

3.2.2.4 Validation

The accuracy of TLS-derived forest fuel structural characteristics is determined primarily by the accuracy assessment of the TLS-derived surface fuel depth and percentage covers at distinct layers against the field survey data at 45 sampling sites. In some plots there are only surface fuel, or combination of both surface and near-surface fuel with elevated fuel missing. Therefore, the number of fuel samples are limited, when we took consideration of availability of three fuel layers (surface, near-surface, and elevated fuel layers) within 1 m^2 in the field. TLS-derived fuel properties compared with field sampling data according to the GPS location of each sampling site, since the Zebedee device has a detachable GPS device. In addition, photographs taken at each sampling site were used to verify the location of the plots. The root mean square error (*RMSE*) is applied to validate the accuracy, which is expressed as:

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(x_i - x_i')^2}{N}}$$

where x_i represents the filed data (surface fuel depth and percentage cover at distinct layers) of fuel sample i, x_i' is defined as the TLS-derived fuel characteristics of fuel sample i and N is the number of fuel samples. The coefficient of determination (R^2) is also calculated as the proportion of the response variable variation that is explained. Moreover, the P value is used to test for statistical significance. In addition, the assumptions and random errors associated with the regression model are also assessed by visualising the statistical graphics, such as, a histogram of raw residuals and a normal probability plot.

3.3 Results

Table 1. Surveyed and TLS-derived fuel characteristics.

		Field measured				LiDAR derived Bias			
Plot ID	Sample ID	Litter-bed Depth (cm)	Litter Cover (%)	Near-surface Plant Cover (%)	Elevated Fuel Plant Cover (%)	Litter-bed Depth (cm)	Litter Cover (%)	Near-surface Plant Cover (%)	Elevated Fuel Plant Cover (%)
1	1	2	90	60	50	1.2	10	11.3	3.5
1	2	2	90	60	75	-0.2	10	4.2	0.3
1	3	2	100	100	80	-0.3	0	0	12
1	4	6	100	100	30	-1	0	0	9.7
1	5	6	100	70	50	-1	0	4.8	-5.5
2	1	5	90	40	100	0	10	-3.8	-3.8
2	2	6	100	60	80	-1	0	1.1	-7.1
2	3	7	100	50	90	1.2	0	-2.5	1.3
2	4	5.5	100	100	50	-0.5	0	0	1
2	5	5	90	80	40	0	10	4.7	0.8
2	6	5.5	100	100	50	-0.5	0	-0.7	-0.9
3	1	13	100	70	90	1.1	0	-2	2
3	2	10	100	30	90	1.2	0	-4	0
3	3	7	100	90	100	-0.4	0	6	0
3	4	6	80	30	90	0.4	1.4	1	5
3	5	6	70	30	80	-0.2	-2.6	-6	-1
3	6	5	60	90	90	-0.1	2.9	6	10
3	7	8	100	90	100	-0.1	0	0	0
3	8	11	100	90	100	0.2	0	1	0
3	9	9	100	90	50	-0.1	0	1	-2
3	10	7	100	80	60	0.1	0	3	0
4	1	1.5	90	40	15	0.1	10	0	-2
4	2	2	90	25	45	0.6	7	5	8
4	3	1.5	80	20	60	-0.1	9	2	-1
4	4	0.5	90	30	40	2.5	8	14	8
4	5	3	80	10	20	-1.6	18	-4	2

4	6	3.5	70	30	30	-1.3	1	5	-4
4	7	2	75	40	40	1.7	11	4	17
4	8	1	50	10	35	-0.7	-6	2	6
5	1	7	90	60	70	-1.6	10	21.9	18.7
5	2	2.5	85	85	65	-1	13	10.8	11.5
5	3	3	100	85	55	-1.1	0	12.5	-14.8
5	4	5	95	75	65	-2	5	19.9	20.3
5	5	2.5	90	75	60	-0.8	10	14.8	0.5
5	6	3.5	100	60	55	-1.5	0	18.5	1
5	7	7	100	80	45	-3.3	0	16	-6.1
5	8	5	95	80	70	-2.5	5	16.2	19.6
6	1	5	100	90	0	0	0	5.5	0.3
6	2	7	90	80	40	-0.5	10	3.4	-22.2
6	3	10	100	80	70	-1.3	0	1.5	15.4
6	4	2	80	85	80	0.2	15.1	-1.7	11.2
6	5	5	100	85	40	-0.2	0	-1.7	-8.9
6	6	5	100	90	30	0.7	0	5.5	-9.3
6	7	4	100	70	40	-0.6	0	0.6	30.3
6	8	3	90	80	60	-1.5	8.1	9.6	-9.6

This study results in three outputs: fuel strata classification, surface fuel depth and fuel percentage cover at distinct fuel layers. The GIS and TLS-derived method produces a more accurate forest fuel strata stratification (Figure 5b) compared to the photograph in Figure 5a. The tree trunks in Figure 5c are separated from branches and leaves compared with the initial fuel layer classification in Figure 3b. The overstorey fuels misclassified by directly applying the height difference are also correctly reassigned as elevated shrubs.

Data on surface fuel depth at 45 sampling locations were collected to validate the TLS-derived fuel structural characteristics (Table 1). The residuals were normally distributed, and the input variables followed the assumptions of linear regression. The R^2 value of 0.9 and *RMSE* values of 1.1 (cm) were produced by comparing the TLS-derived surface fuel depths with the surveyed depths (Figure 6). A correlation coefficient value of 0.4482 described in Table 2 shows a strong relationship between the surface litter fuel depth and elevated fuel percentage cover.

Table 2. The correlation coefficients among fuel layers.

Correlation Coefficient	Litter-bed Depth (cm)	Litter Cover (%)	Near-surface Plant Cover (%)	Elevated Plant Cover (%)
Litter-bed Depth (cm)	1	0.2092	0.1145	0.4482
Litter Cover (%)	-	1	0.4583	0.0129
Near-surface Plant Cover (%)	-	-	1	0.062
Elevated Plant Cover (%)	-	-	-	1

Direct application of the initial fuel layer classification based on vertical height ranges resulted in tree trunks not being detected and misclassification occurring (Figure 3), therefore, a reclassification of fuel strata was necessary before assessing fuels. The GIS and TLS - based method had very small discrepancies compared with the observed values at each fuel strata. The relationship was found to be statistically significant therefore we can have confidence in using TLS to classify understory fuel layers, and also to represent forest fuel coverage for surface, near-surface fuel, and elevated fuel layers (Figure 7). The TLS-derived fuel percentage covers had statistically significant relationship with surveyed results at surface fuel layer (R^2 = 0.8, *RMSE* = 5.4%), near-surface fuel layer (R^2 = 0.9, *RMSE* = 6.9%), and elevated fuel layer (R^2 = 0.9, *RMSE* = 9.9%) (Figure 7a,b,c). The total of TLS-derived fuel cover against field measured values produced values of R^2 (0.9) and *RMSE* (7.6%) (Figure 7d). A normal distribution of the data were confirmed by a visual interpretation of histogram and normal probability plot of residuals.

Figure 5. TLS-derived fuel structural classification compared with a photograph taken at Plot 2. 5a. A photography of forest fuel; 5b. An overview of LiDAR derived fuel strata; 5c. The classified fuel strata from top to bottom, including tree trunks, elevated fuel, near surface fuel, and surface fuel.

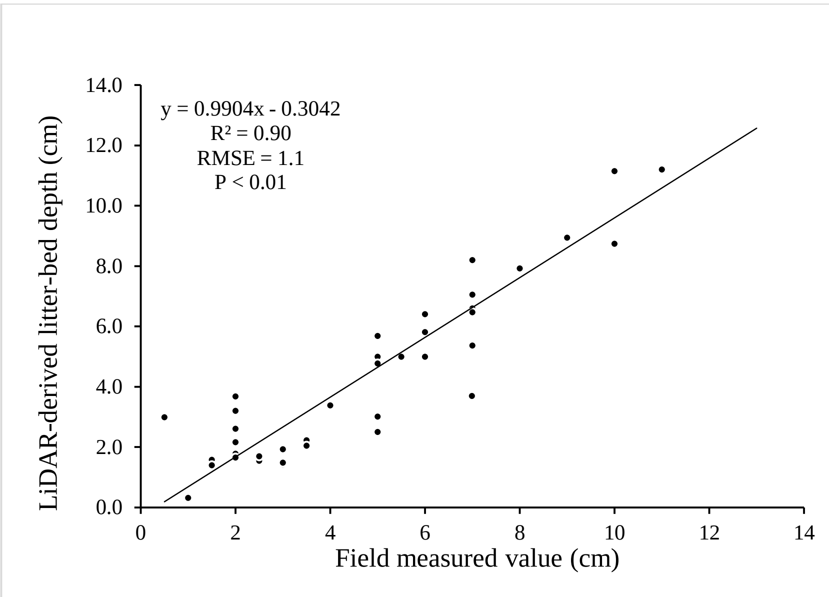


Figure 6. Scattergram of TLS-derived against measured litter bed depth with linear regression (n = 45). (Note: some sample points are very close to each other and appear overlapped.)

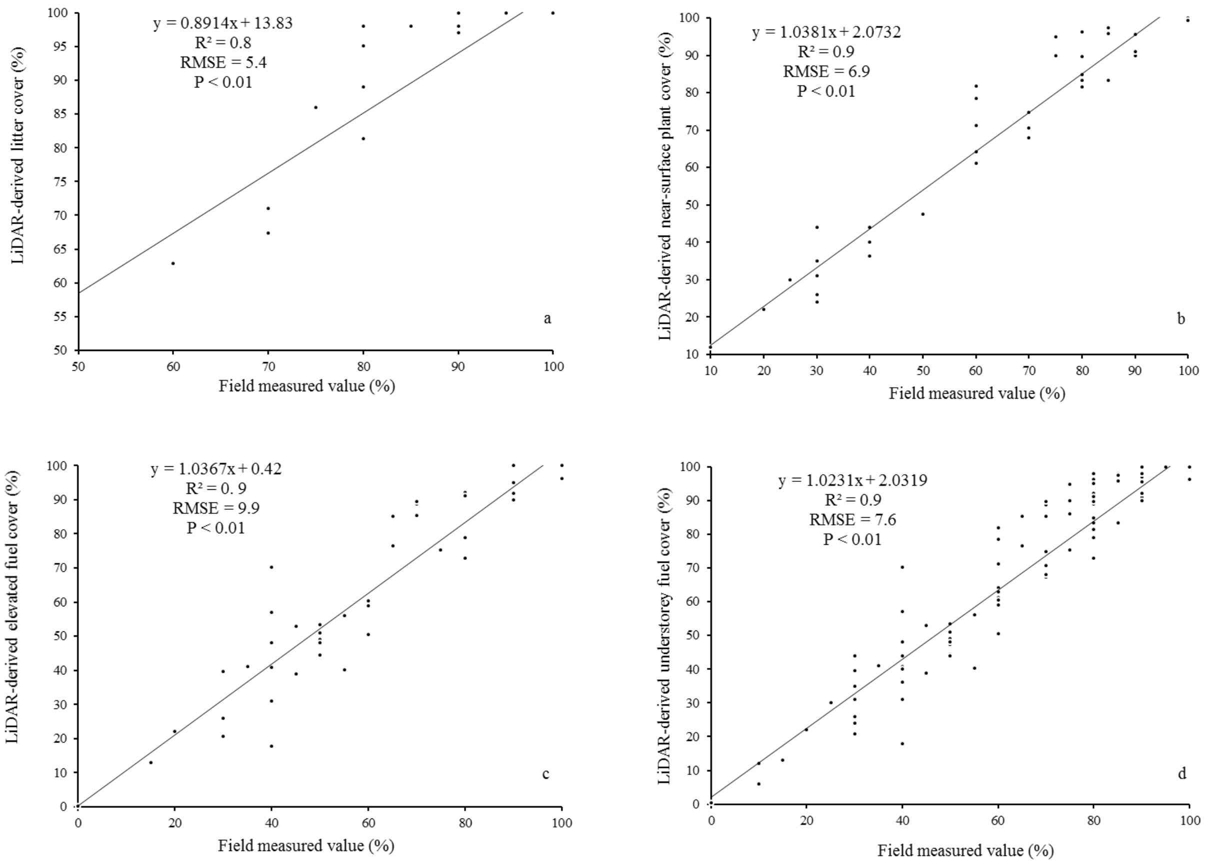


Figure 7. TLS-derived and field measured fuel cover scattergram with linear regression. 7a. Litter cover (n = 45); 7b. Near-face cover (n = 45); 7c. Elevated cover (n = 45); 7d. Understorey fuel cover (n = 135). (Note: some sample points are very close to each other and appear overlapped.)

3.4 Discussion

Current fire danger rating systems and fire behaviour prediction models share a common challenge in quantifying fuels, since the fuel varies between sites and even within homogeneous vegetation depending on forest fuel types, local environment and previous fire disturbances (Deeming *et al.*, 1977; Tolhurst *et al.*, 2008; Gould *et al.*, 2014). Accurately describing forest surface fuel load and fuel structure is significant for understanding bushfire behaviour and suppression difficulties. Traditionally, surface fuel load is determined by field sampling, oven drying, and weighing (McArthur, 1962; McCarthy, 1996; McCarthy *et al.*, 1998), which can be time and labour intensive at large scales. McArthur’s positive relationships

(1962) between surface fuel load and surface fuel depth have been used as a rapid method to support fire hazard-reduction burns in Eucalypt forests in Australia, instead of directly measuring surface fuel load. In addition, forest vertical structure is a function of species composition, microclimate, site quality and topography, which has a significant influence on productivity and fuel accumulation (Dubayah *et al.*, 1997; Dubayah and Drake, 2000). Therefore, the development of accurate, reliable and efficient methods to quantify forest surface fuel depth and fuel strata can be useful for surface fuel load estimation and fire hazard assessment.

In our study, the fuel structure classification based on the integration between TLS and GIS was proposed as a means to provide accurate, consistent and objective information for describing forest fuel characteristics. It could be used to assist visual fuel hazard assessment, when visual assessment is restricted by local complex terrain. It could also be useful for validating the result of visual assessment, which is error-prone and subjective. The TLS-derived surface fuel depth is also of interest in surface fuel load estimation for assessing fuel hazards as well as predicting fire behaviour potential.

Currently accepted methods used by fire fighters and land managers for field measurements are susceptible to bias. To be more specific, during the fuel assessment, the observer measures the surface fuel depth by direct measurements at one site, the finalised depth is determined by an average value of 5 measurements within the site. The observer also assesses the percentage cover of the vegetation for each fuel layer based on his or her empirical knowledge and visual assessing skills. Field-based surface fuel and near-surface fuel assessment can be more straightforward compared with assessing elevated shrubs because of the heights of the fuel layer and the position of the observer. Visually assessing elevated fuels may also create inconsistency as a result of individual survey error and local environment factors. Therefore, currently used visual assessment could be less objective compared with TLS data.

In contrast, this GIS-based fuel structure classification can be used to effectively and efficiently to assess forest fuel hazard and to estimate forest fuel inventory. The complex GIS procedure is edited, compiled and implemented in ArcGIS ModelBuilder. It can be used to automatically classify fuel strata and quantify surface fuel depth for assessing forest fuel hazards for open eucalypt forests with complex understorey vegetation and trains. The quantification of forest fuel structure and depth can assist surface fuel load estimation for fire-related management and operations.

TLS is sensitive to vertical and horizontal change in vegetation availability (Loudermilk *et al.*, 2009). The plot 5 and 6 trend to have more bias in elevated fuel cover (Table 1). These slight discrepancies indicate visual assessment can be more subjective in describing structural information of elevated fuel. Table 2 describes the independence among layers based on their correlation coefficients. The percentage cover of elevated fuel is not correlated with any other fuel layers, but it has a strong positive relationship with surface litter depth. From a fuel accumulation concept, litter fuel accumulates over time depending on the difference between rates of fuel accession and decomposition (Peet, 1971). Understory shrubs contribute to increasing fuel accession rates thereby litter accumulates with the similar environmental condition and forest fuel type (Gould *et al.*, 2008). A positive relationship between fuel cover at surface layer and near-surface layer (table 2) reflects understorey recovery with litter fuel accumulation and lower vegetation regrowth after the previous fire event (Fox *et al.*, 1979).

However, it should be noted that the classification could be affected by the choice of slicing interval and threshold. For instance, increasing the thickness of horizontal slices raises both accuracy and processing time. We suggest using 1 m as the height interval; the thinner the slice, the more processing time required. The accuracy of reference trunk identification could be affected by choosing the threshold (*r*) value. A rise in *r* value may lead to overestimation of the diameter of the stems. The sensitivities of the thickness of slices and the *r* value need to be tested. This method is also restricted by empirical knowledge of forest fire history and the minimum height of the tree branches (*h*).

Tree heights, DBHs and number of trees are not validated since they are not essential for assessing fuel hazard. For future study, DBHs could be tested in order to assess the accuracy of TLS-derived forest inventory. An overall forest fuel hazard assessment requires fuel depth and percentage cover at individual fuel layers, as well as a description of bark fuel as inputs. Bark fuel can be described by ease of ignition, the way it attaches to the trunks, the quantity of combustible bark, and burn out time according to the thickness, size, and shape of bark pieces. However, LiDAR has difficulty in assessing bark fuels, since assessing bark fuels requires more complex empirical knowledge to describe the texture and to assess the effect of bark on suppression difficulties. The application of TLS in quantifying and assessing forest fuels is restricted by scanning angle, scale (vertical and horizontal) and position. In order to overcome these restrictions, terrestrial and airborne LiDAR observations can be integrated to provide a more complete forest fuel hazard assessment.

3.5 Conclusion

Traditional wildland fuel load measurements are based on destructive samplings in order to directly measure the dry weight of fuels, which is time and labour intensive. The current sampling-based visual assessment is rapid but it can be subjective when extrapolated to infer fuels across larger landscape scales. LiDAR technology can provide more efficient, consistent and accurate information for measuring forest vegetation biomass. This paper has introduced an approach based on an integration between TLS and GIS to automatically classify forest fuel strata and assess fuel characteristics. The complex GIS-based processing procedures were edited and compiled in ArcGIS ModelBuilder, and then implemented with an ArcGIS toolkit. The outcome suggests that the integrated method can provide objective, consistent and efficient information to describe fuel structural characteristics for forest fuel hazard assessment and forest fuels management as an alternative of the visual assessment. Additionally, accurate and efficient quantification of fuel structure and surface fuel depth has its significance in estimation of forest surface fuel load. The proposed method is beneficial for understanding fire behaviour in multilayered Eucalypt forests.

Acknowledgement

Appreciation is extended to Monash University and the Bushfire and Natural Hazards CRC for assisting this research through providing PhD scholarships. Special thanks to Robert Zlot, CSIRO Australia for providing the Zebedee three-dimensional Mapping System, and to Nick Bauer, DELWP VIC Australia for providing useful feedback on a draft of this paper. Sincere gratitude to Musa Kilinc for his guidance and support in early phase of the project, and to Adam Leavesley, Thomas Jovanovic, Senthuran Arunthavanathan, Dean Yulindra Affandi, Yang Di, Zhan Wang, Saadia Majeed, Yingying Qiao, and Darren Hocking for their fieldwork support.

Chapter 4 statement

Chapter 4 has been submitted to the Journal of Environmental Modelling and Software in 2016. This chapter describes the development of a predictive model for estimating forest litter-bed fuel load in Australian eucalypt forests with LiDAR data. This study has developed a new depth-to-load model for litter-bed fuel load estimates through multiple regression analysis. This model indicates how the surface fuel load relates to litter-bed fuel depth, forest fuel type, fuel characteristics, topography, and previous fire disturbance.

Chapter 4. Development of a Predictive Model for Forest Surface Fuel Load in Australian Eucalypt forests with LiDAR Data

Abstract

The accurate description of forest surface fuel load is an important factor in understanding bushfire behaviour and suppression difficulties, predicting ongoing fires for operational activities, assessing potential fire hazards and assisting in fuel hazard-reduction burns to reduce fire risks to the community and the environment. Bushfire-related studies and current operational activities share a common challenge in quantifying fuels, due to how fuel load varies across the landscape. This paper evaluates how the spatial variation in surface fuel load relates to litter-bed depth, fuel characteristics, topography and previous fire disturbance through statistical analysis. It also presents a predictive model (R^2 = 0.89 and *RMSE* = 20.7 g) that efficiently and accurately estimates quantities of surface fuel in Australian south eastern Eucalypt forests. Light Detection and Ranging was used to quantify forest structural characteristics and terrain features. The model established in this study may be used as an efficient approach to assist in forest fuel management and fire-related operational activities.

Key words: surface fuel load, litter-bed fuel depth, airborne LiDAR, terrestrial LiDAR, multiple regression

4.1 Introduction

Fuel can be described by grouping vegetation communities into fuel types based on how similarly they contribute to potential fire behaviour (Anderson, 1982). However fuel quantity and distribution are often not directly related to vegetation types; they may be extremely complex (Pyne *et al.*, 1996). For instance, the aspect and slope position influence soil moisture and litter decomposition rates, and seasonal and diurnal changes in precipitation impact the moisture content of the leaf litter (Rollins *et al.*, 2004). The variation in surface dry fuel load in eucalypt forests may be attributed to variability in species composition, the extent and severity of previous disturbance events (e.g. fires and erosion), the site quality (e.g. soil quality, stocking rates and plant cover), weather, and the terrain features (McCarthy, 2004; Tolhurst *et al.*, 2008).

Determining surface fuel load traditionally involved collecting fine fuel from a defined sample area, sorting it to remove fuel elements with a thickness greater than 6 mm, drying in an oven and then weighing to determine weight per unit area (McArthur, 1962; McCarthy *et al.*, 1998). A landscape-scale fuel load was then estimated through extensive field inventories with sampling and statistical inference, which could be labour intensive and time consuming (Brown and Bevins, 1986; Burgan *et al.*, 1998). A positive correlation between the depth of surface litter bed and the quantity of surface litter (depth-to-load relationship) proposed by McArthur (1962) has been used as a means of rapidly estimating fuel loads for fuel hazard-reduction burns in eucalypt forests (McCarthy, 2004). However the number of measurements taken in an area influences its accuracy, since large variation in surface fuel depth could be found at any given site with homogeneous vegetation (Gould *et al.*, 2014). In addition, the fuel depth-to-load relationships vary between and across sites due to the high-degree of natural variability of overstorey and understorey vegetation species, topography, weather and previous fire severity and intensity (McArthur, 1962; Birk and Simpson, 1980).

The quantity of forest fuel after fire depends on the balance between rates of fuel accession and decomposition (Agee *et al.*, 1973). When yearly decomposition equals yearly accession, fuel does not accumulate; when accession is more than decomposition, fuel builds up. Fuel accumulation models are used to estimate and predict quantities of fuel, which have been used to assist land management agencies in the decision making process (Gill, 1997; McCarthy *et* *al.*, 1998). Fuel generally accumulates rapidly and steadily for a period of time after fires, and then the rate of accumulation reduces gradually to the level of equilibrium (Olson, 1963). This trend was described and modelled by several studies (Olson, 1963; Birk and Simpson, 1980; Raison *et al.*, 1983; 1986; Burrows, 1994; Gould *et al.*, 2011) using a general form of an exponential function rising to a steady-state fuel load (a maximum):

$$w_t = w_{ss}(1 - e^{kt}) \tag{1}$$

where w_t represents the weight of surface litter fuel accumulated at time *t* years since the last fire, w_{ss} is the weight of surface fuel accumulated under steady state conditions, *k* is defined as the decomposition constant. Given by the general form of the fuel accumulated model, years since last fire is the only independent variable to predict fuel load growth, and it therefore cannot be utilised to estimate spatial variation in fuel load within homogeneous vegetation. As a result, the pattern of fuel accumulation varies with vegetation species and environmental conditions (Fox *et al.*, 1979; Birk and Simpson, 1980; Walker, 1981; Raison *et al.*, 1983; Burrows, 1994; Chatto, 1996; Tolhurst and Kelly, 2003).

