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ESTIMATING CARBON STOCKS AND BIOMASS IN SURFACE FUEL LAYERS

Milestone 3.1.3 Final report of fuel condition/vegetation model

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Cover: Dense understorey and thick litter layer in forested site in Wombat State Forest. Source: Danica Parnell

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ABSTRACT

In this report we describe a simple model that can be used to estimate carbon (C) stocks in surface fuel layers for C accounting purposes. We used empirical data collected from dry sclerophyll forests from a range of sites in Victoria, New South Wales and the Australian Capital Territory. This information was used to develop an easy-to-use tool to improve estimates of C emissions from prescribed burning. Models developed using data from each state have been reported previously – here we present an evaluation of a universal model developed using the complete empirical dataset for all sites in all three states, and two separate models ('universal' models) developed using data from all the sites burnt by prescribed fires and nearby unburnt sites.

Samples of the near-surface fuel layer were separated into three fractions: fine fuel (<9 mm diameter), intact leaves, and twigs and other material such as fruits, flowers and bark. The dry weight and C content of each fraction was determined. To model biomass and C content of surface fuels, a mixture design was used. For each site, the proportion of the total fuel load of each of the three surface litter fractions was used as an independent factor (x1, x2, and x3), and the corresponding total fuel load (t ha^{-1}) or C content (t C ha^{-1}) was used as the dependent factor. A response surface was fitted to the mixture design using a Generalised Blending Mixture model (GBM) and a polynomial equation for each response was generated by running the GBM with varying numbers of terms included in the response surface equation. To determine the best fitting equation, Akaike information criterion (AICc) was used as a measure of the relative quality of the response surface for a given set of data in relation to other model iterations. Data were randomly assigned into an 80:20 split for training and testing of the response surface of the model. Models were also validated against a second set of data collected from high and low productivity forest sites. This additional information improved data spread and, thus, model testing.

The response surfaces fitted to data showed reasonable agreement with the data but the universal model (burnt and unburnt data from all sites combined) tended to be unreliable with both over- and underpredictions depending upon which dataset was being used for testing or validation. Universal models created using data from all burnt or unburnt sites were better than other trained models for predicting of biomass or C content in relation to fire history.

END-USER STATEMENT

Dr Felipe Aires, New South Wales National Parks and Wildlife Service, NSW

Universal models for predicting biomass or carbon content of fine fuels in relation to fire history presented in this report have been developed over the past 2 years and were progressively reported in milestones, conference proceedings and newsletters (e.g. Milestones 2.1.3, 2.2.2, 2.3.2, 2.4.3; Possell *et al.*, 2019; February 2019 project newsletter). This final technical report summarises the information about the fine fuel model presented in previous milestones and provides further detail describing model refinement and application.

The 'How to use' guide at the conclusion of the report shows how the fine fuel models developed in this research can be used to estimate biomass and the carbon content of the different components of surface fuel with reasonable accuracy. Estimates of biomass can help inform fire planners understand the potential fire behaviour and the latter, carbon content, can be used for estimating carbon emissions from this fuel layer during prescribed burning.

1. INTRODUCTION

Prescribed burning is widely used in Australia for mitigating the risk of unplanned bushfires by reducing fuel loads. This process involves temporarily removing accumulated fuels, primarily in surface and near-surface fuel layers (Fernandes and Botelho, 2003), but also elevated and bark fuels. As the intent of prescribed fire is most often to reduce the risk to life and property, the environmental effects are often a secondary consideration (Sohngen and Haynes, 1997; Butry *et al*., 2001; Fried *et al*., 2004). Fire can have a variety of effects in an ecosystem, one being a disruption to carbon (C) cycling. In forests, C is stored aboveground in live vegetation and dead material and belowground in live roots and dead soil organic matter (SOM). As forests collectively represent a large fraction of global C pools, and small disturbances could potentially affect global C cycling, it is important to understand C partitioning in forest biomass and how it may change after fire (Schulze *et al*., 2000; Lal, 2004).

