# Estimation of forest surface fuel load using airborne LiDAR data

Yang Chen*[a,b], Xuan Zhu[a], Marta Yebra[c,b], Sarah Harris[a,b], Nigel Tapper[a,b]

[a]School of Earth, Atmosphere & Environment, Faulty of Science, Monash University, Wellington Rd, Clayton, VIC, Australia 3168

[b]Bushfire & Natural Hazards CRC, Albert St, East Melbourne, VIC, Australia 3002

[c]Fenner School of Environment & Society, College of Medicine, Biology & Environment, Australian National University, Canberra, ACT, Australia 2601

## ABSTRACT

Accurately describing forest surface fuel load is significant for understanding bushfire behaviour and suppression difficulties, predicting ongoing fires for operational activities, as well as assessing potential fire hazards. In this study, the Light Detection and Ranging (LiDAR) data was used to estimate surface fuel load, due to its ability to provide three-dimensional information to quantify forest structural characteristics with high spatial accuracies. Firstly, the multilayered eucalypt forest vegetation was stratified by identifying the cut point of the mixture distribution of LiDAR point density through a non-parametric fitting strategy as well as derivative functions. Secondly, the LiDAR indices of heights, intensity, topography, and canopy density were extracted. Thirdly, these LiDAR indices, forest type and previous fire disturbances were then used to develop two predictive models to estimate surface fuel load through multiple regression analysis. Model 1 was developed based on LiDAR indices, which produced a $R^2$ value of 0.63. Model 2 ($R^2 = 0.8$) was derived from LiDAR indices, forest type and previous fire disturbances. The accurate and consistent spatial variation in surface fuel load derived from both models could be used to assist fire authorities in guiding fire hazard-reduction burns and fire suppressions in the Upper Yarra Reservoir area, Victoria, Australia.

**Keywords:** airborne LiDAR, surface fuel load, mixture distribution, multiple regression

## 1. INTRODUCTION

Bushfires have occurred in southeast Australia for millions of years as frequent annual events, and are an essential part of the ecology of the continent [1-3]. In fact, Australian natural ecosystems have evolved with fire [4] and their biological diversity has been shaped by both historical and recent patterns of fire [5]. However, in bushfire prone areas, bushfires are also considered as a threat to the community and the environment, since they cause potential damage to the land and property and even loss of life. The primarily reliable method to reduce fire risks is through modifying fuel availability. Therefore, more accurate and consistent methods to quantify forest surface fuel can assist fire hazard-reduction burns and fire behaviour studies [6-8].

Traditionally, surface fuel load was determined by field sampling, oven drying, and weighing [9-11], which can be time and labour intensive at large scales. McArthur's positive relationships between surface fuel load and surface depth have been used as a quick manner to support fuel hazard-reduction burns in Eucalypt forests in Australia, instead of directly measuring fuel load. However, the relationships vary with forest types and environmental conditions [11, 12]. Quantities of surface fuel can also be estimated by fuel accumulation models [1]. Fuel accumulation is described and modelled by several studies with a general form of an exponential function [13]. In these models, years since last fire is the only indicator to predict fuel growth within homogeneous vegetation; therefore, they have the limitation in estimating spatial variation in surface fuel load across different vegetation communities and forest types [14-16].

*yang.chen2@monash.edu; phone +61 (03) 99054424

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Forest surface fuel load accumulates over time, which depends on the rates difference between fuel accession and decomposition [1], which is further reliant on the results of a complex interaction of separate and related influencing factors (e.g. forest type, productivity of understorey and overstorey vegetation, density of canopy as well as environmental conditions) [17]. Several studies, including for example that of [18, 19], described vertical profile of forest vegetation using theoretical distribution functions of airborne LiDAR indices. These studies applied a unimodal structure (e.g. a Weibull distribution function) in LiDAR indices to represent forest structural characteristics. However, in a multilayered forest, the LiDAR representation of forest vertical profile tends to have a mixture distribution (e.g. a bimodal distribution) depending on the complexity of the understorey vegetation [20].