Unlike fuel accumulation models, other studies used the influencing factors as predictors to estimate the spatial variation in surface fuel load. Agee et al. (1973) used basal area as an index of crown volume and plotted a polynomial relationship between basal area of *blue gum* (*Eucalyptus globulus*) and its dry weight of fuel, including duff, litter and large debris. The result shows that as basal area increases, the total dry fuel weight rises, which may also be explained from a fuel accession perspective, where a greater crown area and crown volume results in more fuel on the surface fuel layer. Bresnehan (2003) suggested that forest fuel type, canopy density and soil type may be used to estimate fuel load as an adjunct to the fuel accumulation models on the sites where elapse (measured in number of years) since last fire is not known. A multiple regression analysis was applied in Gilroy and Tran (2006) to describe how the surface fuel load relates to more predictors, including years since last fire, fuel depth, canopy cover, and average annual rainfall since fire. The model in their study suggests that years since last fire, fuel depth and canopy cover contribute more to surface fuel loading compared with the average rainfall in the study area. These authors suggested that their model could be enhanced by inclusion of other surface fuel load related predictors. Consequently, the development of such predictive models requires specific inputs.

The development of remote sensing technologies could potentially increase the accuracy and also reduce the time required to quantify fuels, by providing a continuous dataset from which to assess fuel conditions across large scales; it also has the potential to update fuel maps quickly and consistently in areas where conditions are dynamic due to disturbances caused by fires and other changes (Keane *et al.*, 2001; López *et al.*, 2002; Skowronski *et al.*, 2007). Optical remote sensing (e.g. ASTER, Landsat, SPOT-HRV, and aerial photo) has been widely used in classifying canopy fuel type, estimating percentage canopy cover and foliage biomass (Saatchi *et al.*, 2007; Arroyo *et al.*, 2008).

Several studies used optical imagery-derived forest and environmental factors as explanatory variables in order to develop the predictive models to describe the spatial variability of forest fuel load (Brandis and Jacobson, 2003; Saatchi *et al.*, 2007). In these studies, multiple regression was applied to determine which independent variables (e.g. spectral bands, forest class, structural stage, potential vegetation type, cover type, elevation, slope and aspect) have more significant impact on the response variable of interest - the fuel load. These models showed a range of 55% to 72% of variability in prediction bias, the major limitation in estimating surface fuel derived from optical remote sensing being an inability to penetrate the canopy (Lovell *et al.*, 2003; Andersen *et al.*, 2005). Radar data has also been used to predict these canopy fuel attributes as well as crown bulk density (Saatchi *et al.*, 2007). However, both satellite and airborne radar have limitations in estimating surface fuel load that requires very fine spatial resolution (cm or mm) (Riaño *et al.*, 2003).

Recently, Laser altimetry or Light Detection and Ranging (LiDAR) including airborne and terrestrial LiDAR has been used in estimating individual tree heights (Gougeon, 2000; Chen *et al.*, 2006; Popescu, 2007), quantifying forest inventory (Næsset, 2004; Maas *et al.*, 2008), leaf area (Béland *et al.*, 2014), biomass (Lefsky *et al.*, 1999; Popescu, 2007; Tao *et al.*, 2014), and safety zone identification for forest fire fighters (Dennison *et al.*, 2014), with its ability to provide three-dimensional information to quantify forest structure with high spatial accuracies of cm or mm. Some studies have explored statistical distribution functions to represent the vertical profile of vegetation structure using full waveform LiDAR (Lefsky *et al.*, 1999; Wagner *et al.*, 2008; Hermosilla *et al.*, 2014), multi-echo LiDAR data (Lovell *et al.*, 2003; Riaño *et al.*, 2003), and terrestrial LiDAR data (Côté *et al.*, 2011; Marselis *et al.*, 2016), which indicates its potential for surface fuel load estimates (Skowronski *et al.*, 2007; Jakubowksi *et al.*, 2013).

The purpose of this study is to develop a fuel load predictive model to estimate quantity of surface fuel in Eucalypt forests in the Upper Yarra Reservoir area, Victoria, Australia through LiDAR and multiple regression. The established model is also used to evaluate how the spatial variation in fuel load relates to the separate and related influencing factors, including litter-bed depth, fuel types and environmental conditions.

4.2 Methods

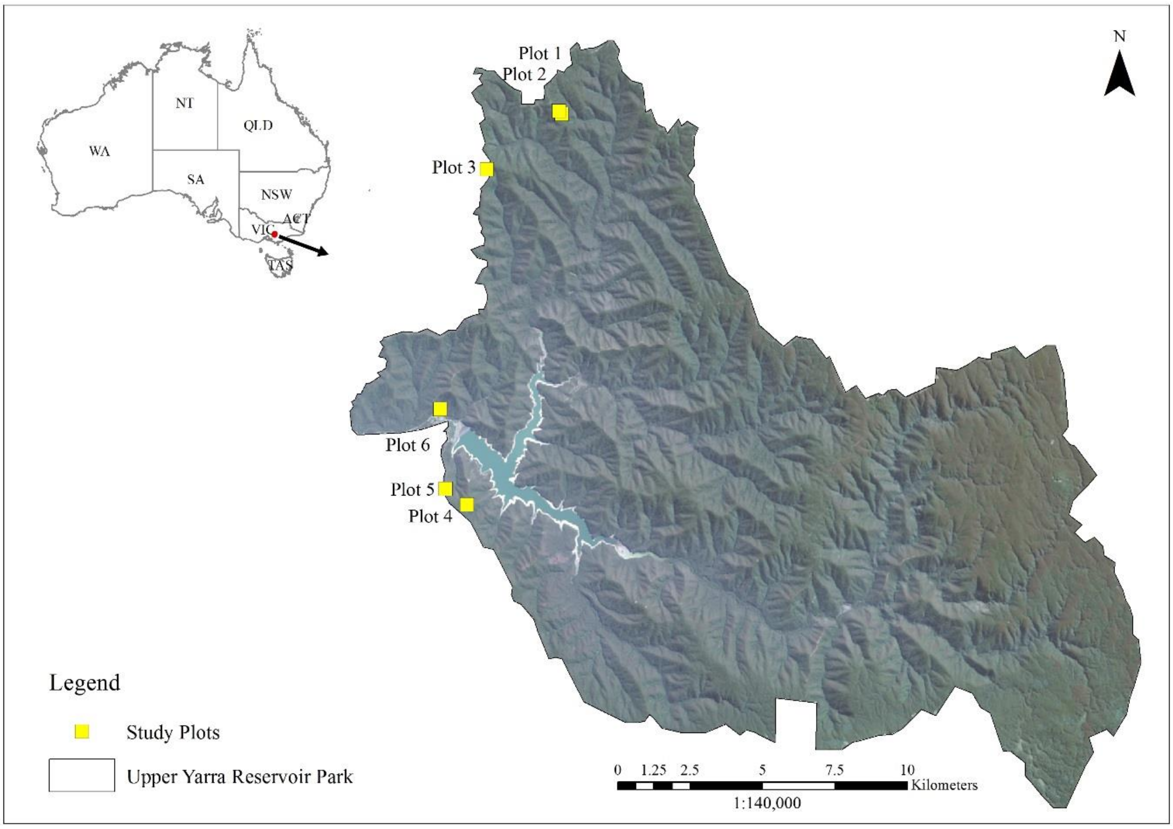


Figure 1. Study area and plot locations (Landsat imagery, August 2015)

4.2.1 Study site

The study was conducted in the Upper Yarra Reservoir Park in south east Australia (Figure 1.). It is located east of Melbourne, within the locality of Reefton (37˚41'S, 145˚55'E). The Reservoir Park is an eucalyptus open forest with a dense shrubby understorey, which has a large number of indigenous eucalypt species, including Manna Gum (e.g. *Eucalyptus viminalis*), Grey Gum (e.g. *Eucalyptus cypellocarpa*), Messmate (e.g. *Eucalyptus obliqua*), Peppermint (e.g. *Eucalyptus croajingolensis*, *Eucalyptus dives*, *Eucalyptus elata*, *Eucalyptus radiata*), Silvertop (e.g. *Eucalyptus sieberi*), Stringybark (e.g. *Eucalyptus baxteri*, *Eucalyptus cephalocarpa*, *Eucalyptus globoidea*), and Candlbark Gum (e.g. *Eucalyptus rubida*). The catchment area is 32,670 ha approximately with elevation ranging from 219 m to 1205 m. The average annual rainfall is approximately 1122 mm, and the main soil type is clay loam.

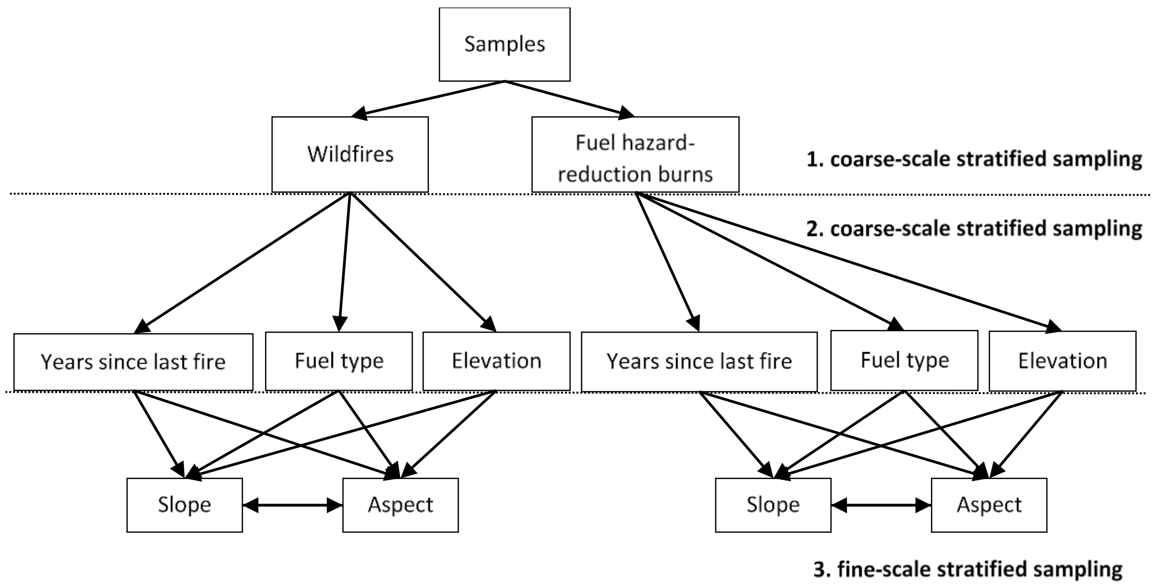


Figure 2. A flow chart of the three-stage stratified systematic sample method

4.2.2 Sample design

A total of forty-one study sites were selected to have different fire history, burn types, forest fuel types, and terrain features using a three-stage stratified systematic sample design (Figure 2). The first stage aimed to divide the study area into two strata, either recent wildfires or recent fuel hazard-reduction burns. Fuel hazard-reduction burns as typical fuel-management activities have been conducted, and wildfires have also occurred over time across this area. The previous burn severity could vary between burns and even within the same burn; we assume these burning conditions were similar for each burn type. Sites were chosen in this area if they were cleared of most understorey fuels and the overstorey fuels were left by previous disturbance of fires.

For the second stage, unique combinations of years since last fire, fuel type (damp shrubby forest or dry shrubby foothill forest) and elevation were then taken into account to stratify the samples for a coarse-scale variability of forest fuel. Due to the availability of the fire history and fuel type, six plots of 50 m by 50 m were allocated across this area as further sampling sites. Years since last fire was applied as fuel accumulates over time, which is one of the key indicators of fuel growth as well as vegetation recovery after fires (Birk and Simpson, 1980). Forest fuel type could directly impact on fuel moisture content, and fuel decomposition rate. Elevation was chosen because it quantifies biophysical gradients (e.g. temperature, moisture, and energy) over the study area.

For the third stage, sampling sites covering 0.5 m by 0.5 m were allocated according to various values of aspect and slope within each of the six plots. These topographic variables quantify and characterize the biophysical potential of a site and also have great impact on fuel dynamics such as fuel type and fuel loading, for a fine-scale variability of forest fuel.

4.2.3 Data collection

The total surface fuel load at each site was weighted directly, as the weight (g) comprised dry weight and moisture content. Dry weight (g) was measured after oven drying for 24 hours at 105 °C (Matthews, 2010). Canopy density (%), elevation (m), slope degree, and aspect were calculated based on airborne LiDAR data acquired in January 2008 with footprint size of 0.26 m (Aldred and Bonnor, 1985; Lefsky *et al.*, 1999; Næsset, 2002; Reutebuch *et al.*, 2003). Terrestrial LiDAR data were acquired simultaneously with the field samplings, using a Zebedee three-dimensional Mapping System developed by CSIRO Australia (Zlot and Bosse, 2014). If one sampling site was covered by a thick layer of surface fuel with no obvious soil exposed, we manually exposed some soil before the scan was conducted. This was done to overcome the limitation of the laser beams of the Zebedee on penetrating thick layers of litter and reach the soil, what it is essential for an accurate generation of the DEM.

The elevation of the lowest point within 0.5 m by 0.5 m grids was used to convert the point cloud derived from the terrestrial LiDAR data to a digital elevation model (DEM). Height values of the point clouds were computed by subtracting the DEM from its elevation. The surface fuel depth (cm) and percentage cover (%) were then estimated depending on the average height difference within sites between a surface fuel layer and the DEM derived from the terrestrial LiDAR data. The surface fuel layer was separated from other fuel layers according to a mixture distribution of LiDAR point density against height values (Jaskierniak *et al.*, 2011). The depth of the surface fuel was computed by subtracting a smoothed DEM from a surface fuel layer; the percentage cover was a ratio between the surface fuel layer and the DEM.

4.2.4 Model development

Modelling of forest litter-bed fuel load was accomplished in three-stages of multiple regression analysis (Graybill, 1970). The first stage aimed to model the forest fuel depth-to-load relationship by exploring the variability in dry weight of forest fuel load (*DW*) as a function of surface fuel depth (*FD*) and years since last fire (*YSF*) (McArthur, 1962).

The second stage was to introduce more quantitative variables in the model, as interactions with *FD* and *YSF* using stepwise regression. These independent variables consist of canopy density (*CD*), surface fuel percentage cover (*PC*), elevation (*E*), aspect (*A*) and slope (*S*). Stepwise regression was used as a variable screening tool when there exists a large number of potentially important independent variables (Draper and Smith, 2014). To keep the number of variables manageable, we used the first-order interaction terms for independent variables, and omitted high-order terms to the model.

Table 1. The variables associated with the model development

Variable	Parameter	Symbol
Quantitative	Years since last fire	*YSF*
Quantitative	Surface litter-bed depth (mm)	*FD*
Quantitative	Surface litter-bed percentage cover (%)	*PC*
Quantitative	Canopy density (%)	*CD*
Quantitative	Elevation (m)	*E*
Quantitative	Aspect (degree)	*A*
Quantitative	Slope (degree)	*S*
Qualitative	Forest fuel type (dry / damp)	*FT*
Qualitative	Burn type (wildfire / fuel hazard-reduction burns)	*BT*

For the third stage, types of burn and fuel as dummy (qualitative) variables were introduced in the models as interactions with these existing independent variables, in order to account for differences among forest fuel types (*FT*) as well as burn types (*BT*). Each component of forest *DW* was modelled using stepwise procedures to identify the best subset of independent variables at the statistical significance level of 0.05. The dependent variable and independent variables associated with the model development are described in Table 1.

4.2.5 Model assumption and error assessment

Statistical graphics (Birk and Simpson, 1980; Atkinson, 1987; Neter *et al.*, 1996; Belsley *et al.*, 2005) were used to verify model assumptions and random errors associated with the regression models and to support improvements to the prediction when the assumptions did not appear to be satisfied. The outliers and the goodness of fit associated with the regression models were assessed through visualizing residual plots according to the following procedures of residual analysis.

A histogram of raw residuals was plotted to examine whether the observations are randomly sampled from a normal distribution; however, detecting normality from a histogram could be difficult when data sets are not large (Chambers *et al.*, 1983). Therefore, a normal probability plot (NPP) of the raw residuals was then plotted to identify substantive departures from normality. Both residual plots were applied to identify outliers, skewness, kurtosis, a need for transformations, and mixtures (Becker and Chambers, 1984). To further examine the outliers that were apparent from the histogram and NPP as well as to assess other potential problems in the models, diagnostics of the linear regression model were made by plotting leverage. A leverage plot is a measure of how far away the independent variable values of an observation are from those of the other observations (Everitt and Skrondal, 2002). If the observation was determined to be an error, it was then removed.

These statistical graphic techniques were then repeated to refit the model till it provided a relatively good fit to most of the dataset and it was also appropriate for the prediction purposes. The residuals were calculated and plotted in MatLAB R2014a (http://au.mathworks.com/products/matlab/matlab-graphics/). Finally, Akaike information criterion (*AIC*) was carried out for model selection as well as restricting overfitting problems.

4.2.6 Model validation

In order to define a dataset to test the model in the training phases, the leave-one-out cross-validation was then used to verify the results of the finalised multiple linear regression model. One of the observations was left out each time as a testing set to validate the model, and used the remaining *(n-1)* observations as a training set to build the model. Each time the function approximation was trained on all the data except for one point and a prediction was made for that point. *DW* defined as the observed value of that point was used to test the error of the prediction at that time. Repeating this procedure for *n* times, the average error across all dataset was computed. Leave-one-out cross-validation (*CV*) could be computed using

$$CV = \frac{1}{n}\sum_{i=1}^{n}[e_i/(1-h_i)]^2 \quad (2)$$

where n is the number of the observations, e_i is the error obtained from fitting the model to n - 1 observations, h_i is the leverage, and i is the repeating step (= 1, 2, …, n) (Good, 2001). Additionally, the predicted values of surface fuel load were then compared with the observed fuel load for a further assessment of the accuracy of the proposed model. This study also compared the developed models with McArthur's depth-to-load model and Gilroy and Tran (2006)'s predictive model.

4.3 Results

The stepwise procedure was used to produce estimates of the model coefficients (*β's*) to select the important variables (Table 2). According to the three-stage model development and the model assumption assessment, three models were produced and are described as follows:

4.3.1 Model 1

Table 2. Model coefficients

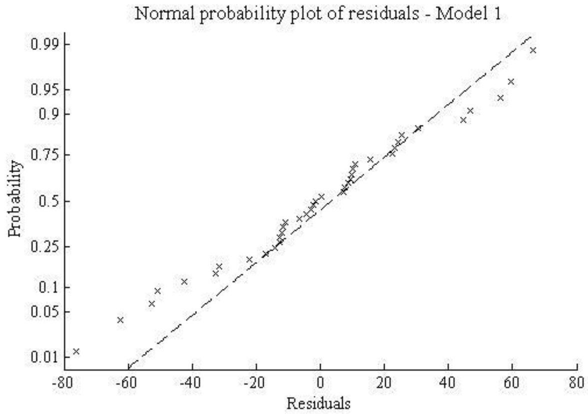
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	*(Constant)*	30.56	12.15		2.5	0.02					
	*YSF*FD*	0.714	0.078	0.83	9.1	<0.001	0.8	0.8	0.8	1	1
2	*(Constant)*	-43.5	15.32		-2.8	0.08					
	*YSF*FD*	0.766	0.057	0.9	13.5	<0.001	0.8	0.9	0.9	0.97	1.03
	*CD*E*	0.12	0.021	0.39	5.8	<0.001	0.2	0.7	0.4	0.97	1.03
3	*(Constant)*	-51.8	15.07		-3.4	0					
	*YSF*FD*	0.744	0.053	0.85	14	<0.001	0.8	0.9	0.8	0.84	1.19
	*CD*E*	0.121	0.02	0.35	6.1	<0.001	0.1	0.7	0.3	0.93	1.08
	*FD*FT*	1.325	0.283	0.28	4.7	<0.001	0.5	0.6	0.3	0.9	1.11

Table 3. Model Summaries

Model	R Square	Std. Error of the Estimate	F	Sig.	AIC	CV
1[a]	0.69	32.9	83	<0.01	385.11	1345.4
2[b]	0.85	23.5	98	<0.01	352.57	836.82
3[c]	0.89	20.7	95	<0.01	343.92	572.6
4[d]	0.61	39.6	62	<0.01	417.95	1650
5[e]	0.69	36.5	27	<0.01	413.06	1502

a. Predictors: (Constant), YSF, FD;
b. Predictors: (Constant), YSF, FD, CD, E;
c. Predictors: (Constant), YSF, FD, CD, E, FT;
d. Predictors: (Constant), sqrt(FD), SPC;
e: Predictors: (Constant), ln(YSF), FD, CD.

a



b

Figure 3. Residual plots of Model 1. a. Residual Histogram plot; b. Normal Probability Plot of Regression Standardized Residual

The independent variables including *FD* and *YSF* were used to describe the variability in *DW* in order to develop the depth-to-load relationship as Model 1. One outlier was detected by the leverage plot. After removing it, the result described in Table 2 shows that *DW* is positively linearly correlated with the product of *FD* and *YSF*. This depth-to-load relationship provides an R^2 value of 0.69 and *Root Mean Squared Error* (*RMSE*) value of 32.9 g (Table 3 and Figure 6a). The histogram of residual plots described in Figure 3a shows a symmetric normal distribution; the NPP (Figure 3b) shows that most errors roughly fall on the straight line and two tails slightly move away from it.

4.3.2 Model 2

In order to improve the depth-to-load relationship, *E, A, S, CD,* and *PC* were then introduced in the model and interacted with *FD* and *YSF* using stepwise regression. The product of *CD* and *E* is positively correlated to the dependent variable; the sum of *FD*YSF* and *CD*E* improves the values of R^2 (0.85) and *RMSE* (23.5 g), after removing another outlier with high value of leverage (Table 3 and Figure 6b); other introduced quantitative variables are excluded due to their statistical insignificance. The residual histogram plot (Figure 4a and 4b) shows that data are sampled from a normal distribution.