Carbon emission factors are used to estimate the quantity of C released per kg of biomass burnt. For this, reliable values for carbon dioxide (CO_2), carbon monoxide (CO), methane (CH_4), and a range of trace gases produced by combustion of fuel from Australian temperate forests have been published (Paton-Walsh *et al.,* 2014). During bushfire, CO_2 is emitted in quantities more than 10-times greater than the next most prevalent gas, CO, the quantity of which is 10-fold greater than the remaining trace gases ((Sommers *et al.,* 2014). On decadal or more time scales, bushfires are thought to be a 'net zero' C emission event because the C released as CO_2 during burning is offset via the net uptake of CO_2 by regenerating vegetation (Bowman *et al.,* 2009). However, the ways in which fire affect forest ecosystems are far more complex, and there may be significant consequences to global C cycling caused by large unplanned bushfire events and smaller but more frequent planned prescribed fire events.

Carbon accounting that relies solely on addition of CO_2 to the atmospheric C pool by vegetation fires and subsequent removal through photosynthesis can create misunderstandings regarding the reliability of C balances due to fires (Schimel and Baker, 2002; Kashian *et al.,* 2006; van der Werf *et al.,* 2010). A variety of approaches to account for C stocks in forest ecosystems have been developed and have inevitably led to different estimates of C emission factors (Helin *et al*., 2013). Accurate quantification of C pools in different fuel strata in forests using empirical data is critical for increasing accuracy in C modelling efforts. Possell *et al.* (2015) estimated that, for prescribed fire in dry sclerophyll eucalypt forests in Australia, up to 86% of C or between 20-139 t C ha^{-1} as CO_2 (73-509 t eCO_2 ha^{-1}) is released to the atmosphere. For *Eucalyptus obliqua* forests in Victoria, CO_2 losses from fine fuels due to low intensity prescribed burning was estimated to be 90% of that fraction, equivalent to 25 t C ha^{-1} (Volkova and Weston, 2013).

Estimates of total aboveground C in forests and woodlands generally quantify biomass held as live fuel in the overstorey, understorey, ground cover (near surface), dead fuel represented by litter (surface fuel), and coarse woody debris either as standing remains of trees or connected to the ground. An important issue with current predictive modelling of C content in forests is both the paucity of good quality data describing near-surface and surface fuels, and when data

are available, there is typically a lack of detail on the composition of the surface fuel layer. The surface fuel is an important component in determining fire behaviour, not only for ascertaining the amount of fuel available to burn, the moisture content and the particle arrangement (Ottmar, 2014; Cruz *et al*., 2018), but also ascertaining the composition and different flammability characteristics of each fraction (Gormley *et al*., 2020). After fire, the conversion of fuel to charcoal, char and ash can change the overall amount of C affected in the natural C cycle and can provide a variety of uncertainties in current emission projections (Sommers *et al.,* 2014).

The surface fuel layer can have several components at different stages of decomposition including from almost entirely decomposed plant material to newly fallen leaves and twigs, partially decomposed debris through to aged humus. As this fuel layer can have the greatest impact on the rate of spread and intensity of fire (Prior *et al.,* 2016; Krix and Murray, 2018), surface fuels deserve to be thoroughly investigated for accurate reporting of C losses from prescribed fire and bushfire. Previous studies have partitioned surface fuels according to organic or inorganic density (>1.8 g cm^{-3}) using various methods (Turchenek and Oades, 1974; 1979; Paul and Van Veen, 1978). Many more studies refer to surfaces fuels as one whole component with no partitioning of the various fractions.

Current C accounting schemes use a range of default values to determine C in surface fuels. For example, default values of 37% (Smith and Heath, 2002), 47% (IPCC, 2004) and 50% (Gifford, 2000; Keith *et al*., 2009; 2012) have been used. Although derived from comprehensive studies, it is not known how reliable these values are as the composition of the surface fuel layer may differ according to a variety of factors, including forest type, environmental conditions and how prevailing or changing conditions affect litter inputs and rates of decomposition; factors which can all vary both spatially and temporally. Seasonal changes in weather can create differences in C pools in individual surface fuel fractions (leaves, twigs, bark), both in quantity and decay state, and can contribute to the overall C pool of surface fuel. Along with temporal variation, biophysical factors including soil type, topography and elevation, vary across the landscape and contribute to variation in surface fuel from location to location. As such, the development of a method which can be used to increase the predictive capacity of C stocks in surface fuels is important for determining site- or region-specific emissions from fires.