This study stratified the multilayered eucalypt forest vegetation layers through an identification of the cut point of the smoothed mixture distribution curves of LiDAR point density to quantify forest structure of the vertical profile. The LiDAR indices (e.g. stratified height variables, intensity, canopy density and topography), forest type and previous fire disturbances were then used to develop two predictive models to estimate surface fuel load in the Upper Yarra Reservoir area, Victoria, Australia through multiple regression. The proposed models also evaluated how the spatial variation in surface fuel load relates to the separate and related influencing factors across the study area.

## 2. METHODS

### 2.1 Data collection

This study used the Upper Yarra Reservoir area as a case study area to estimate eucalypt forest surface fuel load using multiple regression analysis. Surface fuel samples were collected at a total of forty-one sampling sites (0.5 m by 0.5 m) in six plots (50 m by 50 m), using the traditional method. These sampling sites were selected to have different fire history and terrain features using a stratified systematic sample design. Dry weight (g) of the fuel samples were measured after oven drying for 24 hours at 105 °C [21-24]. Datasets of forest types (dry or damp eucalypt forest) and burn types (wildfire or fuel hazard-reduction burns) were provided by Victoria Department of Environment, Land, Water and Planning (DELWP).

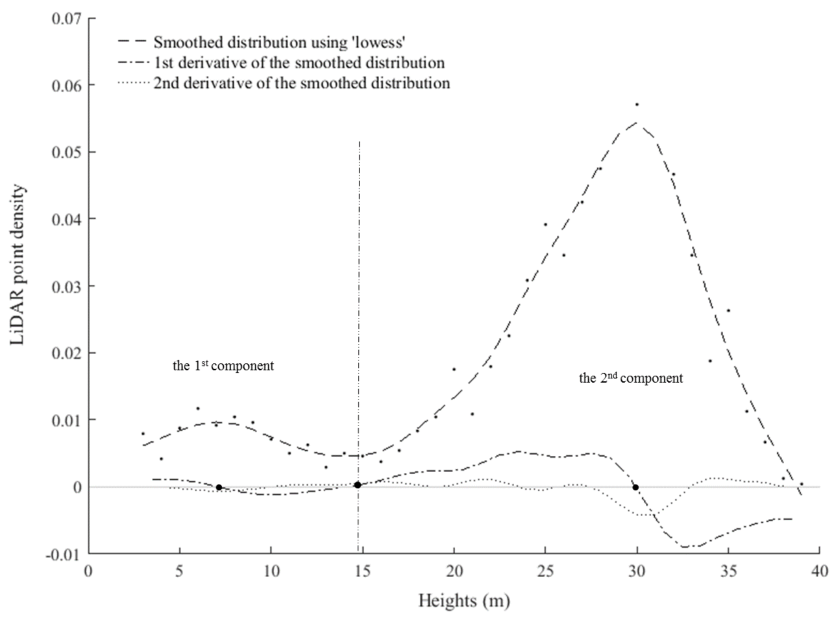



Figure 1. The vertical profile of the forest structures derived from airborne LiDAR data.

## 2.2 Extraction of LiDAR indices

The following three steps describe the extraction of LiDAR indices.

### *2.2.1 Stratification and characterization*

*Generation of height values*

A digital elevation model (DEM) with 0.5 m resolution was generated using geo coordinates of the last return of LiDAR point clouds, which was then used to convert the elevation values of the LiDAR points to its height values above the bare earth. The height values were calculated by subtracting a smoothed DEM from the elevation values for the following stratification.

*Generation of forest vertical profiles*

A scatter diagram (Figure 1) was generated by plotting the density of LiDAR points against heights. The vertical profile of the forest structures in the study area tends to follow a bimodal distribution. LiDAR points with height lower than 3 m were identified as lower vegetation, which were excluded in the bimodal distribution [20], due to the structural complexity of the lower understorey vegetation caused by the various fire events.

*Stratification of forest structure*

As described in Figure 1, 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 stratification of the forest vegetation between overstorey and understorey was then carried out by identifying the cut point between the two components. Firstly, a non-parametric fitting strategy - Locally Weighted Scatterplot Smoothing (LOWESS) was applied to smooth the scatter plot without assuming the shape of distribution for each component. Secondly, the first derivative was computed to identify the peaks and bottoms of the smoothed bimodal curve. Finally, the cut point was identified by a satisfaction in the maximum value of the second derivative at the peaks and bottoms values of the first derivative curve (Figure 1). The cut point between the two components of the bimodal curve was then utilized to stratify the multilayered eucalypt forest, characterise the vertical structure of the forest, and derive LiDAR indices (Table 1) for distinct vegetation layers.