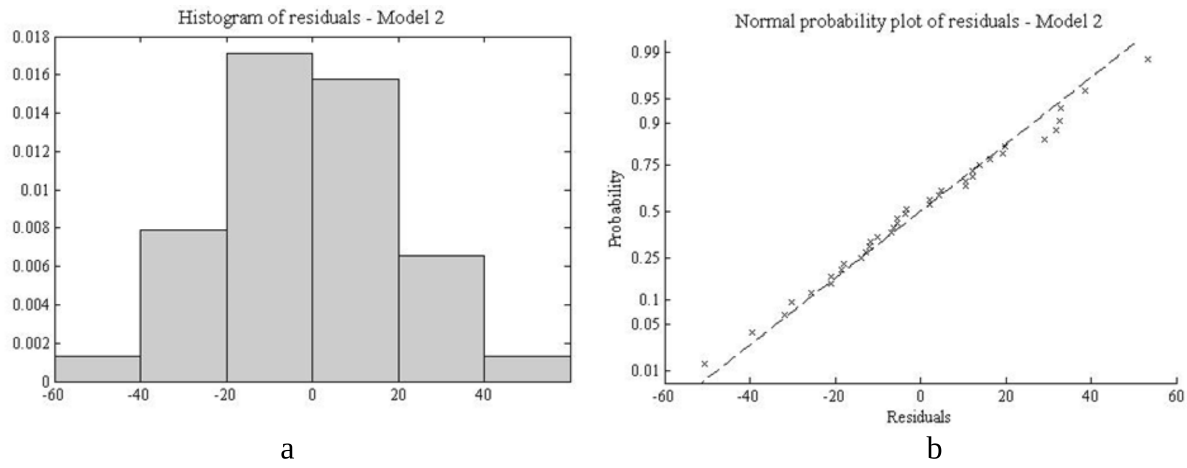
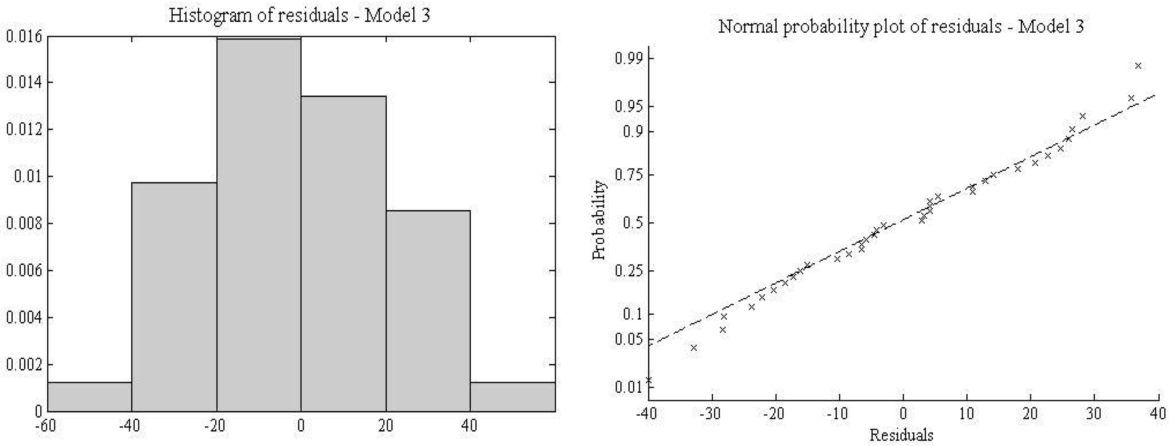


Figure 4. Residual plots of Model 2. a. Residual Histogram plot; b. Normal Probability Plot of Regression Standardized Residual

4.3.3 Model 3

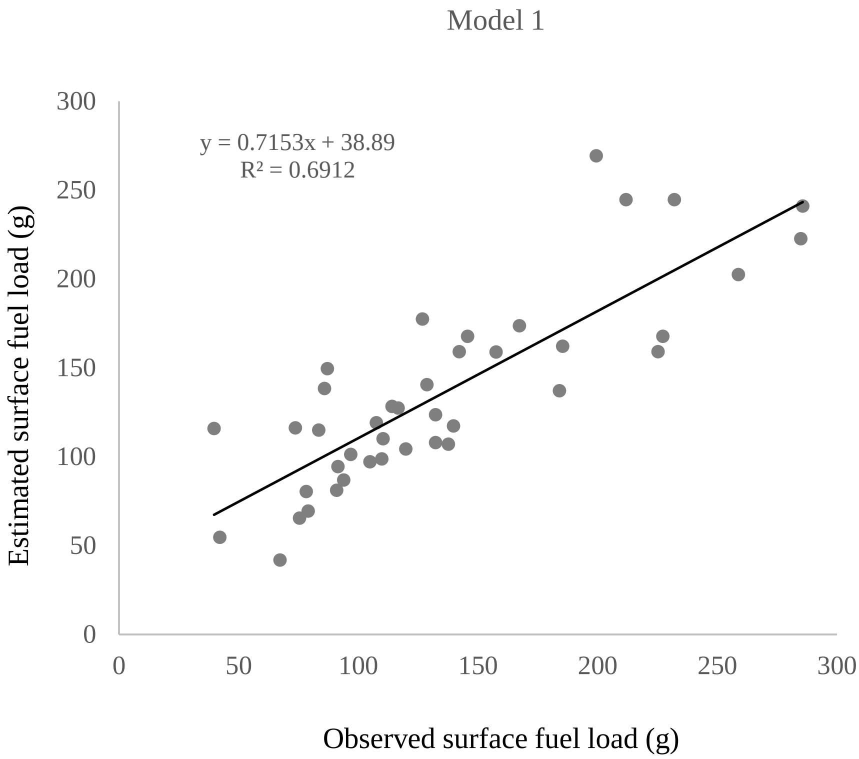
Model 3 described in Table 2 shows the improvement in the prediction by introducing *FT* as a qualitative variable to interact with *FD*. The product of *FD* and *FT* is also positively related to *DW*; BT is omitted in the model due to the lower significance. *A* R^2 value of 0.89 and a *RMSE* value of 20.7 g were produced by plotting Model 3 predicted dry weight of surface fuel against observed values (Table 3 and Figure 6c). The histogram of residual (Figure 5a) plots a fairly symmetric normal distribution; Figure 5b described the normal probability plot of the residuals is approximately linear supporting the condition that the error terms are normally distributed. Model 3 produced the lowest *AIC* and *CV* values of 343.92 and 572.60, respectively (Table 3).

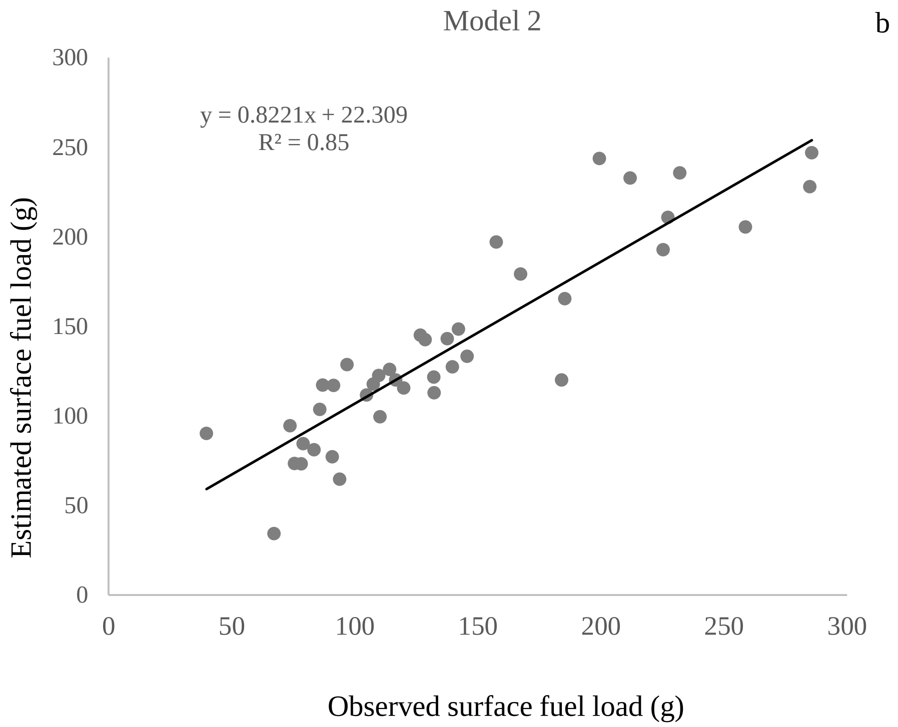


a b

Figure 5. Residual plots of Model 3. a. Residual Histogram plot; b. Normal Probability Plot of Regression Standardized Residual

a





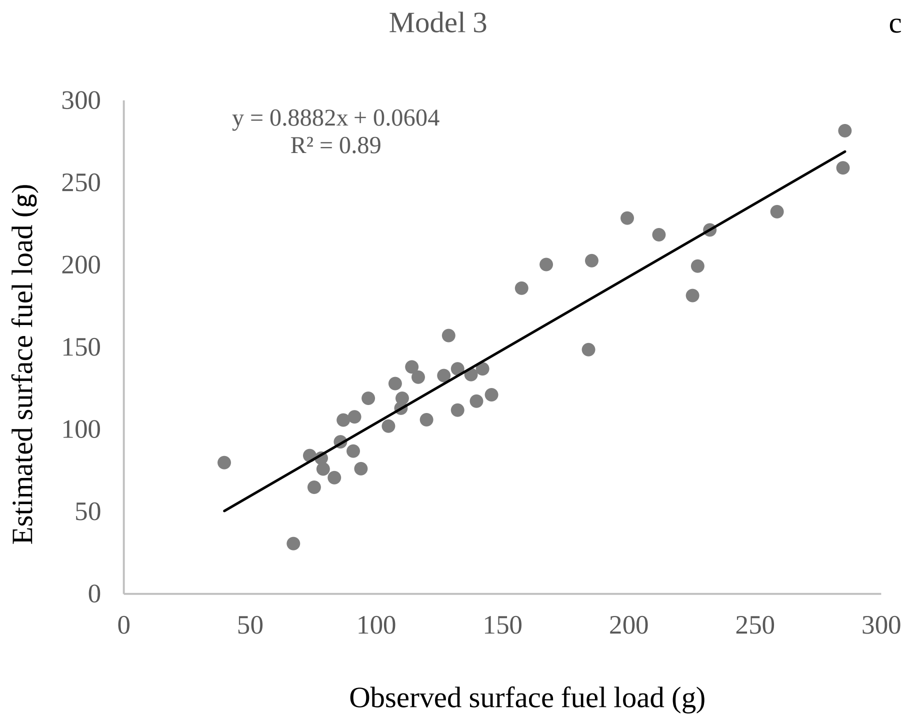


Figure 6. Surface fuel load scattergram of Model 1 (a), 2 (b), and 3 (c).

McArthur's model (Model 4) and Gilroy and Tran (2006)'s model (Model 5) were also assessed with data collected from this study area. Model 4 described in Table 3 overestimated surface fuel load and produced an R^2 value of 0.61 and a *RMSE* value of 39.6 g. Model 5 involved three independent variables, including the natural logarithm of *YSF*, *CD* and *FD*. This model produced a value R^2 of 0.69 and a *RMSE* value of 36.5 g with the same dataset.

4.4 Discussion

Current fire danger rating systems and fire behaviour prediction models have a common challenge in quantifying fuels, since the fuel load varies between sites and even within homogeneous vegetation (Deeming *et al.*, 1972; Deeming *et al.*, 1977; Anderson, 1982; Tolhurst *et al.*, 2008; Gould *et al.*, 2014). Traditionally, surface fuel load at sampling locations is calculated by oven-dried weight and estimated fuel load across a landscape through statistical inference. The measurement of fuel load can be labour intensive and inefficient. Fire authorities and agencies have been using litter-bed depth and fuel accumulation models as faster alternatives to estimate litter fuel load growth for making fire hazard-reduction related regional decisions (Conroy, 1993; Fernandes and Botelho, 2003; Gilroy and Tran, 2006). Fuel accumulation models following a general form of an exponential function are a simplification of the factors that influence fuel loading, which cannot describe how the spatial variation in surface fuel load relates to the influencing factors (Conroy, 1993; Fernandes and Botelho, 2003). The rate of accumulation is further reliant on the results of a complex interaction of the separate and related influencing factors (e.g. fuel type, productivity of understorey and overstorey, density of canopy and environmental conditions) (Miller and Urban, 2000).

Quantities of surface litter fuel load vary spatially with fuel characteristics and environmental conditions; therefore, to model surface fuel load with local variation, a spatial continuity of these variations is necessary. LiDAR was applied in the study to provide a continuity of spatial variation in surface fuel depth and cover, topography and canopy density. This study used the Upper Yarra Reservoir Park area as a case study area to model forest surface fuel load using multiple regression analysis. Unlike the fuel accumulation studies, it assessed how the spatial variation in fuel load relates to other predictors. The topographic variables and canopy density were derived from Airborne LiDAR data. Terrestrial LiDAR was used to represent the spatial continuity of surface litter-bed depth as a replacement of the direct measurement. The LiDAR-derived independent variables can also improve the efficiency and the accuracy in developing the predictive model of surface fuel load for eucalypt forests with high a spatial resolution.

The three-stage modelling process indicates that surface litter depth and years since last fire are most significantly related to quantities of litter fuel load. To be more specific, the product of surface litter depth and years since last fire explained 69% variation in dry litter fuel load of the total dataset (Model 1, Table 3). Model 4 used a non-linear positive relationship between fuel load and surface litter depth, and also introduced percentage cover of understorey shrubs (*SPC*) in the model to enhance the performance of the depth-to-load relationship. Compared with Model 4, Model 1 explained 6% extra variation in fuel load of entire dataset. This improvement is explained by introducing years since last fire to the linear correlation between litter-bed depth and surface fuel quantity. The selected sites experienced understorey vegetation cleared up by the previous fires, therefore the quantity of understory vegetation would be highly related to the time since the previous disturbances. The application of Model 1 for fuel management activities would be comparatively time effective than the McArthur's load-to-depth relationship, since access to the information of fire history is more convenient than estimation of understorey vegetation percentage cover. From an operational perspective, Model 1 may be a quicker alternative to McArthur's relationship; the litter-bed depth, however, still needs to be measured in the field.

Model 5 emphasized the significance of litter-bed depth, fire history and canopy density in the prediction of fuel load; it also transformed years since last fire to its natural logarithm. Compared to Model 5, Model 2 explained an extra 16% variation in fuel load of the dataset and also reduced the value of *RMSE* by 12 g/m^2, by introducing elevation in the model to interact with other dependent variables. It also describes that both canopy density and elevation positively influence the prediction of fuel load in the study area, and elevation is also more statistically significant than other topographic variables. Canopy density directly impacts on fuel accession, and elevation indirectly influences fuel productivities and decomposition rates due to its effect on temperature (McArthur, 1962; Birk and Simpson, 1980; McCaw *et al.*, 1996; Schaub *et al.*, 2008). If litter-bed depth and fire history are the essential predictors to the estimation of litter fuel load, canopy density and elevation may be the subsidiary indicators. Therefore, accurate information of both canopy density and elevation has its significance in the development of predictive models for litter fuel load estimates.

Three models were gradually developed in the study, and Model 3 produced the best results due to the lowest values of *AIC* and *CV*. Like Model 1 and Model 2, this model also indicates that litter fuel load is primarily influenced by surface litter-bed depth, years since last fire, canopy density, and elevation. To be more specific, the estimated effect of changing litter-bed depth from 0.3 to 5 cm is an increase in dry weight of litter fuel load of between 0.64 and 0.96 (kg/m^2), and increasing years since last fire from 5 to 8 years raises the dry fuel load up to 0.28 (kg/m^2), with 95% confidence. A rise in both canopy density (0.28 - 0.99) and elevation (281 – 905) positively influences dry fuel load, raising it from 0.2 to 0.44 (kg/m^2). Through introducing the qualitative variation in fuel type in the model, extra 4% variation of the dataset in fuel load was explained. It also suggests fuel type has a more statistically-significant contribution to the prediction compared with burn type, since fuel type directly influences the composition of understorey and overstorey vegetation as well as their productivities and forest fuel type. Dry eucalypt forests tend to produce (0.12 to 0.28 kg) more dry weight of litter fuel per square meter than damp eucalypt forest, which indicates that overall fuel hazard in the dry forests is comparatively higher than in wet forests that underwent the same previous fire events. In conclusion, these significant fuel characteristics (e.g. litter-bed depth, canopy and fuel type), environmental factors (e.g. topography) and fire disturbances may be used to estimate litter fuel load across the local area. From a practical perspective such fuel characteristics and its influencing factors-based predictive model provides bushfire authorities an alternative approach to accurately and efficiently predict litter fuel load in order to assist forest fuel and fire-related management activities.

The predictive model was developed based on a limited number of observations (n = 41). The number of observations should be increased to reduce the prediction error. Further study should investigate other potential important predictors which may also influence wildland forest litter fuel load, including species composition of overstorey and understorey vegetation, soil type, seasonal and diurnal changes in rainfall and temperature, and the extent and severity of previous disturbance events including fires and erosion.

4.5 Conclusion

Quantifying surface fuel load is an ongoing requirement for fire authorities and fire management agencies, due to its importance in predicting fire behaviour and assessing potential fire risks. This study has integrated multiple regression analysis and LiDAR-derived metrics to propose a new relationship between the quantity of forest surface fuel, fuel depth and years since last fire, and found that the spatial variation in surface litter fuel load also highly relates to canopy density, elevation, and fuel type across the study area. LiDAR data were used as an effective means to provide spatial continuity in fuel depth and topography estimates with high spatial accuracy. The calibrated models may be used to predict forest surface fuel load and therefore assist forest fuel management, assess suppression difficulties and identify potential fire hazards in the Upper Yarra Reservoir area.

Acknowledgement

Appreciation is extended to Monash University and the Bushfire and Natural Hazards CRC for assisting this research through providing PhD scholarships. Special thanks to Robert Zlot, CSIRO Australia for providing the Zebedee three-dimensional Mapping System. Sincere gratitude to Musa Kilinc for his guidance and support in the early phase of the project, and to Adam Leavesley, Thomas Jovanovic, Senthuran Arunthavanathan, Dean Yulindra Affandi, Yang Di, Zhan Wang, Saadia Majeed, Yingying Qiao, and Darren Hocking for their fieldwork support.

Chapter 5 statement

Although TLSs can accurately describe understorey fuel structural characteristics, mapping litter-bed fuel load across the landscape cannot be achieved by TLSs due to its scanning scales. Therefore, Chapter 5 evaluates how litter-bed fuel load relates to airborne LiDAR system (ALS) - derived fuel structural characteristics and terrain features, as well as fire history. This has led to the development of a novel approach to estimate spatial variation in forest litter fuel load for eucalypt forests at a large scale. The accurate information derived from this model can be used to assist forest fuel management, assess suppression difficulties, predict ongoing fires for operational activities, and assess potential fire hazards in the study area. This chapter has been submitted to the Journal of Remote Sensing of Environment in 2016.

Chapter 5. Stratifying Eucalypt Forest Structures Using Airborne LiDAR Indices to Map Litter-bed Fuel Load

Abstract

Accurate description of forest litter-bed fuel load is significant for modelling fire behaviour and for assessing fuel hazards. However, quantities of litter-bed fuel can be highly variable across a large scale due to the high-degree of natural variability of overstorey and understorey vegetation species and composition, topography, weather, and disturbances of previous fires and erosion. In this study, airborne Light Detection and Ranging (LiDAR) data was used to estimate litter-bed fuel load in multilayered forests located at the Upper Yarra Reservoir area, Victoria, Australia. First, the forest was stratified into vertical vegetation layers by identifying the division point of the smoothed mixture distribution of LiDAR point density. Second, the stratified height indices were computed for the distinct vegetation layers. Other LiDAR indices including initial intensity and canopy density as well as topographic attributes were also extracted. Finally, two predictive models were developed using multiple regression based on the LiDAR indices, topography, forest fuel types and fire history. The final model was determined by assessing the cross-validation (*CV*) and Akaike information criteria (*AIC*). It estimated litter-bed fuel load with a prediction error of 0.16 (kg/m^2) and R^2 value of 0.63, which was then utilised to map litter-bed fuel load on a landscape scale. This model provides accurate and consistent information on litter-bed fuel load that is beneficial to fire authorities in guiding fire hazard-reduction burns and fire suppressions in the study area. The LiDAR-based forest vegetation stratification can be beneficial for forest habitat mapping and ecosystem monitoring.

Keywords: ALS; forest vertical stratification; Litter-bed fuel load; Mixture distribution; Multiple regression

5.1 Introduction

Australia's native Eucalypt forests are among the most fire-prone in the world due to high fuel accumulation rates, aerodynamic bark material, high flammability of the fuel and high climate variability (Adams, 2013). Projected changes in the frequency and intensity of extreme climate and weather could increase the occurrence of 'mega-fires' - extreme fire events with dramatic impacts on people and environment (Stephens *et al.*, 2014). The most reliable method to reduce fire risk is through modifying fuel availability (Fernandes and Botelho, 2003). Therefore, accurate and consistent methods to quantify forest fuel load can assist fire-related studies and operational activities to reduce fire risk (Andrew *et al.*, 2000). Fuel load is defined as the amount of surface fuel or litter-bed fuel (fine leaf and twig materials that are less than 6 mm in diameter), measured in tonnes per hectare, which has significant impacts on fire ignition, rate of spread and propagation (Anderson, 1982; Gill *et al.*, 1987; Neumann and Tolhurst, 1991). However, the quantification of litter-bed fuel can be extremely complex at landscape scales, since litter-bed fuel load is often not directly related to vegetation types (Pyne *et al.*, 1996; Falkowski *et al.*, 2005), and also highly varies with environmental conditions (Brown and Bevins, 1986).

Traditionally, litter-bed fuel load was determined by field sampling, oven drying at 105°C for 24 hours, and immediate weighing (McArthur, 1962), which can be time and labour intensive when applying this method on large scales. McArthur (1962) found positive relationships between litter-bed fuel load and litter-bed depth known as the depth-to-load relationships that have been used as a rapid alternative to support fuel hazard-reduction burns in Eucalypt forests in Australia, instead of directly measuring fuel load (McArthur, 1962; Birk and Simpson, 1980).

In addition, litter-bed fuel load can also be estimated using fuel accumulation models that describe a simplification of the difference between fuel accession and decomposition rates

(Agee *et al.*, 1973). These models follow an exponential distribution (Peet, 1971; Birk and Simpson, 1980; Raison *et al.*, 1983; 1986; Gould *et al.*, 2011):

$$w_t = w_{ss}(1 - e^{kt}) \tag{1}$$

where w_t is defined as the dry weight of litter-bed fuel accumulated at time t years since the last fire, w_{ss} is the dry weight of the fuel accumulated under steady state conditions, and k is defined as the decomposition constant. These models are constrained to estimate spatial variations in litter-bed fuel load within homogeneous vegetation that previously experienced the same fire events. The accumulation curve is shaped by both forest fuel type and time since last fire. In reality, fuel accumulation is caused by a complex interaction among forest composition and structure and ancillary factors (e.g. topography, aspect, seasonal and diurnal changes in rainfall and temperature, the extent and severity of previous disturbance events) that indirectly influence fuel accumulation (Fox *et al.*, 1979; Birk and Simpson, 1980; Walker, 1981; Miller and Urban, 2000). Quantifying the composition of understorey and overstorey vegetation as well as the ancillary factors is significant in understanding spatial variations in litter-bed fuel load. Remote sensing (RS) is a breakthrough technology for modelling terrain features, monitoring weather, understanding forest ecosystems, as well as mapping resources for forest planning and management (Lefsky *et al.*, 2002). However, measuring forest structure is relatively challenging compared to the estimation of other factors which determine litter-bed fuel load (Zimble *et al.*, 2003).

Application of RS technologies in forest management generally involves either the use of imagery from passive RS systems (e.g. aerial photography and Landsat Thematic Mapper) or radar sensors (e.g. RADARSAT) (Waring *et al.*, 1995). However, passive sensors cannot penetrate the forest canopy to detect understory fuel structure (Dubayah and Drake, 2000; Lefsky *et al.*, 2002). Radar sensors are known as lesser degree active RS systems due to their relative low frequency and spatial accuracy. They also have significant limitations in fine-scale forest application, since their sensitivity and spatial accuracy decline with increasing aboveground biomass and LAI (Waring *et al.*, 1995; Carlson and Ripley, 1997; Turner *et al.*, 1999). Moreover, these passive and active RS sensors produce two-dimensional images of canopy vegetation and cannot completely represent the three-dimensional structure of multilayered forests due to the limited information about understorey vegetation.

In contrast to radar systems, LiDAR sensors have higher frequency and shorter wavelength. Most conventional Airborne LiDAR scanning (ALS) systems have a multi-echo capability and capture between two and five returns for each laser pulse by penetrating beyond the first reflective surfaces of the canopy. ALS systems directly measure three-dimensional forest structure in various forestry applications due to the sensitivity of their waveforms to the structural changes through forest succession (Dubayah and Drake, 2000).

LiDAR-derived vertical distribution of intercepted surfaces provides new insights into forest structure. Several studies, including Hermosilla et al. (2014) and Jakubowksi (2013) described vertical profiles of forest vegetation using theoretical distribution functions of ALS indices. More specifically, these studies applied a unimodal structure (e.g. a Weibull distribution function) in LiDAR to represent forest structural characteristics. However the form of the distribution of LiDAR points can be highly variable among forest fuel types, previous disturbance, and age classes. In a multilayered forest, the vertical profile of the vegetation in LiDAR tends to follow mixture distributions (e.g. bimodal distributions) depending on the complexity of the understorey vegetation (Jaskierniak *et al.*, 2011). In statistics, a mixture model is a probabilistic model for describing the existence of two or more subpopulations within an overall statistical population (Lindsay, 1995).