Current methods of estimating aboveground biomass range from simple allometric equations through to highly technical remote sensing technology (e.g. LIDAR; Ottmar *et al*., 2009; Ottmar, 2014; Valbuena *et al*., 2017). To be of value, both simple allometrics and remote sensing methods require thorough calibration to ensure accuracy between predicted and observed data (Valbuena *et al*., 2017). Once aboveground biomass has been characterised and validated, C content can be calculated according to the type of vegetation and its varying components. As presented in Parnell *et al*., (2018; 2019), based on a detailed analysis of C content for various fuel fractions, good estimates of C in surface fuel fractions can now be made.

Planning of prescribed burns is becoming necessarily more and more sophisticated, and land managers and fire agencies are also expected to be

more accountable for their activities. This creates a need for better estimation and prediction of C emissions from fire. In this report, we outline the development of a model that can estimate C stocks in surface fuel layers for C accounting purposes. Empirical data were used to describe C pools in surface fuels from a range of dry sclerophyll forests occurring in eastern Australia, and the resultant model has been developed into an easy-to-use tool which can assist in improving emission estimates of C and predictions of surface fuel biomass, before and after fire.

2. DATA COLLECTION AND ANALYSIS

2.1 STUDY AREA

The study area included prescribed burns at four sites in the Australian Capital Territory (ACT), nine sites in New South Wales (NSW) and seven sites located in Victoria (VIC) (Table 1). For the ACT and NSW, each of the sites were sampled within 2-4 weeks of the ignition date of the prescribed fire. Comparable sites were selected from unburnt forests nearby. Each site was sampled using three burn units – a pair of circular plots located in burnt and unburnt areas (spatial separation). Sampling protocols have been described in Gharun *et al.* (2015; 2017). Sites in the ACT have been described in detail in Gharun *et al.* (2015; 2017) and sites in NSW have been described in Gharun *et al.* (2018) and Bell *et al.* (2018). For sites located in VIC, plots were sampled 2-12 weeks prior to prescribed burning and resampled within 1 week after prescribed burning (temporal separation) as described in Jenkins *et al.* (2016).

Validation data were collected from three completely independent sites in NSW in the Blue Mountains (Brooker Road and Whitecross Road) and in the greater Marulan area (Arthursleigh). For sites in the Blue Mountains, 24 samples were collected from three plots located in burnt and unburnt locations in May 2018 (Table 1). For sites referred to as Arthursleigh, 20 samples were collected each from unburnt Stringybark Forest and unburnt Grassy Box Woodland in September 2018 (Table 1).

2.2 COLLECTION OF SURFACE FUEL

Near-surface and surface fuel layers were collected using a circular sampling ring (0.1 m^2 area). Live near-surface material (live and dead) was clipped at ground level and separated from surface fuels. Care was taken to avoid collecting mineral soil along with the fine organic material, but this was not always avoidable, particularly at sites with sandy soils.

Samples of surface fuels were dried in a fan-forced convection oven (Model TD-78T-2-D, Thermoline Scientific, Wetherill Park, NSW Australia) for 48 h at 60°C then separated into different fractions using a 9 mm sieve. Larger material (>9 mm) was separated into leaf, twig and 'other' fractions. The 'other' fraction comprising small seeds and fruits was typically a small fraction, so it was amalgamated with the twig fraction. Fine material (<9 mm) was classified as the 'fine fraction' and included fragments of organic material in various stages of decomposition, as well as small seeds, fruits and sometimes sand. Dry weight of each surface fuel fraction was recorded and, where necessary, the weight of the fine fraction was adjusted to consider the weight of non-organic material (e.g. sand). Due to the fragility of samples from burnt plots they may have contained large (>9 mm) fragments of charred leaves, twigs and bark and there may have been ash and charred organic matter in the fine (<9 mm) fraction.

Table 1. Details of prescribed fires in Victoria (VIC; plots 1-27), the Australian Capital Territory (ACT; plots 28-39) and New South Wales (NSW; plots 40-66). For sites in Victoria, sampling occurred before fire and within 1 week after prescribed burning using the same plot location. Sites in ACT and NSW were sampled 2-4 weeks after prescribed burning in burnt and nearby unburnt areas.