Table1. LiDAR-derived height and intensity indices.

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

### *2.2.2 Stratified heights and initial intensity*

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*). 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).

### 2.2.3 *Canopy density and topography*

Canopy density (*CD*) 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 by at least four times of the point spacing of the LiDAR system (0.26 m). The DEM was used to estimate the elevation (*E*), slope (*S*), and aspect (*A*) with 0.5 m resolution in order to keep consistency with field measured fuel samples. These LiDAR indices were extracted using ArcGIS 10.3 (http://desktop.arcgis.com/en/arcmap/).

## 2.3 Estimation of surface fuel load

### 2.3.1 *Model development*

The two predictive models of surface fuel load were developed based on the extracted LiDAR indices (*H*, *I*, *CD*, *E*, *S* and *A*), time since last fire (*TSF*), eucalypt forest type (*FT*), burn type (*BT*), and the field measured dry weight (*DW*) of the fuel samples through multiple regression analysis. 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.

### 2.3.2 *Model error assessment*

The model errors were assessed through Cook's distance plot, histogram of residuals and the normal probability plot (NPP). The predicted values of surface fuel load were then compared with the observed fuel load for a further assessment of accuracy of the proposed models. In order to limit overfitting problems, the leave-one-out cross-validation was then used to verify the result of the finalised multiple regression models. Leave-one-out cross-validation (*CV*) could be computed using equation 1.

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

where n is the number of the observations, ei is the error obtained from fitting the model to n - 1 observations, hi is the leverage, and i is the repeating step (= 1, 2, …, n) [25, 26].

## 3. RESULTS AND DISCUSSION

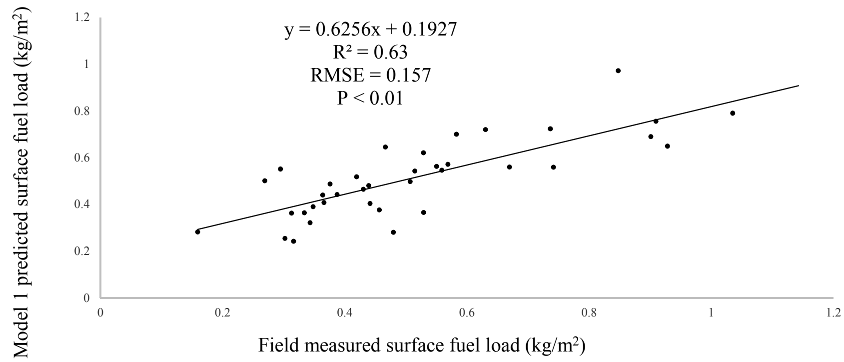
A symmetric normal distribution of residuals was detected that indicated the observations were randomly sampled from a normal distribution. The NPP of the residuals (the error terms) was approximately linear supporting the condition that the error terms were normally distributed and no obvious patterns were detected. Cook's distance detected three potential outliers. After removing the outliers, the finalized two predictive models for different uses depending on the data availability are described as follows.

Model 1:

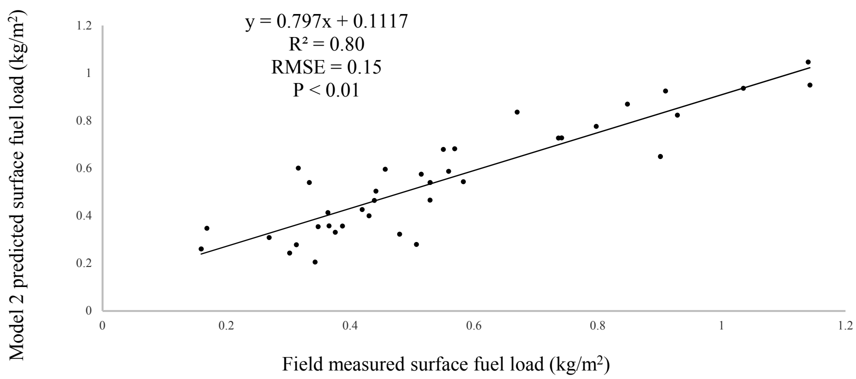
$$DW=-107.53-0.22*H_{meanS}+3.914*log(H_{maxC})-8.2367*log(H_{meanC})-0.15183*log(A)-0.03*H_{medianS}*H_{StdS}-27.79*log(H_{medianC})*log(E)+8.95*log(H_{StdC})*log(E) \qquad (2)$$