Previous studies found that merchantable timber could be estimated by fitting the irregular diameter frequency distributions of mixed-species or uneven-aged forest stands to mixture models (Zhang *et al.*, 2001; Liu *et al.*, 2002; Zhang and Liu, 2006). Jaskierniak et al. (2011) applied bimodal models to represent LiDAR height distributions to estimate plot level structural characteristics. The Generalised Additive Model for Location, Scale and Shape (GAMLSS) was used for generation of the bimodal models. The GAMLSS are semi-parametric univariate regression models, where all the parameters of the assumed distribution for the response variable can be modelled as additive functions of the explanatory variables (Rigby and Stasinopoulos, 2009). The GAMLSS produced 1936 combinations of possible bimodal distributions. Jaskierniak et al. (2011) determined likely candidate distributions of the canopy vegetation layer in the second component of the bimodal model to reduce the number of candidate bimodal distributions to 390 for their study plots. Extrapolating and evaluating the amount of likely candidate bimodal distributions requires high performance computer systems and more computing time.

Forest vertical structure is a function of species composition, microclimate, site quality and topography, which has a significant influence on productivity and fuel accumulation (Dubayah *et al.*, 1997; Dubayah and Drake, 2000). Therefore, LiDAR indices relating to crown height, canopy density, depth and closure of, both understorey and overstorey layers as well as topography, are useful for quantifying litter-bed fuel. Unlike the approach in Jaskierniak et al. (2011), the present study stratified multilayered eucalypt forests through identification of the division points of the smoothed bimodal curves to quantify vertical forest structure through a non-parametric fitting strategy as well as derivative functions. The stratified LiDAR height indices, initial intensity, canopy density and topography, forest fuel type and previous fire disturbances were then used to develop predictive models to estimate litter-bed fuel load through multiple regression analysis. Two candidate models were then assessed using the observed litter-bed fuel load that was directly measured. The finalised model was then used to map litter-bed fuel load across the Upper Yarra Reservoir Park area, Victoria, Australia. The predictive model provides accurate spatial information for decision making in regional forest fuel management. The LiDAR-based stratification of forest vegetation is also useful for land cover classification, habitat mapping, and forest ecosystem and wildlife management.

5.2 Materials and Methods

5.2.1 Study Area and Data

The study area is located in Upper Yarra Reservoir National Parks southeast Australia (37°34'32''S, 145°56'17''E) (Figure 1). It is eucalypt dominated open forests with a large range of indigenous species, including Manna Gum (*Eucalyptus viminalis*), Grey Gum (*Eucalyptus cypellocarpa*), Messmate (*Eucalyptus obliqua*), Peppermint (*Eucalyptus croajingolensis*, *Eucalyptus dives*, *Eucalyptus elata*, *Eucalyptus radiata*), Silvertop (*Eucalyptus sieberi*), Stringybark (*Eucalyptus baxteri*, *Eucalyptus cephalocarpa*, *Eucalyptus globoidea*), and Candlebark Gum (*Eucalyptus rubida*), and understorey vegetation, including species of Wattle Silver (*Acacia dealbata*), Cinnamon Wattle (*Acacia leprosa*), Myrtle Wattle (*Acacia myrtifolia*), Prickly Currant (*Coprosma quadrifida*), Common Ground-fern (*Calochlaena dubia*) and Rough Tree-fern (*Cyathea australis*). The average annual rainfall is approximately 1122 mm; the main soil type is clay loam; the elevation ranges from 219 m to 1205 m. Controlled burns as a typical fuel-management activity have been conducted in this area, and wildfires also occurred over time after recovery from the Black Friday fires of 13th January 1939. Plot 1, plot 2 and plot 3 underwent wildfires in February 2009, while plot 4, plot 5, and plot 6 experienced controlled burns in March 2010, April 2008 and April 2007, respectively.

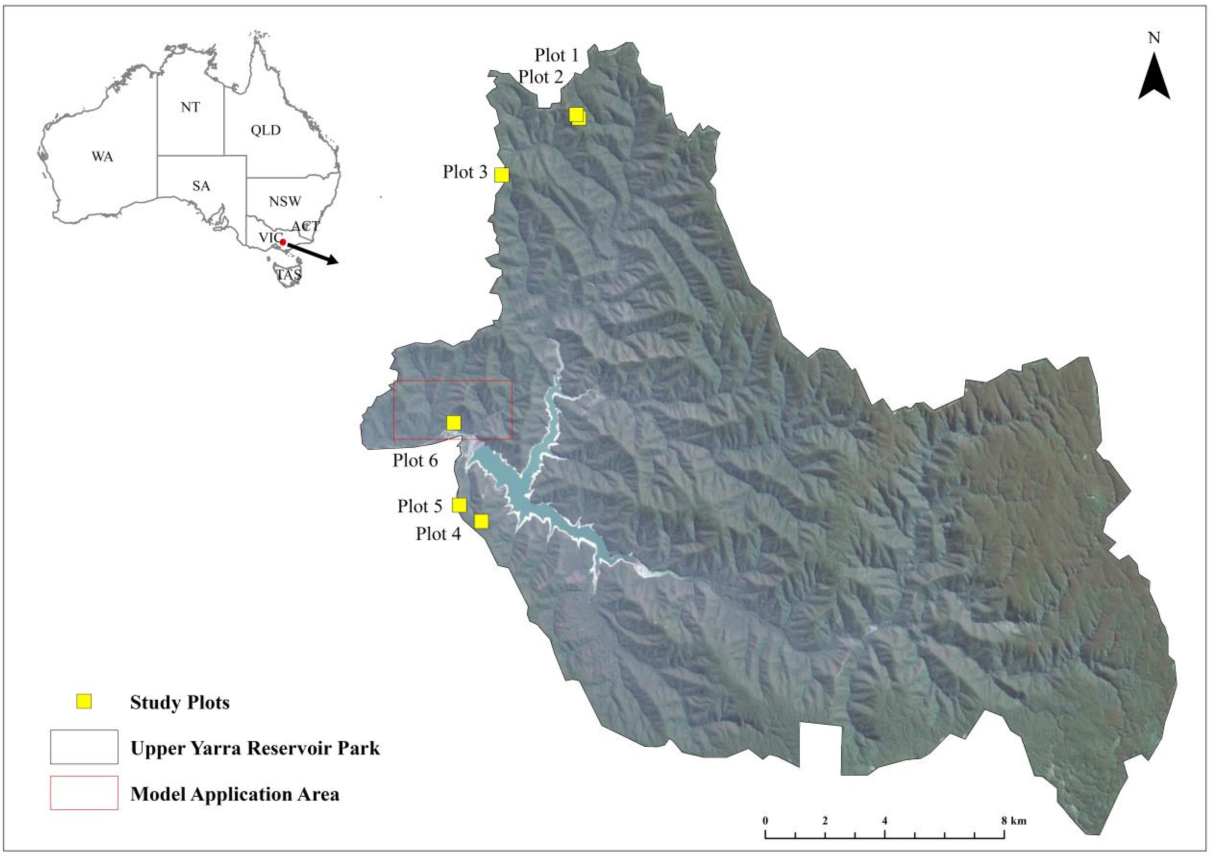


Figure 1. Study area and plot locations over a true colour composite of Landsat imagery (August 2015).

Datasets of forest fuel types and burn types (wildfires or fuel hazard-reduction burns) were provided by the Victorian State Department of Environment, Land, Water and Planning (DELWP). Forest fuel type was derived from Native Vegetation - Modelled 2005 Ecological Vegetation Classes with Bioregional Conservation Status, known as NV2005_EVCBCS (http://services.land.vic.gov.au/catalogue/metadata?anzlicId=ANZVI0803003495&publicId=guest&extractionProviderId=1).

Multi-echo ALS data were acquired in January 2008 with footprint size of 0.26 m. A stratified sampling method was used to collect litter-bed fuel load in various terrains and fire histories. A total of forty-one 0.5 m by 0.5 m samples from six 50 m by 50 m plots were taken. The plots sites were selected as follows. First, the study area was divided into two strata according to previous burn types (wildfires or fuel hazard-reduction burns). Second, unique combinations of years since last fire, fuel type (damp shrubby forest or dry shrubby foothill forest) and elevation were taken into account to stratify the samples for coarse-scale variability of forest fuel. Last, sampling sites were allocated according to various values of aspect and slope within each of the six plots. Dry weights (g) of these samples were immediately and directly weighed, after oven drying for 24 hours at 105 °C (Matthews, 2010) in the laboratory.

5.2.2 Stratification of Vegetation Layers

A non-parametric fitting strategy and two derivative functions were applied to identify the division points of the bimodal distributions. The division point between two components of the bimodal curve was then utilised to stratify the multilayered eucalypt forest, characterise the vertical structure of the forest, and derive LiDAR indices for distinct vegetation layers. More specific procedures are described as follows.

1) Generation of height values: The first step is the generation of height values. A digital elevation model (DEM) with 0.5 m resolution was generated using the last returns of LiDAR point clouds, which was then used to convert the elevation values of the LiDAR points to their height values above the bare earth. The height values were calculated by subtracting a smoothed DEM from the elevation values for the following stratification.

2) Generation of forest vertical profile: A scatter-diagram was generated by plotting the density of LiDAR points against height (Figure 2). The values of height range from 3 m across the vertical profile of the forest structure with 1 m interval. LiDAR points with height lower than 3 m were identified as lower vegetation that was excluded in the bimodal distributions (Jaskierniak *et al.,* 2011), due to the high variation in lower vegetation heights as a result of the complexity in fire history and species composition.

3) Stratification of forest structure: The vertical profile of the forest structures in the study area tended to follow a bimodal distribution. The stratification of the forest vegetation between overstorey and understorey was then carried out by identifying the division point between the two components of the bimodal distribution. The division point was identified in four steps. First, the scatter plot of LiDAR point density against heights was smoothed using Locally Weighted Scatterplot Smoothing (LOWESS) to create a smooth curve through the scatter plot without assuming the shape of distribution for each component. Second, the first derivative of the smoothed data was generated to identify the peaks and troughs of the smoothed bimodal curve. This was conducted by identification of derivative value of 0. Third, the second derivative of the smoothed data was created. Fourth, the maximum value of the second derivative at the peak and trough values of the first derivative curve was defined as the division point. As described in Figure 2, the 1st component of the mixture model represents the density distribution of LiDAR points across vertical profile of understorey shrubs; the 2nd component of the mixture model plots the density distribution of LiDAR points in overstorey vegetation. The following three steps describe the extraction of LiDAR indices.

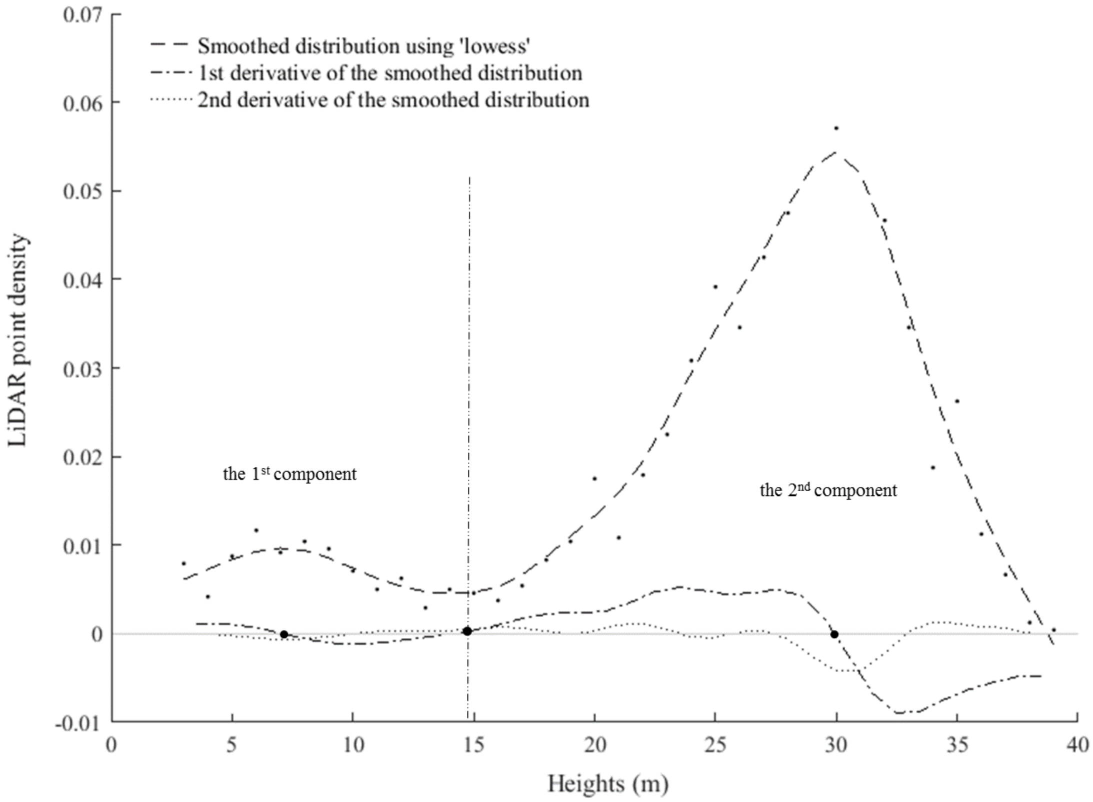


Figure 2. Density distribution of LiDAR points (H >= 3m) for plot 1.

5.2.3 Extraction of LiDAR Indices

After stratifying plot-based forest vegetation, the LiDAR height indices (*H*) were generated based on the distinct vegetation layers, including canopy (*C*), understorey shrubs (*S*) and lower vegetation (*L*) (Table 1). The plot-based extraction of the stratified *H* and the initial intensity (*I*) described in Table 1 were computed in MatLAB R2014a (http://au.mathworks.com).

Canopy density (%) was estimated as the ratio of the number of stratified canopy return LiDAR points to the total number of points within small equal-sized units (1.5 m). The unit size was determined to be at least four times of the point spacing of the LiDAR system (0.26 m in this case). The DEM was used to estimate the elevation (m), slope (degree), and aspect (degree) with 0.5 m resolution in order to keep consistency with the field measured fuel samples. These LiDAR indices were extracted using ArcGIS 10.3 (http://desktop.arcgis.com/en/arcmap/).

Table 1. LiDAR derived indices of height and intensity.

LiDAR Indices		Maximum	Minimum	Mean	Median	Standard Deviation	Percentile 99th	Percentile 95th - Percentile 5th	Percentile 1st
Height (*H*)	***Overstorey vegetation(C)***	H_{maxC}	H_{minC}	H_{meanC}	$H_{medianC}$	H_{StdC}	$H_{99^{th}prctileC}$	$H_{95^{th}prctileC} - H_{5^{th}prctileC}$	$H_{1^{st}prctileC}$
	Understorey shrubs (S)	H_{maxS}	H_{minS}	H_{meanS}	$H_{medianS}$	H_{StdS}	$H_{99^{th}prctileS}$	$H_{95^{th}prctileS} - H_{5^{th}prctileS}$	$H_{1^{st}prctileS}$
	Lower vegetation(L)	H_{maxL}	H_{minL}	H_{meanL}	$H_{medianL}$	H_{StdL}	$H_{99^{th}prctileL}$	$H_{95^{th}prctileL} - H_{5^{th}prctileL}$	$H_{1^{st}prctileL}$
Intensity Indices (*I*)		I_{max}	I_{min}	I_{mean}	I_{median}	I_{Std}	$I_{99^{th}prctile}$	$I_{95^{th}prctile} - I_{5^{th}prctile}$	$I_{1^{st}prctile}$

(Note: Percentile ranges from 1st to 99th with an interval of 5.)

5.2.4 Estimation of Litter-bed Fuel Load

5.2.4.1 Model development

Two assumptions were made for the development of the litter-bed fuel load model: 1) the spatial variations in forest litter-bed fuel load were closely correlated to LiDAR height and intensity indices, which led to the formulation of Model 1; 2) the spatial variations in forest litter-bed fuel load were also highly related to previous disturbances and fuel types, which resulted in Model 2. The predictive models of litter-bed fuel loads (Model 1 and 2) were developed based on the extracted LiDAR indices, years since last fire, eucalypt forest fuel type (dry or damp), burn type (fire hazard-reduction burn or wildfires), and the field measured dry weight of the fuel samples through multiple regression. These variables are listed in Table 2. The stepwise procedure was used to produce estimates of the model coefficients to select the important variable at the statistical significance level of 0.05. The first-order interaction terms for independent variables were applied to keep the number of variables manageable, and to omit high-order terms to the models.

Table 2. Variables used for forest litter-bed fuel load model development.

Descriptions	**Variables**
Litter-bed fuel load (kg)	*DW*
Maximum intensity / heights at stratified vegetation layers (m)	I_{max} / H_{maxC} / H_{maxS}/ H_{maxL}
Minimum intensity / heights at stratified vegetation layers (m)	I_{min} / H_{minC} / H_{minS} / H_{minL}
Mean intensity / heights at stratified vegetation layers (m)	I_{mean} / H_{meanC} / H_{meanS} / H_{meanL}
Median intensity / heights at stratified vegetation layers (m)	I_{median} / $H_{medianC}$ / $H_{medianS}$/ $H_{medianL}$
Standard deviation of intensity / heights at stratified vegetation layers (m)	I_{Std} / H_{StdC} / H_{StdS} / H_{StdL}
99th Percentile of intensity / height distribution at stratified vegetation layers	$I_{99^{th}prctile}$ / $H_{99^{th}prctileC}$ / $H_{99^{th}prctileS}$ / $H_{99^{th}prctileL}$
…	...
1st Percentile of intensity /height distribution at stratified vegetation layers	$I_{1^{st}prctile}$ / $H_{1^{st}prctileC}$ /$H_{1^{st}prctileS}$ / $H_{1^{st}prctileL}$
Canopy density (%)	*CD*
Elevation (m)	*E*
Aspect (degree)	*A*
Slope (degree)	*S*
Forest fuel type (dry / damp eucalypt forest)	*FT*
Burn type (wildfire / fuel hazard-reduction burns)	*BT*
Time since last fire (year)	*YSF*

5.2.4.2 Model error assessment

The model assumptions were assessed through Cook's distance plot, the histogram of residuals and the normal probability plot (NPP). *AIC* was computed for model selection as well as for restricting overfitting problems. The *AIC* value of the candidate models is calculated using the following equation (2).

$$AIC = 2k - 2\ln(L) \tag{2}$$

where *L* is the maximum value of the likelihood function for the model, and *k* is the number of estimated parameters in the candidate model. In this study, *ln(L)* is replaced by *N* times the log of the variance of the noise, defined as *N*log(RSS/N). N* is the number of observations, and *RSS* is the residual sum of squares.

The leave-one-out cross-validation was then used to verify the result of the candidate models. Leave-one-out cross-validation (*CV*) could be computed using equation 3,

$$CV = \frac{1}{n}\sum_{i=1}^{n}[e_i/(1 - h_i)]^2 \tag{3}$$

where *n* is the number of the observations, e_i is the error obtained from fitting the model to *n* - 1 observations, h_i is the leverage, and *i* is the repeating step (= 1, 2, …, *n*) (Kohavi, 1995; Good, 2001). The preferred model-predicted values of litter-bed fuel load were then compared with the observed fuel load for a further assessment of accuracy of the prediction. Finally, sensitivity analysis was also conducted to further assess how the uncertainty in the model output can be apportioned to the uncertainty in its inputs.

5.3 Results

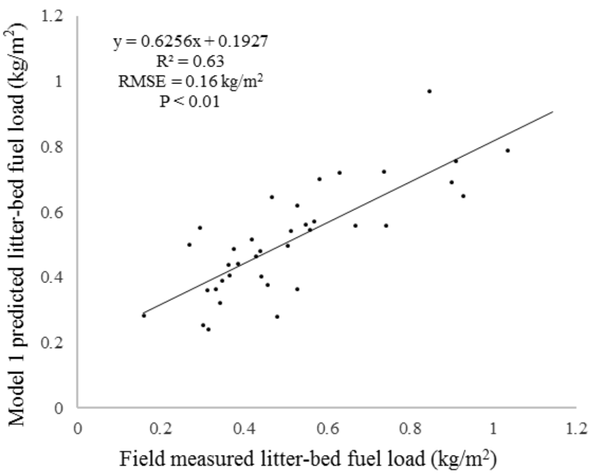
5.3.1 LiDAR-derived predictive model

Table 3. Forest litter-bed fuel load performance summaries for the different model formulations explored in this study.

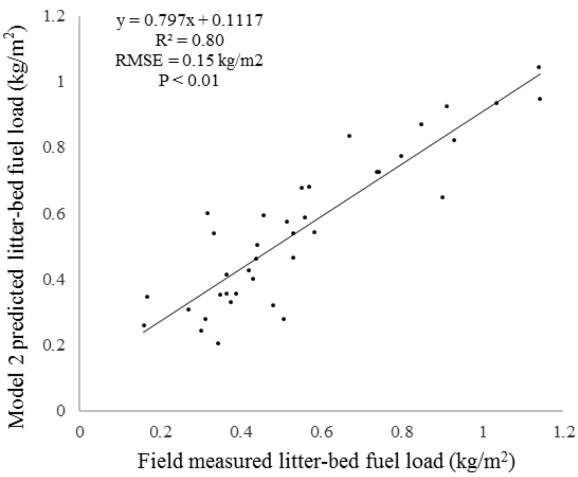
Model	Predictors	*Coefficients*	*Std. Error of the Estimate*	*t*	*P*	*F*
1	*(Intercept)*	-107.53	29.86	-3.60	< 0.01	
	H_{meanS}	-0.22	0.06	-3.62	< 0.01	13.13
	$log(H_{maxC})$	3.91	1.86	2.11	0.04	4.44
	$log(H_{meanC})$	-8.24	3.78	-2.18	0.04	4.75
	$log(A)$	-0.15	0.08	-1.92	0.06	3.70
	$H_{medianS}*H_{StdS}$	-0.03	0.01	-4.35	< 0.01	18.95
	$log(H_{medianC})*log(E)$	-27.79	7.43	-3.74	< 0.01	13.97
	$log(H_{StdC})*log(E)$	8.95	3.55	2.52	0.02	6.34
2	*(Intercept)*	29.47	12.38	2.38	0.03	
	H_{meanS}	-0.04	0.02	-1.74	0.1	3.03
	$log(H_{minC})$	-2.96	0.62	-4.74	< 0.01	22.50
	CD	0.66	0.21	3.16	< 0.01	9.99
	$log(E)$	-10.45	4.81	-2.17	0.04	4.72
	$log(S)$	0.52	0.13	3.87	< 0.01	14.94
	BT	5.14	2.34	2.19	0.04	4.81
	$H_{maxS}*H_{StdS}$	-0.03	0.01	-5.90	< 0.01	34.75
	$H_{StdS}*log(A)$	-0.19	0.07	-2.77	0.01	7.67
	$log(H_{StdC})*log(A)$	2.56	0.88	2.91	0.01	8.48
	$log(A)*FT$	-1.16	0.25	-4.63	< 0.01	21.42

During the error assessment of forest litter-bed fuel load model development, a symmetric normal distribution of residuals was detected, which indicated the observations were randomly sampled from a normal distribution. The NPP of the residuals (the error terms) was approximately linear supporting the condition that the error terms were normally distributed and no obvious patterns were detected. Cook's distance detected three potential outliers. According to the model assumptions, the two models were produced as summarised in Table 3.

Model 1 was developed based on the LiDAR-derived height indices and topography. It is a linear regression model with eight terms in nine predictors, including H_{meanS}, $log(H_{maxC})$, $log(H_{meanC})$, $log(A)$, $H_{medianS}*H_{StdS}$, $log(H_{medianC})*log(E)$, $log(H_{StdC})*log(E)$. It explained the majority of the variation in the observed litter-bed fuel load. LiDAR-derived *I* indices were excluded in the model due to their low statistical significance in the model prediction. Model 1 produced an R^2 value of 0.63 and *Root Mean Squared Error* (*RMSE*) value of 0.16 kg/m^2, when compared with the model-predicted dry weight of litter-bed fuel load with observed values (Figure 3a).



a



b

Figure 3. Scattergrams of Model 1 (a) and Model 2 (b) estimated forest litter-bed fuel load against field observed values.

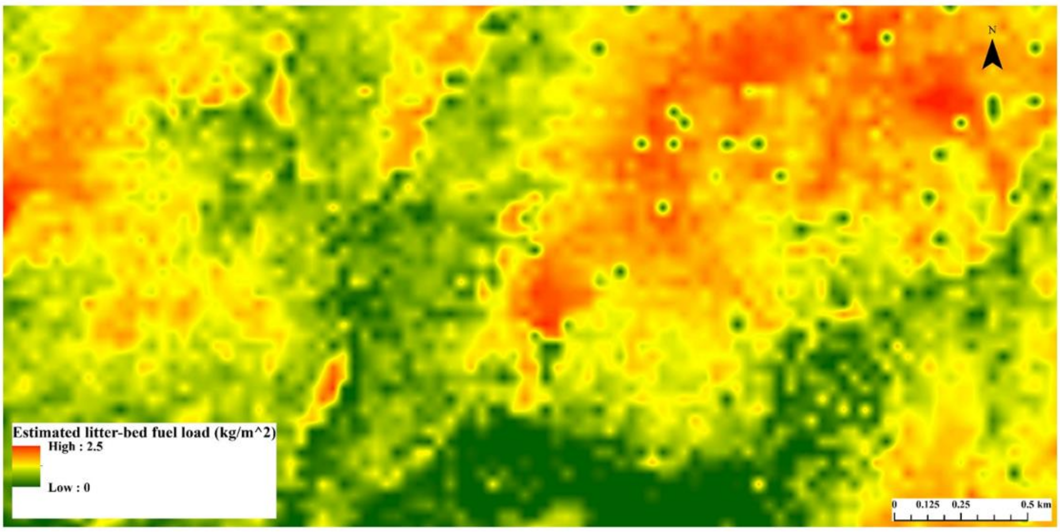
Model 2 introduced other variables (*FT* and *BT)* to interact with the LiDAR-derived indices. *CD* and *log(S)* were included in Model 2 due to their statistical significance in the model prediction. Both models resulted in similar prediction errors (*CV*) through leave-one-out cross-validation (Table 4). Model 2 explained an extra 17% of the observed variations in litter-bed fuel load, and also improved *RMSE* to 0.15 kg/m^2 (Figure 3b). However, it included two more predictors (forest fuel types and fire history) that increased the *AIC* value by 25, compared to Model 1 (Table 4). Both models involve inputs of LiDAR indices (heights and topographic variables). However, Model 2 requires extra specific data inputs including forest fuel type and fire history. Its output may also be sensitive to the accuracy of the forest fuel type and fire history. Therefore, Model 1 is recommended for forest application, such as mapping litter-bed fuel load and assessing forest fuel hazards on a landscape scale. A complete litter-bed fuel load map in the Upper Yarra Reservoir Park could not be created due to the limited LiDAR data availability. Model 1 estimated spatial variations in litter-bed fuel load across 200 ha in the study area (Figure 4). The cell size or resolution (40 m by 40 m in Figure 4c) of the litter-bed fuel load estimation is the unit in which ALS indices were extracted and vegetation layers were then stratified. Model 1 consequently was utilised to compute the litter fuel load over these individual units. The size of the unit can be flexible depending on whether the scatter plot of laser point density against height follows a continuous mixture distribution. The following discussion is focused on the established model - Model 1.

Table 4. Forest litter-bed fuel load model comparison.

Model	*R Square*	*RMSE*	*F*	*Sig.*	*AIC*	*CV*
1	0.63	0.16	3.34	<0.01	-116.22	0.073
2	0.80	0.15	5.76	<0.01	-90.87	0.078

a

b



c

Figure 4. Spatial variations in fire history (a), canopy density (%) (b), and litter-bed fuel load (kg) (c) in the study area.

5.3.2 Sensitivity analysis

Model 1 indicates that litter-bed fuel load can be primarily predicted by stratified LiDAR height indices and topography. Forest litter-bed fuel load is linearly related to H_{meanS}, $log(H_{maxC})$, $log(H_{meanC})$, $log(A)$, $H_{medianS}*H_{StdS}$, $log(H_{medianC})*log(E)$, and $log(H_{StdC})*log(E)$. However, the uncertainty in the model-predicted litter fuel load can be apportioned to different sources of uncertainty in the inputs (Saltelli, 2002; Saltelli *et al.*, 2008). Model outputs are more sensitive to H_{meanS} and $log(H_{meanC})$ (Figure 5). Changing H_{meanS} from 0 (no understorey shrubs) to 12 m decreases litter fuel load by 2.6 kg/m^2, given all other parameters are held constant. It suggests that the mean heights of understorey shrubs may negatively influence the litter-bed load in the study area. Maximum canopy height is positively related to the load in the study area. A rise of $log(H_{maxC})$ from 1.43 to 1.67 (maximum canopy height changing from 27 to 47 m) increases the quantity of litter fuel by 0.9 kg/m^2, when other parameters are held constant. There is a strong relationship between H_{maxC} and forest fuel type in the study area (Figure 6). The canopy height of dry eucalypt forest (in green) tends to be lower than 35 m; the canopy heights of wet eucalypt forests (in orange) are generally higher than 35 m. In this area, dry forests produce more litter fuel on the forest floor leading to a higher fire hazard than wet forests. Increasing $log(H_{meanC})$ from 1.3 to 1.59 (mean canopy height changing from 20 m to 39 m), holding other parameters constant, decreases quantity of litter fuel by 2.3 kg/m^2. Raising $log(A)$ from 1 to 2.6 decreases the litter fuel load by 0.2 kg/m^2 (Figure 5). The model prediction is least sensitive to the variation in aspect compared its main effect index with other predictors. In the study area, forests with east, southeast, and south aspects may produce more litter-bed fuel load than forests with north, northwest and west aspects (Figure 7b).

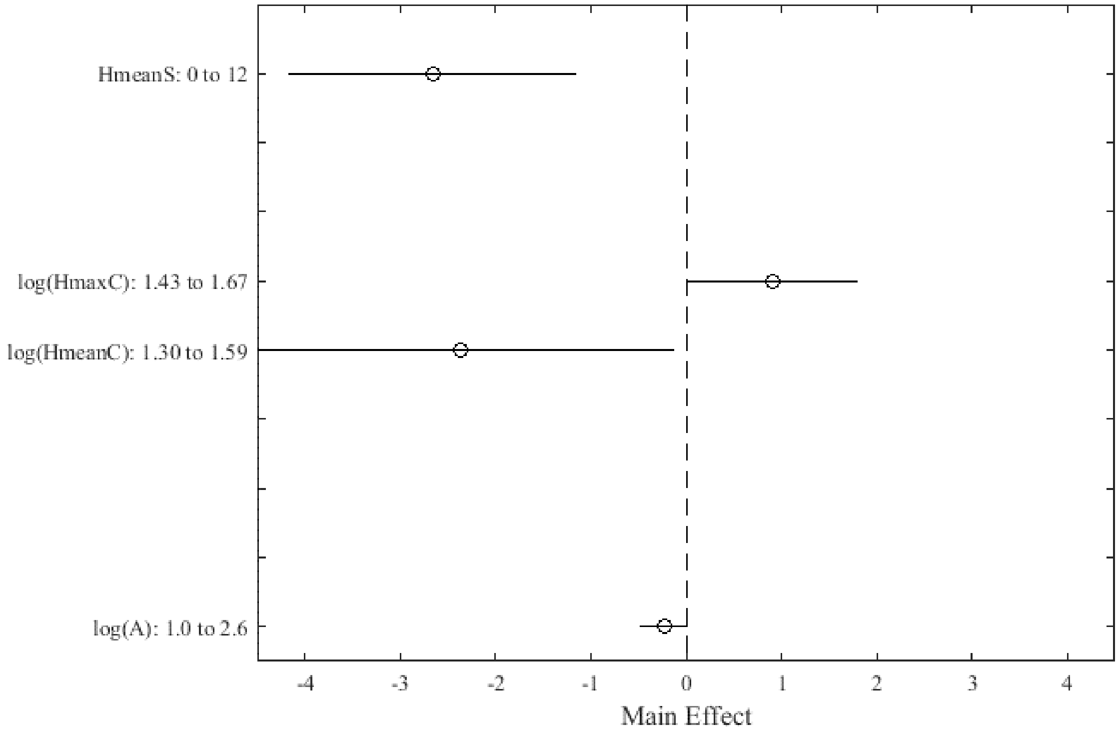


Figure 5. Main effect of the independent variables (*HmeanS, log(HmaxC), log(HmeanC*) and *log(A)*) of Model 1 in prediction of forest litter fuel load. The horizontal lines represent confidence intervals for these predictions. It measures the effect of varying one of the input parameters and averaged variations in other input parameters.

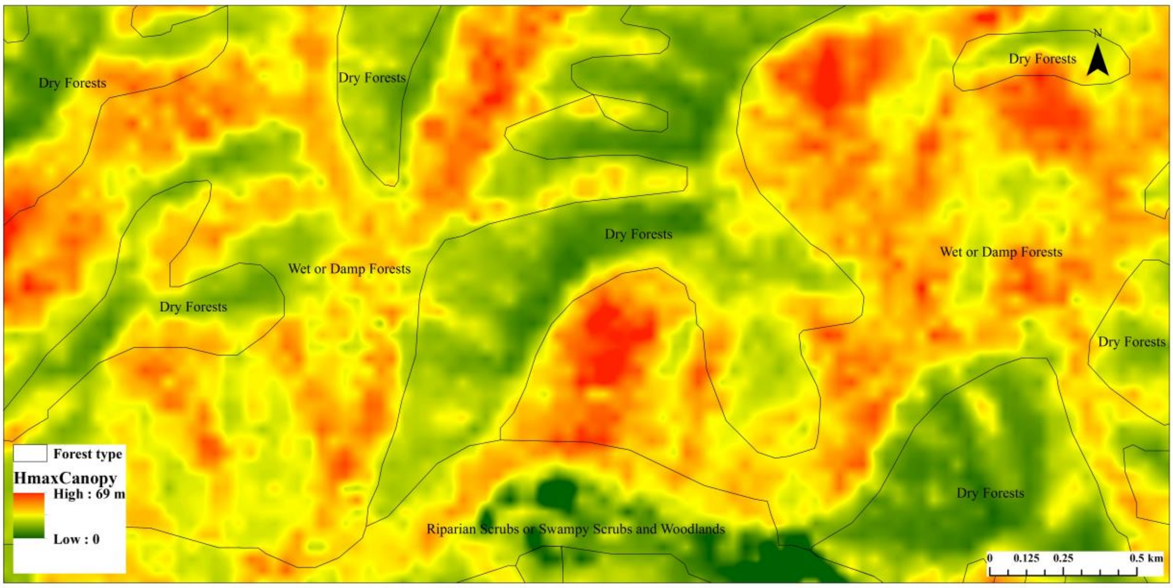
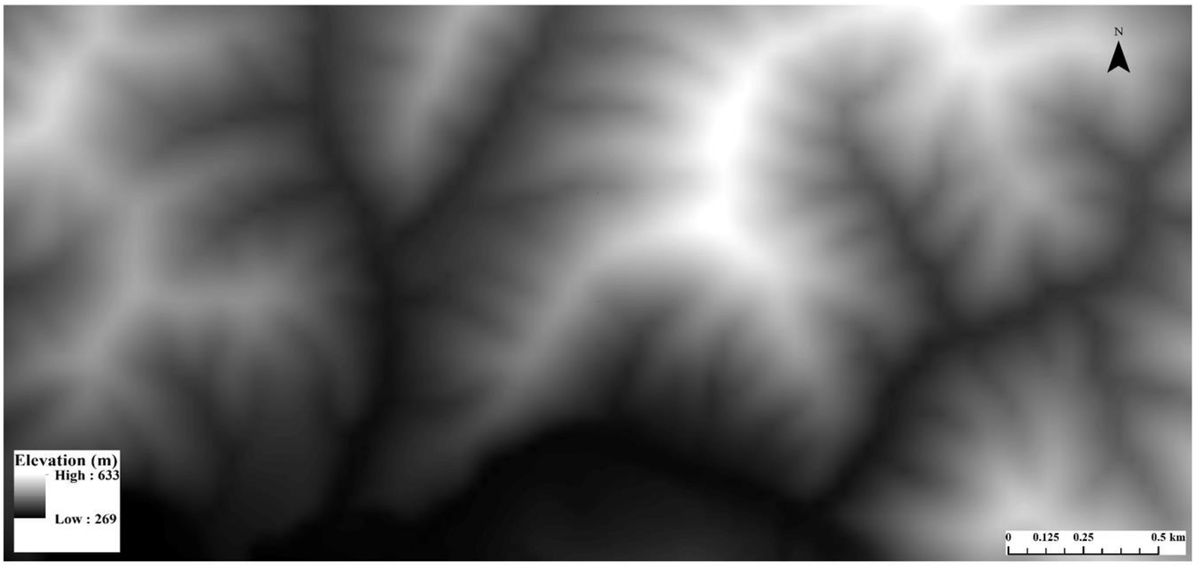
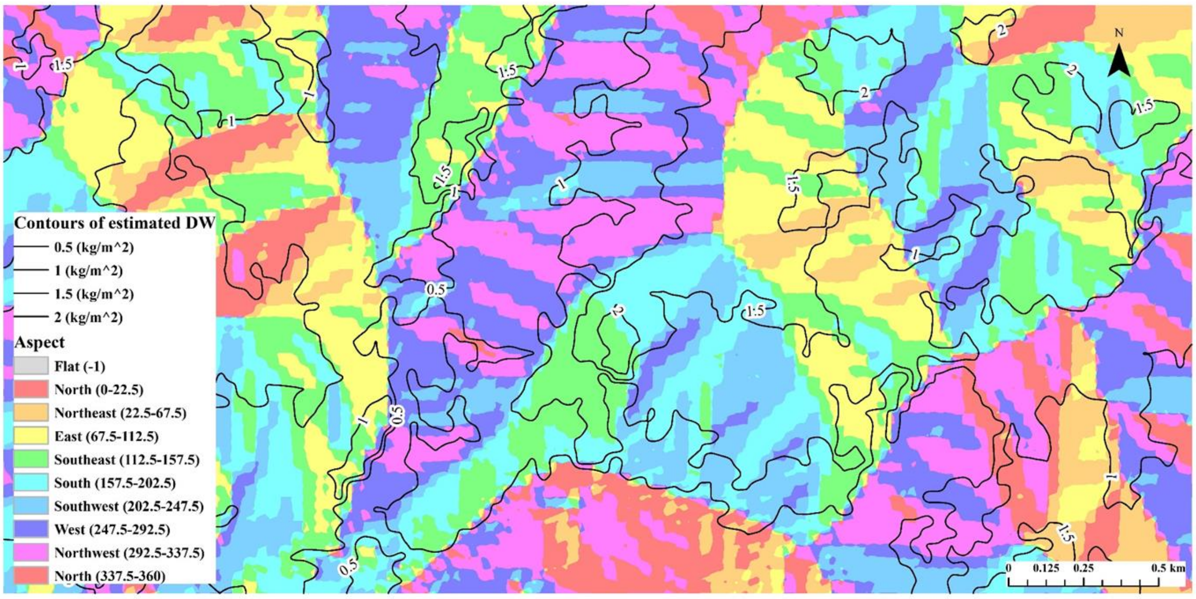


Figure 6. Forest fuel type in relation to LiDAR-derived *HmaxC* (m).



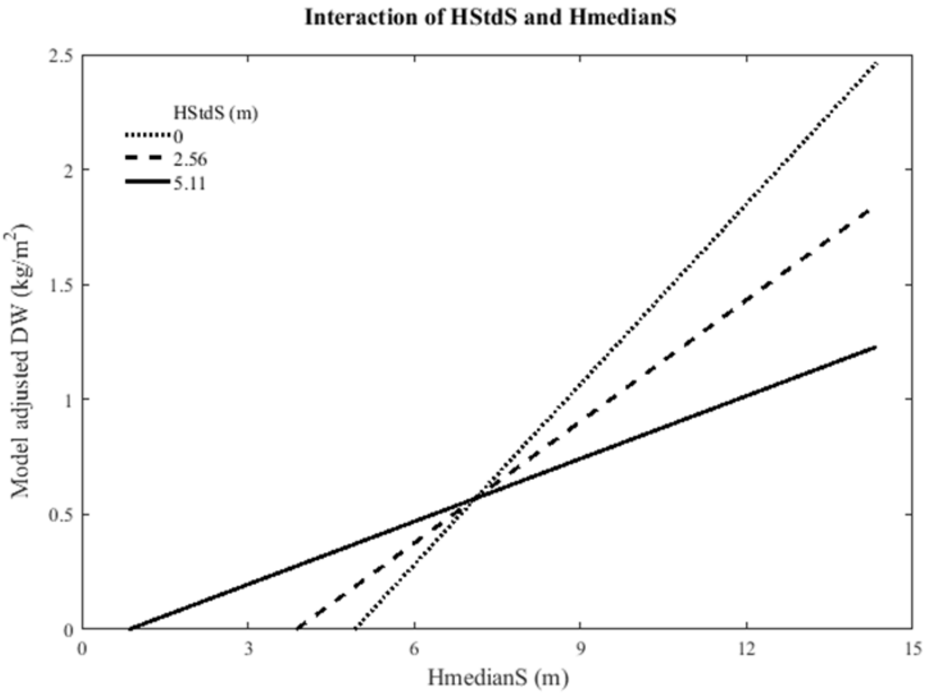
a

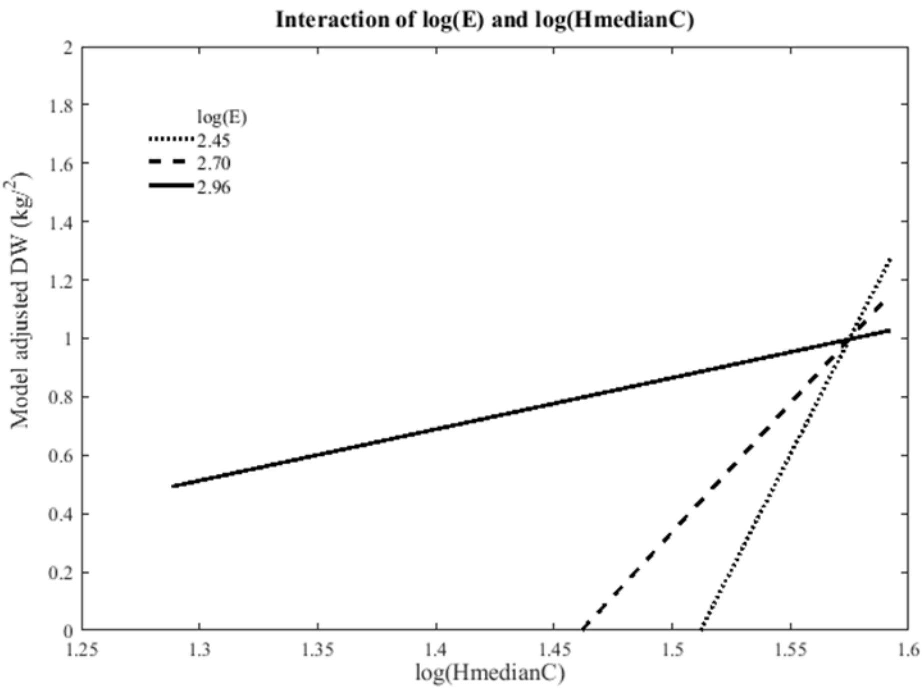


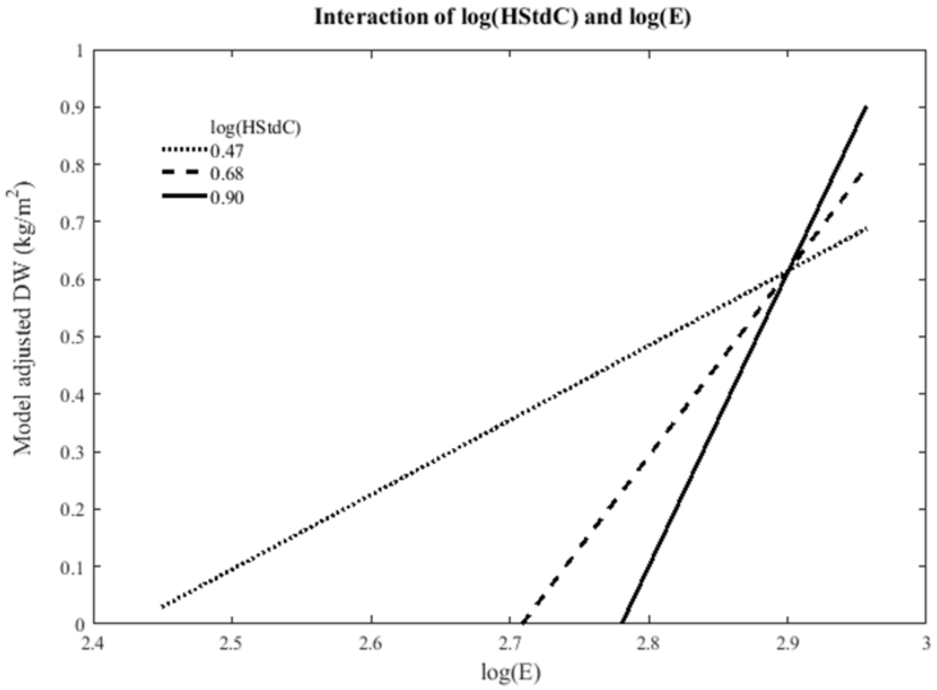
b

Figure 7. Terrain features in the study area. a. Elevation; b. Aspect in relation to contours of the estimated fuel load.

The above sensitivity analysis, however, does not identify the output uncertainty caused by the interactions (White and McBurney, 2012). Model 1 involves the interaction of the parameters that simultaneously cause variations in the output, which is examined as follows. Changing H_{StdS} from 0 to 5.11 m increases the quantity of litter fuel when $H_{medianS}$ is constant and lower than 7 m, whereas increasing H_{StdS} within the same range may decrease the litter fuel load when the constant $H_{medianS}$ is higher than 7 m (Figure 8a). Forests with lower understorey vegetation tend to have more litter-bed fuel when heights of understorey vegetation are inconsistent; forests with higher shrubs can also yield more litter-bed fuel when heights of understorey vegetation are consistent. Increasing elevation raises the litter fuel load when $H_{medianC}$ is constant and lower than 37 m; rising elevation also reduces the litter fuel load when $H_{medianC}$ is constant and higher than 37 m (Figure 8b). As described in Figure 7, in the study area maximum height tends to be lower than 35 m for dry eucalypt forests, and wet eucalypt forests are higher than 35 m. Therefore, the dry forest located at a higher elevation may produce more litter-bed fuel load, and the wet forests located at a lower elevation tend to have more litter-bed fuel load. Figure 8c shows that changing $log(H_{StdC})$ from 0.47 to 0.9 reduces the litter fuel load, while holding $log(E)$ fixed and lower than 2.9; and the increase in $log(H_{StdC})$ also raises the litter fuel load when $log(E)$ is constant and higher than 2.9. When elevation is constant and lower than 800 m, increasing standard deviation of canopy height from 3 m to 8 m reduces litter-bed fuel load, and also increases the load when elevation is higher than 800 m. Thus, increasing the consistency in canopy vegetation heights may increase the amount of litter-bed fuel load when forests are located at a certain elevation below 800 m. However, this increase reduces the fuel load when forests are located at a certain elevation above 800 m.