Model 2:

$$DW=29.47-0.04*H_{meanS}-2.95*log(H_{minC})+0.66*CD-10.45*log(E)+0.52*log(S)+5.14*BT-0.03*H_{maxS}*H_{StdS}-0.19*H_{StdS}*log(A)+2.56*log(H_{StdC})*log(A)-1.16*log(A)*FT \qquad (3)$$




2a




2b

Figure 2. Scattergram of Model 1 (a) and Model 2 (b)

Model 1 indicated that surface fuel load can be primarily estimated by LiDAR height indices of canopy and shrubs ($H_{max}$, $H_{mean}$, $H_{media}$n and $H_{Std}$) and topography (*A* and *E*). This model produced an $R^2$ value of 0.63 and *Root Mean Squared Error* (*RMSE*) value of 157 g/m$^2$ when comparing the predicted dry weight of surface fuel load per m$^2$ with observed values (Figure 2a).

Model 2 improved the values of $R^2$ and *RMSE* to 0.8 and 150 g/m$^2$, respectively, by introducing *CD*, *FT* and *BT* in the model and interacting with the LiDAR derived *H* indices (Figure 2b). Model 2 reduced the prediction error from 169 to 77.6 g/m$^2$ compared with Model 1 through the leave-one-out cross-validation.

Other studies used unimodal structures to represent vertical profiles of forest structure. However, mixture models can capture a more complete representation of the continuous LiDAR point density in order to quantify the stratified LiDAR height indices [20]. Jaskierniak et al. [20] 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. [20], the LOWESS was used for fitting a smooth curve to data point without the assumption of that the data must fit some distribution shapes. The computation proposed by our study was relatively efficient and does not require a high performing computing system to generate its result within a reasonable time. In addition, our study identified the cut point of mixture distributions to stratify forest vegetation layers, which could be beneficial for forest vegetation classification, forest habitat mapping, as well as forest wildlife conservation.

Forest vertical structure is a function of species composition, microclimate, site quality and topography, which has a significant influence on productivity and fuel accumulation [27, 28]. Therefore, LiDAR indices relating to crown height, canopy density, depth and closure of understorey and overstorey layers as well as topography, are useful for quantifying surface fuel. Statistically, the LiDAR height indices (e.g. *Hmean, Hmedian and HStd*) contribute more to the prediction than other LiDAR indices of height percentile and intensity. *TSF* is not a key indicator to the prediction of spatial variations in *DW*, despite surface fuel accumulates over time. Two established model indicates that *E* and *A* are more statistically significant than *S*. Because elevation indirectly influences fuel productivities and its decomposition rates due to its effect on temperature; aspect is an indicator to surface fuel moisture content that indirectly influences rates of surface fuel decomposition [11, 12, 29, 30].

## 4. CONCLUSION

Quantifying surface fuel load is still an ongoing requirement for fire authorities and fire management agencies, due to its importance in predicting fire behaviour and assessing potential fire risks. Two predictive models of forest surface fuel load were developed in this study using LiDAR indices, forest types and previous fire disturbances. Both models can be used to estimate accurate and consistent quantities of surface fuel at a landscape scale. Model 1 is applicable when forest types and previous fire disturbances are not available. This study established an accurate and consistent method to estimate spatial variation in forest surface fuel load. The information derived from the models can be used in forest fuel management, suppression difficulty assessment, and potential fire hazard evaluation in the Upper Yarra Reservoir area. This study also developed an efficient method to stratify multilayer forest vegetation through integration between a non-parametric fitting strategy and derivative functions. The LiDAR derived stratification method has its significant contribution in vegetation classification, forest habitat mapping, as well as forest wildlife conservation.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