Interaction of HStdS and HmedianS
HStdS (m)
0
2.56
5.11
Model adjusted DW (kg/m^2)
HmedianS (m)
0
3
6
9
12
15
0.5
1
1.5
2
2.5
a


Interaction of log(E) and log(HmedianC)
log(E)
2.45
2.70
2.96
Model adjusted DW (kg/^{2})
log(HmedianC)
1.25
1.3
1.35
1.4
1.45
1.5
1.55
1.6
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
b



c

Figure 8. Interaction plots to describe the model-adjusted prediction when holding one predictor fixed and changing the other interacted predictor.

Statistically, the stratified LiDAR height indices (e.g. H_{max}, H_{mean}, H_{median} and H_{Std}) contribute more to the model prediction than the height percentile and intensity. *YSF* is not the key indicator of spatial variations in litter fuel load, despite litter-bed fuel accumulating over time. Fire intensity and severity can be highly variable with different fire histories, even within one fire. It is critical to apply physical boundaries of fire history to estimate litter-bed fuel load. In order to reduce the amount of uncertainty of outputs caused by model inputs, Model 1 is the recommended model in this study. This model shows that both elevation and aspect are more statistically significant than slope. Some fuel accumulation studies show that elevation indirectly influences fuel productivities and decomposition rates due to its effect on soil moisture; aspect is an indicator of litter-bed fuel moisture content that indirectly influences the decomposition rates (McArthur, 1962; Birk and Simpson, 1980; McCaw *et al.*, 1996; Schaub *et al.*, 2008). This study found that the impact of elevation on litter-bed fuel load could be restricted by canopy height indices in the study area, and the LiDAR-derived canopy height indices are closely correlated with forest fuel type (wet/dry eucalypt forests). In other words, forest fuel types contribute differently to litter-bed fuel load with a change in elevation. Rising elevation for dry forests may increase litter-bed fuel load, and increasing elevation in wet forests may decrease litter-bed fuel load. Greater quantities of litter-bed fuel tended to be located on east, southeast and south aspects in the study area.

5.4 Discussion

Accurate prediction and description of wildfire behaviour is essential to sound forest fire management, including fire danger rating, prescribed burning and wildfire control (Burrows, 1999). However traditional measurement requires extensive field sample collection and laboratory work when a large area is involved. Currently, Australian fire authorities and land management agencies are using direct measurement of litter-bed fuel depth to assess litter-bed fuel hazards (Watson *et al.*, 2012). However, both methods have limitations in describing spatial variations in litter-bed fuel load, as they depend on statistical extrapolation of the field samplings to a greater scale. The accumulation models tend to follow a general form of an exponential function (Gould *et al.*, 2014), in which years since last fire is the only independent variable used to predict fuel growth within homogeneous vegetation (Conroy, 1993; Fernandes and Botelho, 2003). In addition, McArthur (1962)'s depth-to-load relationships as well as Gilroy and Tran (2006)'s model use forest litter-bed depth to predict litter-bed fuel load. However current methods are restricted in measuring spatial variations in litter-bed fuel depth across landscape scales. Therefore, it is impossible to compare the predicted fuel load derived from these models to the spatial variation estimated from our model in our study area, as the forests have mixed fuel types and species with various fire events.

Forest vegetation composition and structure, as well as terrain features shape forest ecosystems and microclimate. These factors also provide significant information for litter-bed fuel load estimation that assists forest management and fire-related operational activities such as fire hazard-reduction burns. This study used LiDAR indices to quantify forest structural information through vegetation stratification according to the height distribution of LiDAR point density. Other studies used unimodal structures to represent vertical profiles of forest structure. However, unimodal distributions cannot capture a complete representation of the continuous LiDAR point density in multilayered forests (Jaskierniak *et al.*, 2011). Jaskierniak et al. (2011) extracted LiDAR indices from the best-fitted bimodal models as a result of an extensive evaluation in goodness of fit among a wide range of candidate bimodal distributions. However, some types of distributions were assumed in advance, and this parametric fitting could lead to fitting a smooth curve that misrepresented the data. Unlike Jaskierniak et al. (2011), the LOWESS was used in this study for fitting a smooth curve to data points without the assumption that the data must fit some distribution shape. Our computation was relatively efficient and does not require a high performing computing system to generate the result within a reasonable time. The structural information was then used to develop a predictive model for litter-bed fuel load estimation. The model prediction error was 0.16 kg/m^2 and explained 63% variation in litter-bed fuel load that observed using the direct measurements. The information derived from the model can be used to assist forest fuel management, and assess potential fire hazards in the Upper Yarra Reservoir area.

This study also demonstrated an efficient method to stratify a LiDAR-derived forest vertical profile - a bimodal distribution through integration between a non-parametric smooth fitting strategy and derivative functions. This method provides a new approach to classify forest vegetation using ALS data, which is replicable and beneficial for various forest applications, such as mapping forest canopy closure, habitat conservation and ecological management. In addition, LiDAR-derived canopy density is typically computed through dividing the amount of non-ground return points by total amount of non-ground return and ground return points in a unit area. This method is applicable in single layer forests. However, it overestimated canopy density in our multilayered forests by taking overstorey and understorey vegetation into account as a complete canopy. Our study computed forest canopy density according to the ratio of the number of LiDAR points returned from stratified overstorey vegetation to the total number of non-ground return points within small equal-sized units, which is more accurate.

5.5 Conclusion

The variation in litter-bed fuel load in eucalypt forests can be attributed to the variability in species composition of overstorey and understorey vegetation, the extent and severity of previous disturbance events including fires and erosion, the site quality including soil quality, stocking rates and plant cover, elevation, aspect and slope position which have impact on fuel moisture and litter decomposition rates, and the moisture content of the leaf litter due to seasonal and diurnal changes in precipitation and radiation (McCarthy, 2004; Tolhurst *et al.*, 2008). Therefore, quantifying litter-bed fuel load using environmental impact factors across the landscape can be challenging. This study developed a predictive model of forest litter-bed fuel load using LiDAR-derived stratified height indices and topography. The predictive model efficiently and consistently estimated the spatial distribution of litter-bed fuel load in multilayered eucalypt forests with various fire history and forest fuel types. Current fuel models use a single indicator (e.g. litter-bed fuel depth, and years since last fire) to estimate fuel load within a homogeneous vegetation community. On contrast, our model revealed spatial variations in litter-bed fuel load using forest understorey and overstory vegetation structural characteristics, and topography through multiple regression with LiDAR data.

This newly-developed model (Model 1) for forest litter-bed fuel load estimation is applicable when data of forest fuel types and previous fire disturbances are not available, although these are among of the key indicators of fuel accumulation used in other studies. This study also found eucalypt forest fuel type is closely correlated to maximum heights of canopy vegetation, which can be used as an alternative to map forest fuel type and to estimate fuel load. Forest fuel types and elevation indirectly influence the productivity of litter-bed fuel. The southeast-facing aspect and the northwest-facing aspect have different impacts on the rate of fuel decomposition due to the change in microclimate and in soil moisture content. This predictive model also indicates that the mean heights of both canopy and shrub vegetation contribute more to the prediction than other predictors. The established model needs to be tested in other areas with a wider range of forest fuel types and fire disturbances, therefore more litter fuel samples should be collected to optimize it in the future.

Acknowledgement

Sincere gratitude is extended to Monash University and Bushfire and Natural Hazards CRC for assisting this research through providing PhD scholarships. Special appreciation to Musa Kilinc for his guidance and support in the early phase of the project, and to Jithya Nanayakkara, Senthuran Arunthavanathan, Dean Yulindra Affandi, Yang Di, Zhan Wang, Saadia Majeed, Yingying Qiao, and Darren Hocking for their fieldwork support.

Chapter 6. Conclusions

The application of LiDAR data in forest fuel load estimation and structural measurements can improve the accuracy and efficiency of forest fuel hazard assessment and fire behaviour prediction. The first section of this chapter summarises the scientific findings of this study in forest fuel measurements, and also discusses the contributions to the field of remote sensing application in forestry. It is followed by a discussion regarding the limitations of this research and by a section that highlights the research directions and recommendations for future studies.

6.1 Findings

- **An automated forest fuel strata classification tool through an integration of TLS data with GIS.** The application of remote sensing in classifying understorey fuel strata is not well understood in current literature. GIS provides flexible, feasible, and easy-to-use tools for forest fuel strata classification that can be implemented more widely by practitioners. This research finding answers the first research question that integration between TLS data and GIS provides a novel method to quantify fuel structural characteristics efficiently and consistently.
- **New relationships among quantity of forest surface fuel, surface fuel depth, fire history and environmental factors.** The fuel load models established in this study indicate that litter-bed depth and fire history are primary predictors in estimating litter-bed fuel load, while canopy density and elevation are the secondary indicators. In another word, litter-bed fuel load is highly correlated to the litter-bed depth and fire history, and also related to canopy density and elevation. This finding addresses the second research question.
- **Spatial distribution of litter-bed fuel load in the study area.** Forest vegetation composition, structure, and terrain features shape forest ecosystems and microclimate, which provide significant information for litter-bed fuel load estimation. This study

developed a perspective model to estimate spatial variation in litter-bed fuel load using forest understorey and overstorey vegetation structural characteristics, and topographic variables through multiple regressions with ALS data. It answers the last research question.

6.2 Contributions

This section discusses the two main contributions of this study, which are forest fuel strata classification and litter-bed fuel load estimation using LiDAR data.

6.2.1 Forest fuel strata classification

This study developed two efficient methods to stratify forest vegetation layers in multilayered eucalypt forests using LiDAR data. The first approach used TLS data to classify understorey forest fuel layers at the plot level with a very fine spatial resolution (mm). This method was implemented by moving searching windows vertically to identify the closest laser points according to the three-dimensional continuity of the forest vegetation. The second approach aimed to stratify overstorey and mid-storey forest vegetation at a landscape scale with a fine resolution (0.5 m). This method was carried out by identifying the division points of the mixture distribution of LiDAR point density against heights.

– **TLS-derived understorey fuel strata classification.** TLS data has been used to reconstruct tree structures in order to estimate biophysical tree parameters, such as tree heights, DBHs, woody volume and leaf areas (Loudermilk *et al.*, 2009; Newnham *et al.*, 2015). Despite that, remote sensing or LiDAR application in forest fuel strata classification is not well understood. The automated tool to classify forest understorey fuel layers efficiently was developed by integrating TLS data and GIS. Forest fuel strata were stratified based on the spatial continuity of the forest biophysical knowledge. This method is not restricted by forest fuel type, fire history and understorey structures. TLS data can accurately and consistently represent three-dimensional forest fuel structures with a high spatial accuracy. The GIS-based analysing and processing procedures allow more objective descriptions of fuel covers and depths for distinct fuel layers compared with currently used visual assessments. The accurate description of forest structural characteristics obtained by this method benefits bushfire operational activities and the development of fire behaviour models. Although TLSs provide a higher spatial resolution for understorey fuel structural measurements; however, they are restricted by the systematic limitation in scanning scales (Rowell *et al.*, 2016). Therefore, application of the TLS-derived method to classify forest vertical fuel strata across landscape can be constrained (Simonse *et al.*, 2003), which leads to a development of a landscape scale forest fuel structural classification using ALS data.

- **ALS-derived overstorey and mid-storey vegetation classification.** This study also developed an efficient method to stratify an ALS-derived forest vertical profile - a bimodal distribution through integration between a non-parametric smooth fitting strategy and derivative functions. Current studies use unimodal structures to represent vertical profiles of forest structure, which fail to capture a more complete representation of the continuous LiDAR point density in multilayered forests (Jaskierniak *et al.*, 2011). Unlike Jaskierniak et al. (2011), the LOWESS was used in our study to fit a smooth curve to the data points without the assumption that the data must follow a certain distribution shape. Forest overstorey and mid-storey vegetation classification was achieved by identifying the division point of the smoothed curve by computing the maximum value of the second derivative. Our computation was relatively efficient and did not require a high performing computing system to generate its result within a reasonable amount of time.

This method is an efficient approach to classify forest vegetation using ALS data, which is replicable and beneficial for various forest applications, such as mapping forest canopy closure, habitat conservation and ecological management. In addition, the ALS-derived canopy density is typically computed by calculating the ratio between the amount of non-ground return points and the total amount of ground and non-ground return points in a unit area. This method can be applied to a single layered forest, but it overestimates canopy density in a multilayered forest, as it mistakes understorey vegetation as a portion of overstorey. Our study computed forest canopy densities using the ratio of the number of LiDAR points returned from stratified overstorey vegetation to the total number of non-ground return points within small equal-sized units. This method results in a more accurate canopy density estimation compared with the typical method.

6.2.2 Litter-bed fuel load estimation

Forest litter-bed fuel load is dynamic at fine spatial and temporal scales (Hudak *et al.*, 2016), and is determined by a complex interaction of factors, such as fuel type, productivity of understorey and overstorey vegetation, weather, and environmental conditions (Miller and Urban, 2000). Spatial variations in litter-bed fuel load across the landscape are difficult to predict and simulate. This study developed two methods to estimate forest surface litter fuel load using LiDAR data, including development of a new depth-to-load relationship and a landscape scale fuel load estimation based on forest fuel vertical structures.

– **Modelling depth-to-load relationship.** This study found a new depth-to-load model using fuel depth, canopy density and terrain features, forest fuel types, and fire history through multiple regressions. ALS data was applied in the study to provide the topographic variables and canopy density; TLS data was used to represent the spatial continuity of surface litter-bed depth as a replacement of direct measurement. The established model indicates that the majority of variations in litter fuel load can be estimated by litter-bed depth and fire history. McArthur (1962)'s depth-to-load model used percentage cover of understorey shrubs to enhance the model performance. In reality, information of fire history is more convenient to obtain than estimation of understorey vegetation percentage cover from a practical perspective. Therefore, our model is more time effective compared with McArthur (1962)'s model. It also indicates that among environmental factors, canopy density and elevation significantly impact on forest surface litter fuel productivity. This study also found that LiDAR-derived independent variables (fuel depth, canopy density, elevation, aspect and slope) could improve the efficiency and accuracy in modelling forest surface litter fuel load.

- **Landscape scale forest litter-bed fuel load estimation.** This study developed a predictive model using ALS data that produces a more accurate and consistent spatial distribution of surface fuel load in multilayered eucalypt forests with various fire histories and forest fuel types. Other fuel models use simple indicators (e.g. surface fuel depth, and years since last fire) to estimate fuel load within a vegetation community and are constrained to estimate spatial variation in fuel load within homogeneous vegetation that previously experienced the same fire events. Our model uses forest structural indices and terrain features derived from ALS data, which is applicable when data on forest fuel types and previous fire disturbances are not available. It also demonstrates how the topographic variables influence the litter-bed fuel load in the study area. Consequently, a landscape scale fuel load map was created corresponding to the established model. These results indicate that multi echo ALS data allow estimation of spatial variations in forest litter-bed fuel load at a landscape scale.

6.3 Limitations

In this study, LiDAR-derived surface fuel depth and fuel cover at distinct fuel layers were assessed by field data that were collected using typical field measurements. However, the validation is contentious and constrained by currently used field measurement methods. Field data that were used to validate the TLS-derived fuel structural characteristics were sampled and collected through visual assessments that are currently used by fire fighters and land managers. However, these visual techniques can be subjective and prone to errors. A more accurate and robust method should be investigated to validate both TLS-derived and visual assessed results. Moreover, field data on surface fuel depth in the field were measured directly using a gauge at one site sized 1m by 1m. The finalised depth was determined by an average value of five measurements within the site. Using the averaged depth of one site to validate the exact values that are derived from TLS data may increase the deviation.

This study investigated relationships among quantities of surface litter fuel, fuel structural characteristics (e.g. depth, cover, and height), fire histories, forest fuel types, and environmental factors. Spatial distribution of litter fuel varies depending on forest composition of overstorey and understorey vegetation, previous fire disturbances, changes in annual and seasonal precipitation, radiation, wind direction and speed, aspect, slope and elevation (Brown and Bevins, 1986). However, weather variables were not considered in the model development due to a coarse resolution of local weather data. This study assumed that terrain features influence fuel productivity and also help to form the microclimate across the study area instead of weather variables.

6.4 Future research

Increasing the number of field observations should be considered in the future to reduce the prediction error in the new depth-to-load relationship. Further studies should also investigate other potential important predictors that may also impact on litter fuel load, such as soil type, seasonal and diurnal changes in precipitation and temperature, and the extent and severity of previous disturbance events including fires and erosion. In addition, the automated tool for eucalypt forest fuel strata classification as well as the novel method to estimate landscape scale spatial distribution in litter-bed fuel load should be tested in other areas and different seasons with a wider range of forest fuel types and fire disturbances. Forest fuel load accumulation is dynamic temporally and spatially. The litter-bed fuel load model developed in this study used field-surveyed fuel load data that was collected during summer. Future studies should investigate the temporal variations in fuel load across landscape, to provide a temporally accurate estimation of forest fuel load for fire behaviour modelling with various fire seasons and weather.

The application of LiDAR in forest fuel measurements provides opportunities to overcome common challenges shared by forest fire behaviour and fire danger rating models as well as fire hazard mitigation activities. In the future, TLS and ALS observations should be integrated to provide a more complete forest fuel representation. It will provide a more comprehensive and accurate description of fuel structural characteristics and estimation of litter-bed fuel load.

LiDAR application in fuel load estimates and fuel structural measurements is still at an early stage. Future studies should focus on how to apply LiDAR-derived fuel data in fire behaviour and danger modelling. It is also necessary to integrate LiDAR-derived landscape scale litter-bed fuel load with forest fuel hazard assessing criteria to assist fire hazard-reduction treatments.

In conclusion, this thesis presents compelling evidence that highlights the benefits of applying LiDAR data in forest fuel measurements. This study has developed objective methods that provide more accurate and consistent description of forest litter-bed fuel load and fuel structures for fuel hazard assessment, fire behavior modelling, and danger rating systems. As a result, the application of this study in fire management can better protect the environment and communities in Australia and other countries that are prone to frequent wildland forest fires.

References

Adams, M. and Attiwill, P., 2011. Burning issues: Sustainability and management of australia's southern forests. CSIRO PUBLISHING.

Adams, M.A., 2013. Mega-fires, tipping points and ecosystem services: Managing forests and woodlands in an uncertain future. Forest Ecology and Management, 294: 250-261. Available from http://www.sciencedirect.com/science/article/pii/S0378112712007153. DOI http://dx.doi.org/10.1016/j.foreco.2012.11.039.

Agee, J.K. and Skinner, C.N., 2005. Basic principles of forest fuel reduction treatments. Forest Ecology and Management, 211(1): 83-96.

Agee, J.K., Wakimoto, R.H., Darley, E.F. and Biswell, H.H., 1973. Eucalyptus fuel dynamics, and fire hazard in the oakland hills. California Agriculture, 27(9): 13-15.

Albini, F.A., 1976. Estimating wildfire behavior and effects. In: General Technical Report INT-30, U. F. Service (Ed.).

Aldred, A.H. and Bonnor, G.M., 1985. Application of airborne laser to forest surveys. In: Information Report PI-X-51. Petawawa National Forestry Institute, Chalk River, Canadian Forest Service: pp: 62.

Allgöwer, B., Harvey, S. and Rüegsegger, M., 1998. Fuel models for switzerland: Description, spatial pattern, index for crowning and torching. In: 3rd International Conference on Forest Fire Research/14th Conference on Fire and Forest Meteorology, Luso, Portugal. pp: 2605-2620.

Andersen, H.E., McGaughey, R.J. and Reutebuch, S.E., 2005. Estimating forest canopy fuel parameters using lidar data. Remote Sensing of Environment, 94(4): 441-449. Available from http://www.sciencedirect.com/science/article/pii/S0034425704003438. DOI http://dx.doi.org/10.1016/j.rse.2004.10.013.

Anderson, H.E., 1970. Forest fuel ignitibility. Fire Technology, 6(4): 312-319. Available from http://dx.doi.org/10.1007/BF02588932. DOI 10.1007/bf02588932.

Anderson, H.E., 1982. Aids to determining fuel models for estimating fire behavior. The Bark Beetles, Fuels, and Fire Bibliography: 143.

Anderson, J.R., 1976. A land use and land cover classification system for use with remote sensor data. US Government Printing Office.

Andrew, N., Rodgerson, L. and York, A., 2000. Frequent fuel-reduction burning: The role of logs and associated leaf litter in the conservation of ant biodiversity. Austral Ecology, 25(1): 99-107.

Andrews, P., 1986. Fire behavior prediction and fuel modeling system. USDA For Serv Res Pap INT-206.

Andrews, P.L. and Bevins, C.D., 2003. Behaveplus fire modeling system, version 2.0: Overview. In: Proceedings of the Second International Wildland Fire Ecology and Fire Management Congress. pp: 17-20.

Andrews, P.L., Bevins, C.D. and Seli, R.C., 2005. Behaveplus fire modeling system user's guide. Version 3.0. USDA For. Serv. Gen. Tech. Rep. RMRS-GTR-106WWW Revised.

Andrews, P.L. and Queen, L.P., 2001. Fire modeling and information system technology. International Journal of Wildland Fire, 10(4): 343-352.

Arroyo, L.A., Healey, S.P., Cohen, W.B., Cocero, D. and Manzanera, J.A., 2006. Using object-oriented classification and high-resolution imagery to map fuel types in a mediterranean region. Journal of Geophysical Research: Biogeosciences (2005–2012), 111(G4).

Arroyo, L.A., Pascual, C. and Manzanera, J.A., 2008. Fire models and methods to map fuel types: The role of remote sensing. Forest Ecology and Management, 256(6): 1239-1252.

Available from http://www.sciencedirect.com/science/article/pii/S0378112708005410. DOI http://dx.doi.org/10.1016/j.foreco.2008.06.048.

Aschoff, T. and Spiecker, H., 2004. Algorithms for the automatic detection of trees in laser scanner data. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36(Part 8): W2.

Atkinson, A.T., 1987. Plots, transformations, and regression. An introduction to graphical methods of diagnostic regression analysis. New York: Oxford Statistical Science Series: Oxford University Press.

Becker, R.A. and Chambers, J.M., 1984. S: An interactive environment for data analysis and graphics. CRC Press.

Béland, M., Widlowski, J.L. and Fournier, R.A., 2014. A model for deriving voxel-level tree leaf area density estimates from ground-based lidar. Environmental Modelling & Software, 51: 184-189. Available from http://www.sciencedirect.com/science/article/pii/S1364815213002399. DOI http://dx.doi.org/10.1016/j.envsoft.2013.09.034.

Bellian, J.A., Kerans, C. and Jennette, D.C., 2005. Digital outcrop models: Applications of terrestrial scanning lidar technology in stratigraphic modeling. Journal of Sedimentary Research, 75(2): 166-176.

Belsley, D.A., Kuh, E. and Welsch, R.E., 2005. Regression diagnostics: Identifying influential data and sources of collinearity. John Wiley & Sons.

Besl, P.J. and McKay, N.D., 1992. Method for registration of 3-d shapes. In: Robotics-DL tentative. International Society for Optics and Photonics: pp: 586-606.

Birk, E.M. and Simpson, R., 1980. Steady state and the continuous input model of litter accumulation and decompostion in australian eucalypt forests. Ecology: 481-485.

Bosse, M., Zlot, R. and Flick, P., 2012. Zebedee: Design of a spring-mounted 3-d range sensor with application to mobile mapping. IEEE Transactions on Robotics, 28(5): 1104-1119. DOI 10.1109/TRO.2012.2200990.

Bradstock, R.A., Gill, A.M. and Williams, R.J., 2012. Flammable australia: Fire regimes, biodiversity and ecosystems in a changing world. Melbourne: CSIRO PUBLISHING.

Bradstock, R.A., Williams, J.E. and Gill, A.M., 2002. Fire regimes and biodiversity: Legacy and vision. In: Flammable australia: The fire regimes and biodiversity of a continent

Brandis, K. and Jacobson, C., 2003. Estimation of vegetative fuel loads using landsat tm imagery in new south wales, australia. International Journal of Wildland Fire, 12(2): 185-194.

Brandtberg, T., Warner, T.A., Landenberger, R.E. and McGraw, J.B., 2003. Detection and analysis of individual leaf-off tree crowns in small footprint, high sampling density lidar data from the eastern deciduous forest in north america. Remote Sensing of Environment, 85(3): 290-303. Available from http://www.sciencedirect.com/science/article/pii/S0034425703000087. DOI http://dx.doi.org/10.1016/S0034-4257(03)00008-7.

Bresnehan, S.J., 2003. An assessment of fuel characteristics and fuel loads in the dry sclerophyll forests of south-east tasmania. University of Tasmania, http://eprints.utas.edu.au/17305/.

Brown, C., Scherl, T., Chylinski, T. and Burns, J., 2011. The use of lidar in fuel hazard characterisation and stratification within the sugarloaf catchment area - towards the automation of understory mapping. Melbourne Water, AFAC & Bushfire CRC Conference 2011, Darling Harbour, Australia, 29 August - 1 September.

Brown, J.K., 1978. Weight and density of crowns of rocky mountain conifers.

Brown, J.K. and Bevins, C.D., 1986. Surface fuel loadings and predicted fire behavior for vegetation types in the northern rocky mountains. US Dept. of Agriculture, Forest Service, Intermountain Research Station.

Brown, J.K., Oberheu, R.D. and Johnston, C.M., 1982. Handbook for inventorying surface fuels and biomass in the interior west.

Burgan, R., Klaver, R. and Klaver, J., 1998. Fuel models and fire potential from satellite and surface observations. International Journal of Wildland Fire, 8(3): 159-170. Available from http://www.publish.csiro.au/paper/WF9980159. DOI http://dx.doi.org/10.1071/WF9980159.

Burgan, R.E., 1988. 1988 revisions to the 1978 national fire-danger rating system.

Burrows, N.D., 1994. Experimental development of a fire management model for jarrah (eucalyptus marginata donn ex sm.) forest. In: Department of Forestry. Australian National University, Canberra.

Burrows, N.D., 1999. Fire behaviour in jarrah forest fuels: 2. Field experiments. CALMScience, 3(1): 57-84.

Byram, G.M., Clements, H.E., Bishop, M.E. and Nelson, R.M., 1966. An experimental study of model fires. In: Final Report. USDA Forest Service.

Campbell, J.B. and Wynne, R.H., 2011. Introduction to remote sensing. Guilford Press.

Carlson, T.N. and Ripley, D.A., 1997. On the relation between ndvi, fractional vegetation cover, and leaf area index. Remote sensing of Environment, 62(3): 241-252.

Ceccato, P., Flasse, S., Tarantola, S., Jacquemoud, S. and Grégoire, J.-M., 2001. Detecting vegetation leaf water content using reflectance in the optical domain. Remote sensing of environment, 77(1): 22-33.

Chambers, M.J., Cleveland, S.W., Tukey, A.P. and Kleiner, B., 1983. Graphical methods for data analysis Duxbury Press.

Chatto, K., 1996. Fuel hazard levels in relation to site characteristics and fire history: Chiltern regional park case study. Parks Victoria.

Chauve, A., Durrieu, S., Bretar, F., Deseilligny, M.P. and Puech, W., 2007. Processing full-waveform lidar data to extract forest parameters and digital terrain model: Validation in an alpine coniferous forest. In: ForestSat Conference'07.

Chen, F., Weber, K.T., Anderson, J. and Gokhal, B., 2011. Assessing the susceptibility of semiarid rangelands to wildfires using terra modis and landsat thematic mapper data. International Journal of Wildland Fire, 20(5): 690-701. Available from http://www.publish.csiro.au/paper/WF10001.

Chen, Q., Baldocchi, D., Gong, P. and Kelly, M., 2006. Isolating individual trees in a savanna woodland using small footprint lidar data. Photogrammetric Engineering & Remote Sensing, 72(8): 923-932. Available from http://dx.doi.org/10.14358/PERS.72.8.923. DOI 10.14358/PERS.72.8.923.

Cheney, N.P., 1981. Fire behaviour. In: Fire and the australian biota, A. M. GillR. H. Groves and I. R. Noble, (Eds.). Australian Academy of Science, Canbena: pp: 151-175.

Cheney, N.P., Gould, J.S. and Knight, I., 1992. A prescribed burning guide of young regrowth forest of silvertop ash. In: Forestry Commission of New South Wales. Research Paper No. 16.

Cheney, N.P., Gould, J.S., McCaw, W.L. and Anderson, W.R., 2012. Predicting fire behaviour in dry eucalypt forest in southern australia. Forest Ecology and Management, 280(0): 120-131. Available from http://www.sciencedirect.com/science/article/pii/S0378112712003325. DOI http://dx.doi.org/10.1016/j.foreco.2012.06.012.

Cheney, N.P. and Sullivan, A., 1997. Grassfires: Fuel, weather and fire behaviour. CSIRO Publishing.

Cheng, Y.-B., Zarco-Tejada, P.J., Riaño, D., Rueda, C.A. and Ustin, S.L., 2006. Estimating vegetation water content with hyperspectral data for different canopy scenarios: Relationships between aviris and modis indexes. Remote Sensing of Environment, 105(4): 354-366.

Chuvieco, E., 2003. Fuel loads and fuel type mapping. In: Wildland fire danger estimation and mapping : The role of remote sensing data, E. Chuvieco, (Ed.). River Edge, N.J. : World Scientific

Chuvieco, E. and Congalton, R.G., 1989. Application of remote sensing and geographic information systems to forest fire hazard mapping. Remote sensing of Environment, 29(2): 147-159.

Chuvieco, E., Riano, D., Aguado, I. and Cocero, D., 2002. Estimation of fuel moisture content from multitemporal analysis of landsat thematic mapper reflectance data: Applications in fire danger assessment. International Journal of Remote Sensing, 23(11): 2145-2162.

Chuvieco, E., Salas, F.J., Carvacho, L. and Rodriguez-Silva, F., 1999. Integrated fire risk mapping. In: Remote sensing of large wildfires. Springer: pp: 61-100.

Clark, K.L., Skowronski, N., Hom, J., Duveneck, M., Pan, Y., Van Tuyl, S., Cole, J., Patterson, M. and Maurer, S., 2009. Decision support tools to improve the effectiveness of hazardous fuel reduction treatments in the new jersey pine barrens. International journal of wildland fire, 18(3): 268-277.

Clarke, H., Lucas, C. and Smith, P., 2013. Changes in australian fire weather between 1973 and 2010. International Journal of Climatology, 33(4): 931-944.

Cohen, W., 1989. Potential utility of the tm tasseled cap multispectral data transformation for crown fire hazard assessment. In: ASPRS/ACSM annual convention proceedings: Agenda for the. pp: 118-127.

Conroy, B., 1993. The changing fire environment in australia. the Department of Continuing Education, pp: 25-31.

Coops, N.C., Hilker, T., Wulder, M.A., St-Onge, B., Newnham, G., Siggins, A. and Trofymow, J.A., 2007. Estimating canopy structure of douglas-fir forest stands from discrete-return lidar. Trees, 21(3): 295-310. Available from http://dx.doi.org/10.1007/s00468-006-0119-6. DOI 10.1007/s00468-006-0119-6.

Côté, J.-F., Fournier, R.A. and Egli, R., 2011. An architectural model of trees to estimate forest structural attributes using terrestrial lidar. Environmental Modelling & Software, 26(6): 761-777. Available from http://www.sciencedirect.com/science/article/pii/S1364815210003294. DOI http://dx.doi.org/10.1016/j.envsoft.2010.12.008.

Côté, J.F., Widlowski, J.L., Fournier, R.A. and Verstraete, M.M., 2009. The structural and radiative consistency of three-dimensional tree reconstructions from terrestrial lidar. Remote Sensing of Environment, 113(5): 1067-1081.

Covington, W.W. and Moore, M.M., 1994. Postsettlement changes in natural fire regimes and forest structure: Ecological restoration of old-growth ponderosa pine forests. Journal of Sustainable Forestry, 2(1-2): 153-181.

Danson, F. and Bowyer, P., 2004. Estimating live fuel moisture content from remotely sensed reflectance. Remote Sensing of Environment, 92(3): 309-321.

Dassot, M., Constant, T. and Fournier, M., 2011. The use of terrestrial lidar technology in forest science: Application fields, benefits and challenges. Annals of Forest Science, 68(5): 959-974.

Dean, T.J., Cao, Q.V., Roberts, S.D. and Evans, D.L., 2009. Measuring heights to crown base and crown median with lidar in a mature, even-aged loblolly pine stand. Forest Ecology and Management, 257(1): 126-133.

Deeming, J.E. and Brown, J.K., 1975. Fuel models in the national fire-danger rating system. J. For., 73(6): 347-350.
Deeming, J.E., Burgan, R.E. and Cohen, J.D., 1977. The national fire danger rating system 1978. In: General Technical Report INT. USDA Forest Service, Intermountain Forest and Range Experiment Station.
Deeming, J.E., Lancaster, J.W., Fosberg, M.A., Furman, R.W. and Schroeder, M.J., 1972. The national fire-danger rating system. In: F. S. U.S. Department of Agriculture, Rocky Mountain Forest and Range Experiment Station, (Ed.), pp: 63.
Dennison, P.E., Fryer, G.K. and Cova, T.J., 2014. Identification of firefighter safety zones using lidar. Environmental Modelling & Software, 59: 91-97. Available from http://www.sciencedirect.com/science/article/pii/S1364815214001480. DOI http://dx.doi.org/10.1016/j.envsoft.2014.05.017.
Devereux, B., Amable, G., Crow, P. and Cliff, A., 2005. The potential of airborne lidar for detection of archaeological features under woodland canopies. Antiquity, 79(305): 648-660.
Dimitrakopoulos, A., 2002. Mediterranean fuel models and potential fire behaviour in greece. International Journal of Wildland Fire, 11(2): 127-130.
Dobson, M.C., Ulaby, F.T., Pierce, L.E., Sharik, T.L., Bergen, K.M., Kellndorfer, J., Kendra, J.R., Li, E., Lin, Y.-C. and Nashashibi, A., 1995. Estimation of forest biophysical characteristics in northern michigan with sir-c/x-sar. IEEE Transactions on Geoscience and Remote Sensing, 33(4): 877-895.
Drake, J.B., Dubayah, R.O., Knox, R.G., Clark, D.B. and Blair, J.B., 2002. Sensitivity of large-footprint lidar to canopy structure and biomass in a neotropical rainforest. Remote Sensing of Environment, 81(2,Äì3): 378-392. Available from http://www.sciencedirect.com/science/article/pii/S0034425702000135. DOI http://dx.doi.org/10.1016/S0034-4257(02)00013-5.
Draper, N.R. and Smith, H., 2014. Applied regression analysis. John Wiley & Sons.
Dubayah, R.O. and Drake, J.B., 2000. Lidar remote sensing for forestry. Journal of Forestry, 98(6): 44-46. Available from http://www.ingentaconnect.com/content/saf/jof/2000/00000098/00000006/art00015.
Dubayah, R.O., Prince, S., JaJa, J., Blair, J., Bufton, J.L., Knox, R., Luthcke, S.B., Clarke, D.B. and Weishampel, J., 1997. The vegetation canopy lidar mission. Land satellite information in the next decade II: sources and applications.
Erdody, T.L. and Moskal, L.M., 2010. Fusion of lidar and imagery for estimating forest canopy fuels. Remote Sensing of Environment, 114(4): 725-737. Available from http://www.sciencedirect.com/science/article/pii/S0034425709003277. DOI http://dx.doi.org/10.1016/j.rse.2009.11.002.
Everitt, B.S. and Skrondal, A., 2002. The cambridge dictionary of statistics. Cambridge: Cambridge.
Falkowski, M.J., Gessler, P.E., Morgan, P., Hudak, A.T. and Smith, A.M., 2005. Characterizing and mapping forest fire fuels using aster imagery and gradient modeling. Forest Ecology and Management, 217(2): 129-146.
Falkowski, M.J., Gessler, P.E., Morgan, P., Hudak, A.T. and Smith, A.M.S., 2005. Characterizing and mapping forest fire fuels using aster imagery and gradient modeling. Forest Ecology and Management, 217(2–3): 129-146. Available from http://www.sciencedirect.com/science/article/pii/S0378112705004263. DOI http://dx.doi.org/10.1016/j.foreco.2005.06.013.
Fassnacht, K.S., Gower, S.T., Norman, J.M. and McMurtric, R.E., 1994. A comparison of optical and direct methods for estimating foliage surface area index in forests. Agricultural and Forest Meteorology, 71(1): 183-207.

Fernandes, P. and Botelho, H., 2004. Analysis of the prescribed burning practice in the pine forest of northwestern portugal. Journal of Environmental Management, 70(1): 15-26.

Fernandes, P., Luz, A., Loureiro, C., Ferreira-Godinho, P. and Botelho, H.n., 2006. Fuel modelling and fire hazard assessment based on data from the portuguese national forest inventory. Forest Ecology and Management, 234(1): S229.

Fernandes, P.M. and Botelho, H.S., 2003. A review of prescribed burning effectiveness in fire hazard reduction. International Journal of wildland fire, 12(2): 117-128.

Ferraz, A., Bretar, F., Jacquemoud, S. and Gonçalves, G., 2009. The role of lidar systems in fuel mapping. Instituto de Engenharia de Sistemas e Computadores de Coimbra, www.inescc.pt.

Flannigan, M., Cantin, A.S., de Groot, W.J., Wotton, M., Newbery, A. and Gowman, L.M., 2013. Global wildland fire season severity in the 21st century. Forest Ecology and Management, 294: 54-61.

Fosberg, M.A. and Furman, R.W., 1971. Fire climate and fire-danger rating areas. R. M. F. a. R. E. S. USDA Forest Service (Ed.). Collins, Colorado: pp: 10.

Fox, B., Fox, M. and McKay, G., 1979. Litter accumulation after fire in a eucalypt forest. Australian Journal of Botany, 27(2): 157-165.

Fuller, M., 1991. Forest fires: An introduction to wildland fire behavior, management, firefighting, and prevention. John Wiley & Sons, Inc.

Gaveau, D.L. and Hill, R.A., 2003. Quantifying canopy height underestimation by laser pulse penetration in small-footprint airborne laser scanning data. Canadian Journal of Remote Sensing, 29(5): 650-657.

Giakoumakis, M., Gitas, I. and San-Miguel, J., 2002. Object-oriented classification modelling for fuel type mapping in the mediterranean, using landsat tm and ikonos imagery—preliminary results. Forest Fires Research & Wildland Fire Safety. Millpress, Rotterdam.

Gill, A., Christian, K., Moore, P. and Forrester, R., 1987. Bushfire incidence, fire hazard and fuel reduction burning. Australian Journal of Ecology, 12(3): 299-306.

Gill, A.M., 1997. Eucalypts and fires: Interdependent or independent. Eucalypt ecology: individuals to ecosystems: 151-167.

Gill, A.M., Groves, R.H. and Noble, I.R., 1981. Fire and the australian biota. Australian Academy of Science.

Gilroy, J. and Tran, C., 2006. A new fuel load model for eucalypt forests in southeast queensland. In: Bushfire Conference 2006. Royal Society of Queensland, Brisbane: pp: 137-143.

Gitas, I., Mitri, G., Kazakis, G., Ghosn, D. and Xanthopoulos, G., 2006. Fuel type mapping in anopolis, crete by employing quickbird imagery and object-based classification. Forest Ecology and Management, 234(1): S228.

Good, P.I., 2001. Resampling methods. Springer.

Gorte, B. and Pfeifer, N., 2004. Structuring laser-scanned trees using 3d mathematical morphology. International Archives of Photogrammetry and Remote Sensing, 35(B5): 929-933.

Gougeon, F.A., 2000. Towards semi-automatic forest inventories using individual tree crown (itc) recognition. Pacific Forestry Centre, Canadian Forest Service.

Gould, J.S. and Cruz, M., 2013. Australian fuel classification - update. In: CSIRO Bushfire Behaviour Science Symposium 2013 Canberra.

Gould, J.S., McCaw, W.L. and Cheney, N.P., 2011. Quantifying fine fuel dynamics and structure in dry eucalypt forest (eucalyptus marginata) in western australia for fire management. Forest Ecology and Management, 262(3): 531-546.

Gould, J.S., McCaw, W.L., Cheney, N.P., Ellis, P.F., Knight, I.K. and Sullivan, A.L., 2008. Project vesta: Fire in dry eucalypt forest: Fuel structure, fuel dynamics and fire behaviour. Melbourne: CSIRO Publishing.

Gould, J.S., Sullivana, A., Cruza, M., Rucinskib, C. and Prakashb, M., 2014. National fire behaviour knowledge base-bringing together the best information for best decisions.

Graybill, F.A., 1970. Theory and application of the linear model. North Scituate, Mass: Duxbury Press.

Heinsch, F.A. and Andrews, P.L., 2010. Behaveplus fire modeling system, version 5.0: Design and features.

Henning, J.G. and Radtke, P.J., 2006. Detailed stem measurements of standing trees from ground-based scanning lidar. Forest Science, 52(1): 67-80.

Hermosilla, T., Ruiz, L.A., Kazakova, A.N., Coops, N.C. and Moskal, L.M., 2014. Estimation of forest structure and canopy fuel parameters from small-footprint full-waveform lidar data. International Journal of Wildland Fire, 23(2): 224-233. Available from http://www.publish.csiro.au/paper/WF13086. DOI http://dx.doi.org/10.1071/WF13086.

Hines, F., Tolhurst, G.K., Wilson, A.G.A. and McCarthy, G.J., 2010. Overall fuel hazard assessment guide. In: Fire and adaptive management report no. 82. Attorney-General's Department of the Australian Government.

Hopkinson, C., Chasmer, L., Young-Pow, C. and Treitz, P., 2004. Assessing forest metrics with a ground-based scanning lidar. Canadian Journal of Forest Research, 34(3): 573-583.

Hosoi, F. and Omasa, K., 2006. Voxel-based 3-d modeling of individual trees for estimating leaf area density using high-resolution portable scanning lidar. Geoscience and Remote Sensing, IEEE Transactions on, 44(12): 3610-3618.

Hudak, A.T., Bright, B.C., Pokswinski, S.M., Loudermilk, E.L., O'Brien, J.J., Hornsby, B.S., Klauberg, C. and Silva, C.A., 2016. Mapping forest structure and composition from low-density lidar for informed forest, fuel, and fire management at eglin air force base, florida, USA. Canadian Journal of Remote Sensing, 42(5): 411-427.

Hug, C., Ullrich, A. and Grimm, A., 2004. Litemapper-5600-a waveform-digitizing lidar terrain and vegetation mapping system. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36(Part 8): W2.

Hyde, P., Dubayah, R., Peterson, B., Blair, J.B., Hofton, M., Hunsaker, C., Knox, R. and Walker, W., 2005. Mapping forest structure for wildlife habitat analysis using waveform lidar: Validation of montane ecosystems. Remote Sensing of Environment, 96(3–4): 427-437. Available from http://www.sciencedirect.com/science/article/pii/S0034425705001112. DOI http://dx.doi.org/10.1016/j.rse.2005.03.005.

Hyyppä, J., Hyyppä, H., Yu, X., Kaartinen, H., Kukko, A. and Holopainen, M., 2009. Forest inventory using small-footprint airborne lidar. Topographic laser ranging and scanning: Principles and processing: 335-370.

Jakubowksi, M.K., Guo, Q., Collins, B., Stephens, S. and Kelly, M., 2013. Predicting surface fuel models and fuel metrics using lidar and cir imagery in a dense, mountainous forest. Photogrammetric Engineering & Remote Sensing, 79(1): 37-49.

Jaskierniak, D., Lane, P.N., Robinson, A. and Lucieer, A., 2011. Extracting lidar indices to characterise multilayered forest structure using mixture distribution functions. Remote Sensing of Environment, 115(2): 573-585.

Kauth, R.J. and Thomas, G., 1976. The tasselled cap--a graphic description of the spectral-temporal development of agricultural crops as seen by landsat. In: LARS Symposia. pp: 159.

Keane, R.E., Burgan, R. and van Wagtendonk, J., 2001. Mapping wildland fuels for fire management across multiple scales: Integrating remote sensing, gis, and biophysical modeling. International Journal of Wildland Fire, 10(4): 301-319.

Koch, B., Heyder, U. and Weinacker, H., 2006. Detection of individual tree crowns in airborne lidar data. Photogrammetric Engineering & Remote Sensing, 72(4): 357-363.

Kohavi, R., 1995. A study of cross-validation and bootstrap for accuracy estimation and model selection. In: Ijcai. pp: 1137-1145.

Koukoulas, S. and Blackburn, G.A., 2005. Mapping individual tree location, height and species in broadleaved deciduous forest using airborne lidar and multi-spectral remotely sensed data. International Journal of Remote Sensing, 26(3): 431-455. Available from http://dx.doi.org/10.1080/0143116042000298289 [Accessed 2015/08/26]. DOI 10.1080/0143116042000298289.

Kourtz, P., 1977. An application of landsat digital technology to forest fire fuel type mapping. In: 11th International Symposium on Remote Sensing of Environment, Ann Arbor. pp: 1111-1115.

Kramer, H.A., Collins, B.M., Kelly, M. and Stephens, S.L., 2014. Quantifying ladder fuels: A new approach using lidar. Forests, 5(6): 1432-1453.

Lasaponara, R. and Lanorte, A., 2007. Remotely sensed characterization of forest fuel types by using satellite aster data. International Journal of Applied Earth Observation and Geoinformation, 9(3): 225-234.

Lefsky, M.A., Cohen, W.B., Acker, S.A., Parker, G.G., Spies, T.A. and Harding, D., 1999. Lidar remote sensing of the canopy structure and biophysical properties of douglas-fir western hemlock forests. Remote sensing of environment, 70(3): 339-361.

Lefsky, M.A., Cohen, W.B., Parker, G.G. and Harding, D.J., 2002. Lidar remote sensing for ecosystem studies. BioScience, 52(1): 19-30.

Lefsky, M.A., Cohen, W.B., Parker, G.G. and Harding, D.J., 2002. Lidar remote sensing for ecosystem studies lidar, an emerging remote sensing technology that directly measures the three-dimensional distribution of plant canopies, can accurately estimate vegetation structural attributes and should be of particular interest to forest, landscape, and global ecologists. BioScience, 52(1): 19-30.

Lefsky, M.A., Harding, D., Cohen, W.B., Parker, G. and Shugart, H.H., 1999. Surface lidar remote sensing of basal area and biomass in deciduous forests of eastern maryland, USA. Remote Sensing of Environment, 67(1): 83-98. Available from http://www.sciencedirect.com/science/article/pii/S0034425798000716. DOI http://dx.doi.org/10.1016/S0034-4257(98)00071-6.

Lim, K., Treitz, P., Wulder, M., St-Onge, B. and Flood, M., 2003. Lidar remote sensing of forest structure. Progress in physical geography, 27(1): 88-106.

Lindsay, B.G., 1995. Mixture models: Theory, geometry and applications. In: NSF-CBMS regional conference series in probability and statistics. JSTOR: pp: i-163.

Liu, C., Zhang, L., Davis, C.J., Solomon, D.S. and Gove, J.H., 2002. A finite mixture model for characterizing the diameter distributions of mixed-species forest stands. Forest Science, 48(4): 653-661.

Liu, X., 2008. Airborne lidar for dem generation: Some critical issues. Progress in Physical Geography, 32(1): 31-49.

Loomis, R.M. and Main, W.A., 1980. Comparing jack pine slash and forest floor moisture contents and national fire danger rating system predictions. USDA Forest Service research paper NC-United States.

López, A.S., San-Miguel-Ayanz, J. and Burgan, R.E., 2002. Integration of satellite sensor data, fuel type maps and meteorological observations for evaluation of forest fire risk at the pan-european scale. International Journal of Remote Sensing, 23(13): 2713-2719.

Available from http://dx.doi.org/10.1080/01431160110107761. DOI 10.1080/01431160110107761.
Loudermilk, E.L., Hiers, J.K., O'Brien, J.J., Mitchell, R.J., Singhania, A., Fernandez, J.C., Cropper, W.P. and Slatton, K.C., 2009. Ground-based lidar: A novel approach to quantify fine-scale fuelbed characteristics. International Journal of Wildland Fire, 18(6): 676-685.
Loureiro, C., Fernandes, P. and Botelho, H., 2002. Optimizing prescribed burning to reduce wildfire propagation at the landscape scale. In: Forest Fire Research and Wildland Fire Safety, Proceedings of the IV International Conference on Forest Fire Research/2002 Wildland Fire Safety Summit. University of Coimbra, Coimbra, Portugal. Millpress, Rotterdam, CD-ROM.
Lovell, J.L., Jupp, D.L.B., Culvenor, D.S. and Coops, N.C., 2003. Using airborne and ground-based ranging lidar to measure canopy structure in australian forests. Canadian Journal of Remote Sensing, 29(5): 607-622. Available from http://dx.doi.org/10.5589/m03-026 [Accessed 2014/05/19]. DOI 10.5589/m03-026.
Luke, R.H. and McArthur, A.G., 1978. Bush fires in australia. Canberra: Australian Government Publishing Service.
Maas, H.G., Bienert, A., Scheller, S. and Keane, E., 2008. Automatic forest inventory parameter determination from terrestrial laser scanner data. International journal of remote sensing, 29(5): 1579-1593.
Marselis, S.M., Yebra, M., Jovanovic, T. and van Dijk, A.I.J.M., 2016. Deriving comprehensive forest structure information from mobile laser scanning observations using automated point cloud classification. Environmental Modelling & Software, 82: 142-151. Available from http://www.sciencedirect.com/science/article/pii/S1364815216301207. DOI http://dx.doi.org/10.1016/j.envsoft.2016.04.025.
Matthews, S., 2010. Effect of drying temperature on fuel moisture content measurements. International Journal of Wildland Fire, 19(6): 800-802. Available from http://www.publish.csiro.au/paper/WF08188. DOI http://dx.doi.org/10.1071/WF08188.
McAlpine, R. and Hobbs, M., 2014. Predicting the height to live crown base in plantations of four boreal forest species. International Journal of Wildland Fire, 4(2): 103-106.
McArthur, A.G., 1962. Control burning in eucalypt forests. Canberra, Australia: Forestry and Timber Bureau. Leaflet.
McArthur, A.G., 1966. Weather and grassland fire behaviour. Forestry and Timber Bureau, Department of national Development, Commonwealth of Australia.
McArthur, A.G., 1967. Fire behaviour in eucalypt forests. Canberra: Forestry and Timber Bureau Leaflet 107, Commonwealth Department of National Development, Canberra ACT.
McCarthy, G.J., 1996. Assessment of overall fuel hazard for a site and its implications for both strategic fuel management and first attack success probability. International Association of Wildland Fire, pp: 79.
McCarthy, G.J., 2004. Surface fine fuel hazard rating: Forest fuels in east gippsland. East Melbourne, VIC: Department of Sustainability and Environment.
McCarthy, G.J., Tolhurst, K.G. and Chatto, K., 1998. Overall fuel hazard guide. In: Victoria Fire Management. Department of Natural Resources & Environment, East Melbourne, VIC.
McCaw, W.L., 1991. Measurement of fuel quantity and structure for bushfire research and management. In: Bushfire Modelling and Fire Danger Rating Systems CSIRO, Division of Forestry, Canberra: pp: 147–155.

McCaw, W.L., Cheney, N.P. and Gould, J.S., 2003. Do eucalypt forest fires burn faster and hotter in older fuels? - implications for hazard reduction burning.

McCaw, W.L., Neal, J.E. and Smith, R.H., 1996. Fuel accumulation following prescribed burning in young even-aged stands of karri (eucalyptus diversicolor). Australian Forestry, 59(4): 171-177. Available from http://dx.doi.org/10.1080/00049158.1996.10674686 [Accessed 2015/10/15]. DOI 10.1080/00049158.1996.10674686.

McGaughey, R., Reutebuch, S., Schreudera, G. and Mercer, B., 2004. Estimating canopy fuel parameters in a pacific northwest conifer forest using multifrequency polarimetric ifsar. Image, 900(3): 74.

McLennan, B.J. and Handmer, J., 2012. Reframing responsibility-sharing for bushfire risk management in australia after black saturday. Environmental Hazards, 11(1): 1-15.

Means, J.E., Acker, S.A., Harding, D.J., Blair, J.B., Lefsky, M.A., Cohen, W.B., Harmon, M.E. and McKee, W.A., 1999. Use of large-footprint scanning airborne lidat to estimate forest atand characteristics in the western cascades of oregon. Remote sensing of environment.

Miller, C. and Urban, D.L., 2000. Connectivity of forest fuels and surface fire regimes. Landscape Ecology, 15(2): 145-154.

Mitsopoulos, I. and Dimitrakopoulos, A., 2014. Estimation of canopy fuel characteristics of aleppo pine (pinus halepensis mill.) forests in greece based on common stand parameters. European journal of forest research, 133(1): 73-79.

Moskal, L.M. and Zheng, G., 2011. Retrieving forest inventory variables with terrestrial laser scanning (tls) in urban heterogeneous forest. Remote Sensing, 4(1): 1-20.

Mutlu, M., Popescu, S.C., Stripling, C. and Spencer, T., 2008. Mapping surface fuel models using lidar and multispectral data fusion for fire behavior. Remote Sensing of Environment, 112(1): 274-285. Available from http://www.sciencedirect.com/science/article/pii/S0034425707001988. DOI http://dx.doi.org/10.1016/j.rse.2007.05.005.

Næsset, E., 2002. Predicting forest stand characteristics with airborne scanning laser using a practical two-stage procedure and field data. Remote Sensing of Environment, 80(1): 88-99. Available from http://www.sciencedirect.com/science/article/pii/S0034425701002905. DOI http://dx.doi.org/10.1016/S0034-4257(01)00290-5.

Næsset, E., 2004. Practical large-scale forest stand inventory using a small-footprint airborne scanning laser. Scandinavian Journal of Forest Research, 19(2): 164-179.

Naesset, E., 1997. Estimating timber volume of forest stands using airborne laser scanner data. Remote Sensing of Environment, 61(2): 246-253.

Næsset, E. and Bjerknes, K.-O., 2001. Estimating tree heights and number of stems in young forest stands using airborne laser scanner data. Remote Sensing of Environment, 78(3): 328-340.

Neter, J., Kutner, M.H., Nachtsheim, C.J. and Wasserman, W., 1996. Applied linear statistical models. Irwin Chicago.

Neumann, F. and Tolhurst, K., 1991. Effects of fuel reduction burning on epigeal arthropods and earthworms in dry sclerophyll eucalypt forest of west-central victoria. Australian Journal of Ecology, 16(3): 315-330.

Newnham, G.J., Armston, J.D., Calders, K., Disney, M.I., Lovell, J.L., Schaaf, C.B., Strahler, A.H. and Danson, F.M., 2015. Terrestrial laser scanning for plot-scale forest measurement. Current Forestry Reports, 1(4): 239-251. Available from http://dx.doi.org/10.1007/s40725-015-0025-5. DOI 10.1007/s40725-015-0025-5.

Noble, I., Gill, A. and Bary, G., 1980. Mcarthur's fire-danger meters expressed as equations. Australian Journal of Ecology, 5(2): 201-203.

North, M., Hurteau, M. and Innes, J., 2009. Fire suppression and fuels treatment effects on mixed-conifer carbon stocks and emissions. Ecological Applications, 19(6): 1385-1396.

Olson, J.S., 1963. Energy storage and the balance of producers and decomposers in ecological systems. Ecology, 44(2): 322-331.

Peet, G., 1965. Fire danger rating and controlled burning guide for the northern jarrah (euc. Marginata sm) forest, of western australia. For. Dept. WA, Bull.: pp: 74.

Peet, G., 1971. Litter accumulation in jarrah and karri forests. Australian Forestry, 35(4): 258-262.

Persson, A., Soderman, U., Topel, J. and Ahlberg, S., 2005. Visualization and analysis of full-waveform airborne laser scanner data. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36(3/W19): 103-108.

Persson, Å., Söderman, U., Töpel, J. and Ahlberg, S., 2005. Visualization and analysis of full-waveform airborne laser scanner data. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36(3/W19): 103-108.

Pfeifer, N. and Winterhalder, D., 2004. Modelling of tree cross sections from terrestrial laser scanning data with free-form curves. International Archives of Photogrammetry, remote sensing and spatial information sciences, 36(Part 8): W2.

Pitkänen, J., Maltamo, M., Hyyppä, J. and Yu, X., 2004. Adaptive methods for individual tree detection on airborne laser based canopy height model. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36(8): 187-191.

Pook, E., 1993. Empirical models evaluated for prediction of fine fuel moisture in australian pinus radiata plantations. New Zealand Journal of Forestry Science, 23(3): 278-297.

Pook, E. and Gill, A., 1993. Variation of live and dead fine fuel moisture in pinus radiata plantations of the australian-capital-territory. International Journal of Wildland Fire, 3(3): 155-168.

Popescu, S.C., 2007. Estimating biomass of individual pine trees using airborne lidar. Biomass and Bioenergy, 31(9): 646-655. Available from http://www.sciencedirect.com/science/article/pii/S0961953407001316. DOI http://dx.doi.org/10.1016/j.biombioe.2007.06.022.

Popescu, S.C., Wynne, R.H. and Nelson, R.F., 2003. Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass. Canadian journal of remote sensing, 29(5): 564-577.

Pyne, S.J., Andrews, P.L. and Laven, R.D., 1996. Introduction to wildland fire. John Wiley and Sons.

Raison, R.J., Woods, P. and Khanna, P.K., 1983. Dynamics of fine fuels in recurrently burnt eucalypt forests. Australian Forestry, 46(4): 294-302.

Raison, R.J., Woods, P. and Khanna, P.K., 1983. Dynamics of fire fuels in recurrently burnt eucalypt forest. Australian Forestry (46): 294-302.

Raison, R.J., Woods, P. and Khanna, P.K., 1986. Decomposition and accumulation of litter after fire in sub-alpine eucalypt forest. Australian Journal of Ecology(11): 9-19.

Reutebuch, S.E., McGaughey, R.J., Andersen, H.-E. and Carson, W.W., 2003. Accuracy of a high-resolution lidar terrain model under a conifer forest canopy. Canadian Journal of Remote Sensing, 29(5): 527-535. Available from http://dx.doi.org/10.5589/m03-022. DOI 10.5589/m03-022.

Riaño, D., Chuvieco, E., Salas, J., Palacios-Orueta, A. and Bastarrika, A., 2002. Generation of fuel type maps from landsat tm images and ancillary data in mediterranean ecosystems. Canadian Journal of Forest Research, 32(8): 1301-1315.

Riaño, D., Chuvieco, E., Ustin, S.L., Salas, J., Rodríguez-Pérez, J.R., Ribeiro, L.M., Viegas, D.X., Moreno, J.M. and Fernández, H., 2007. Estimation of shrub height for fuel-type mapping combining airborne lidar and simultaneous color infrared ortho imaging. International Journal of Wildland Fire, 16(3): 341-348.

Riaño, D., Meier, E., Allgöwer, B., Chuvieco, E. and Ustin, S.L., 2003. Modeling airborne laser scanning data for the spatial generation of critical forest parameters in fire behavior modeling. Remote Sensing of Environment, 86(2): 177-186. Available from http://www.sciencedirect.com/science/article/pii/S0034425703000981. DOI http://dx.doi.org/10.1016/S0034-4257(03)00098-1.

Rigby, R. and Stasinopoulos, D., 2009. A flexible regression approach using gamlss in r. London Metropolitan University, London.

Robert, A.S., 2007. Remote sensing: Models and methods for image processing. By Elsevier Inc. All rights reserved: p300-304.

Roberts, D., Green, R. and Adams, J., 1997. Temporal and spatial patterns in vegetation and atmospheric properties from aviris. Remote sensing of environment, 62(3): 223-240.

Rollins, M.G., Keane, R.E. and Parsons, R.A., 2004. Mapping fuels and fire regimes using remote sensing, ecosystem simulation, and gradient modeling. Ecological Applications, 14(1): 75-95.

Rothermel, R.C., 1972. A mathematical model for predicting fire spread in wildland fuels. United States Department of Agriculture Forest Service, 115: 40.

Rothermel, R.C. and Anderson, H.E., 1966. Fire spread characteristics determined in the laboratory.

Rowell, E.M., Seielstad, C.A. and Ottmar, R.D., 2016. Development and validation of fuel height models for terrestrial lidar–rxcadre 2012. International Journal of Wildland Fire, 25(1): 38-47.

Ryding, J., Williams, E., Smith, M.J. and Eichhorn, M.P., 2015. Assessing handheld mobile laser scanners for forest surveys. Remote Sensing, 7(1): 1095-1111.

Saatchi, S., Halligan, K., Despain, D.G. and Crabtree, R.L., 2007. Estimation of forest fuel load from radar remote sensing. Geoscience and Remote Sensing, IEEE Transactions on, 45(6): 1726-1740. DOI 10.1109/TGRS.2006.887002.

Saatchi, S.S. and Moghaddam, M., 2000. Estimation of crown and stem water content and biomass of boreal forest using polarimetric sar imagery. IEEE Transactions on Geoscience and Remote Sensing, 38(2): 697-709.

Sabins Jr, F.F., 1978. Remote sensing. Remote sensing.

Saltelli, A., 2002. Sensitivity analysis for importance assessment. Risk Analysis, 22(3): 579-590.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M. and Tarantola, S., 2008. Global sensitivity analysis: The primer. John Wiley & Sons.

Sampath, A. and Shan, J., 2007. Building boundary tracing and regularization from airborne lidar point clouds. Photogrammetric Engineering & Remote Sensing, 73(7): 805-812.

Sandberg, D.V., Ottmar, R.D. and Cushon, G.H., 2001. Characterizing fuels in the 21st century. International Journal of Wildland Fire, 10(3/4): 381-387.

Schaub, M., Jenni, L. and Bairlein, F., 2008. Fuel stores, fuel accumulation, and the decision to depart from a migration stopover site. Behavioral Ecology, 19(3): 657-666.

Schlobohm, P. and Brain, J., 2002. Gaining an understanding of the national fire danger rating system. National Wildfire Coordinating Group, PMS, 932.

Scott, J.H. and Burgan, R.E., 2005. Standard fire behavior fuel models: A comprehensive set for use with rothermel's surface fire spread model. The Bark Beetles, Fuels, and Fire Bibliography: 66.

Scott, J.H. and Reinhardt, E.D., 2001. Assessing crown fire potential by linking models of surface and crown fire behavior.
Simmons, D. and Adams, R., 1986. Fuel dynamics in an urban fringe dry sclerophyll forest in victoria. Australian Forestry (49): 149-154.
Simonse, M., Aschoff, T., Spiecker, H. and Thies, M., 2003. Automatic determination of forest inventory parameters using terrestrial laserscanning. In: ScandLaser Scientific Workshop on Airborne Laser Scanning of Forests. pp: 252-258.
Skolnik, M.I., 1962. Introduction to radar. Radar Handbook, 2.
Skowronski, N., Clark, K., Nelson, R., Hom, J. and Patterson, M., 2007. Remotely sensed measurements of forest structure and fuel loads in the pinelands of new jersey. Remote Sensing of Environment, 108(2): 123-129. Available from http://www.sciencedirect.com/science/article/pii/S0034425706004548. DOI http://dx.doi.org/10.1016/j.rse.2006.09.032.
Sneeuwjagt, R.J. and Peet, G.B., 1985. Forest fire behavior tables for western australia, 3rd ed. Department of Conservation and Land Management, Perth, Western Australia.
Stephens, S.L., Burrows, N., Buyantuyev, A., Gray, R.W., Keane, R.E., Kubian, R., Liu, S., Seijo, F., Shu, L. and Tolhurst, K.G., 2014. Temperate and boreal forest mega-fires: Characteristics and challenges. Frontiers in Ecology and the Environment, 12(2): 115-122.
Stocks, B.J., Lynham, T., Lawson, B., Alexander, M., Wagner, C.V., McAlpine, R. and Dube, D., 1989. Canadian forest fire danger rating system: An overview. The Forestry Chronicle, 65(4): 258-265.
Suárez, J.C., Ontiveros, C., Smith, S. and Snape, S., 2005. Use of airborne lidar and aerial photography in the estimation of individual tree heights in forestry. Computers & Geosciences, 31(2): 253-262.
Tao, S., Guo, Q., Li, L., Xue, B., Kelly, M., Li, W., Xu, G. and Su, Y., 2014. Airborne lidar-derived volume metrics for aboveground biomass estimation: A comparative assessment for conifer stands. Agricultural and Forest Meteorology, 198: 24-32.
Thenkabail, P.S., Lyon, J.G. and Huete, A., 2012. Hyperspectral remote sensing of vegetation. CRC Press Boca Raton, FL.
Thies, M. and Spiecker, H., 2004. Evaluation and future prospects of terrestrial laser scanning for standardized forest inventories. Forest, 2(2.2): 1.
Tolhurst, K.G. and Kelly, N., 2003. Effects of repeated low-intensity fire on fuel dynamics in a mixed eucalypt foothill forest in south-eastern australia. Department of Sustainability and Environment.
Tolhurst, K.G., McCarthy, G.J. and Chatto, K., 1996. Estimating overall fuel hazard for forest fuels. Department of Conservation and Natural Resources, Melbourne, Victoria.
Tolhurst, K.G., Shields, B. and Chong, D., 2008. Phoenix: Development and application of a bushfire risk management tool. Australian Journal of Emergency Management, 23(4): 47.
Turner, D.P., Cohen, W.B., Kennedy, R.E., Fassnacht, K.S. and Briggs, J.M., 1999. Relationships between leaf area index and landsat tm spectral vegetation indices across three temperate zone sites. Remote sensing of environment, 70(1): 52-68.
Van Leeuwen, M. and Nieuwenhuis, M., 2010. Retrieval of forest structural parameters using lidar remote sensing. European Journal of Forest Research, 129(4): 749-770.
Van Wagner, C., 1987. Development and structure of the canadian forest fire weather index system. In: Forestry Technical Report 35. Canadian Forest Service, Petawawa Forest.
Van Wagner, C., Stocks, B., Lawson, B., Alexander, M., Lynham, T. and McAlpine, R., 1992. Development and structure of the canadian forest fire behavior prediction system. Forestry Canada Fire Danger Group Information Report ST-X-3.(Ottawa, ON).

Van Wagtendonk, J.W. and Root, R.R., 2003. The use of multi-temporal landsat normalized difference vegetation index (ndvi) data for mapping fuel models in yosemite national park, USA. International Journal of Remote Sensing, 24(8): 1639-1651.
Wagner, C.V., 1977. Conditions for the start and spread of crown fire. Canadian Journal of Forest Research, 7(1): 23-34.
Wagner, W., Hollaus, M., Briese, C. and Ducic, V., 2008. 3d vegetation mapping using small-footprint full-waveform airborne laser scanners. International Journal of Remote Sensing, 29(5): 1433-1452.
Wagner, W., Ullrich, A., Ducic, V., Melzer, T. and Studnicka, N., 2006. Gaussian decomposition and calibration of a novel small-footprint full-waveform digitising airborne laser scanner. ISPRS Journal of Photogrammetry and Remote Sensing, 60(2): 100-112.
Walker, J., 1981. Fuel dynamics in australian vegetation. Fire and the Australian biota: 101-127.
Walker, J., 1981. Fuel dynamics in australian vegetation. In: A. M. GillR. H. Groves and I. R. Noble, (Eds.) Australian Academy of Science, pp: 101-149.
Waring, R.H., Way, J., Hunt, E.R., Morrissey, L., Ranson, K.J., Weishampel, J.F., Oren, R. and Franklin, S.E., 1995. Imaging radar for ecosystem studies. BioScience, 45(10): 715-723.
Watson, P.J., Penman, S.H. and Bradstock, R.A., 2012. A comparison of bushfire fuel hazard assessors and assessment methods in dry sclerophyll forest near sydney, australia. International Journal of Wildland Fire, 21(6): 755-763.
White, T.L. and McBurney, D.H., 2012. Research methods. Cengage Learning.
Widlowski, J.L., Lavergne, T., Pinty, B., Verstraete, M. and Gobron, N., 2006. Rayspread: A virtual laboratory for rapid brf simulations over 3-d plant canopies. In: Computational methods in transport. Springer: pp: 211-231.
Wilson, A.A.G., 1992. Assessing fire hazard on public lands in victoria: Fire management needs, and practical research objectives. Department of Conservation and Environment.
Wilson, A.A.G., 1992. Eucalypt bark hazard guide. Department of conservation and natural resources, victoria. In: Research Report No. 32. Melbourne, Victoria.
Wilson, A.A.G., 1993. Elevated fuel guide. Department of Conservation and Natural Resources.
Wilson, A.A.G., 1993. Elevated fuel guide. Department of conservation and natural resources, victoria. In: Research Report No. 35. Melbourne, Victoria.
Wing, B.M., Ritchie, M.W., Boston, K., Cohen, W.B., Gitelman, A. and Olsen, M.J., 2012. Prediction of understory vegetation cover with airborne lidar in an interior ponderosa pine forest. Remote Sensing of Environment, 124: 730-741.
Xu, H., Gossett, N. and Chen, B., 2007. Knowledge and heuristic-based modeling of laser-scanned trees. ACM Trans. Graph., 26(4): 19. DOI 10.1145/1289603.1289610.
Yebra, M., Chuvieco, E. and Riaño, D., 2008. Estimation of live fuel moisture content from modis images for fire risk assessment. Agricultural and Forest Meteorology, 148(4): 523-536.
Yebra, M., Dennison, P.E., Chuvieco, E., Riaño, D., Zylstra, P., Hunt Jr, E.R., Danson, F.M., Qi, Y. and Jurdao, S., 2013. A global review of remote sensing of live fuel moisture content for fire danger assessment: Moving towards operational products. Remote Sensing of Environment, 136: 455-468. Available from http://www.sciencedirect.com/science/article/pii/S0034425713001831. DOI http://dx.doi.org/10.1016/j.rse.2013.05.029.
Zhang, L., Gove, J.H., Liu, C. and Leak, W.B., 2001. A finite mixture of two weibull distributions for modeling the diameter distributions of rotated-sigmoid, uneven-aged stands. Canadian Journal of Forest Research, 31(9): 1654-1659.

Zhang, L. and Liu, C., 2006. Fitting irregular diameter distributions of forest stands by weibull, modified weibull, and mixture weibull models. Journal of Forest Research, 11(5): 369-372.

Zimble, D.A., Evans, D.L., Carlson, G.C., Parker, R.C., Grado, S.C. and Gerard, P.D., 2003. Characterizing vertical forest structure using small-footprint airborne lidar. Remote sensing of Environment, 87(2): 171-182.

Zlot, R. and Bosse, M., 2014. Efficient large scale three dimensional mobile mapping for underground mines. Journal of Field Robotics, 31(5): 758-779.