Plot number	Site name	Latitude	Longitude	Ignition date	Sampling date (pre/post)
VIC					
1-3	Frogs Hollow	-37.65	148.05	8 Feb 2011	Feb/Feb 2011
4-6	Upper Tambo	-37.76	147.88	6 Mar 2011	Feb/Mar 2011
7-9	Poddy	-37.68	148.96	8 Apr 2011	Feb/Apr 2011
10-12	South Boundary	-37.82	148.02	25 Feb 2011	Feb/Feb 2011
13-15	Sandy Point	-37.60	148.31	24 Feb 2011	Feb/Feb 2011
16-18	Oliver	-37.70	148.85	2 Apr 2012	Jan/Apr 2012
19-21	Gravel	-37.72	148.78	3 Apr 2012	Jan/Apr 2012
22-24	Patrol	-37.68	148.90	10 Apr 2013	Feb/Apr 2013
25-27	Pettmans	-37.76	148.01	9 Apr 2013	Feb/Apr 2013
ACT					
28-30	Googong	-35.51	149.28	11 Mar 2015	Apr 2015
31-33	Tidbinbilla	-35.46	148.90	17 Mar 2015	Apr 2015
34-36	Wrights Hill	-35.87	148.93	Mar 2015	Apr 2015
37-39	Cotter	-35.61	148.82	30 Mar 2015	May 2015
NSW					
40-42	Haycock Trig	-33.45	151.09	19 Aug 2015	Sep 2015
43-45	Helicopter Spur	-33.80	150.51	17 Aug 2015	Sep 2015
46-48	Spring Gully	-34.09	151.15	14 Aug 2015	Sep 2015
49-51	Paterson	-33.53	150.58	19 Aug 2015	Oct 2015
52-54	Lakesland	-34.16	150.49	13 Sep 2015	Oct 2105
55-57	Martins Creek	-34.30	150.44	8 Mar 2016	Apr 2016
58-60	Joadja	-34.37	150.21	8 Apr 2016	Apr 2016
61-63	Kief Trig	-33.29	150.94	17 Apr 2016	May 2016
64-66	Left Arm	-33.36	150.80	3 Apr 2016	May 2016
Validation sites					
94-96	Blue Mountains; Brooker Road	-33.65	150.64	Unburnt	May 2018
97-99	Blue Mountains; Whitecross Road	-33.66	150.61	Unburnt	May 2018
100-102	Arthursleigh, Stringybark Forest	-34.56	150.00	Unburnt	Sep 2018
103-105	Arthursleigh, Grassy Box Woodland	-34.56	150.00	Unburnt	Sep 2018

2.3 DETERMINATION OF CARBON CONTENT

Subsamples of surface fuel fractions (leaves, fine fuel and twigs and other) were finely ground and C content (% dry weight) was measured by combustion analysis (Elementar Vario Max CNS, Analysensysteme GmH, Hanau, Germany).

2.4 ESTIMATING TOTAL BIOMASS AND TOTAL CARBON

The total biomass (t ha^{-1}) was calculated as the sum of the fuel load of each fraction, as described in Equation 1:

$$\text{Total biomass fuel load} = (\alpha + \gamma + \beta) \quad (1)$$

Where α is the leaf litter fraction, γ is the fraction containing twigs and other materials and β is the fine fuel fraction.

The C content of surface fuel (t C ha^{-1}) was calculated as a weighted average of the fuel load of each fraction, multiplied by the respective C content as described in Equation 2:

$$\frac{\text{itd}_{100}\text{aaa bo}}{} = \frac{}{100} + \frac{}{100} \quad (2)$$

Where α is the leaf litter fraction, γ is the fraction containing twigs and other materials and β is the fine fuel fraction.

2.5 ERROR PROPAGATION AND DETECTION OF OUTLIERS

Propagation of uncertainty is defined as the effect of the uncertainty of variables, such as values of experimental measurements that have uncertainties due to measurement limitations (i.e. Instrument precision), which disseminate due to the combination of variables in the function (Taylor, 1982). Two different instruments were used across the study period for weighing material, and as such, there is a degree of uncertainty to the potential error across both scales. As there are measured values for quantities X, Y and Z, and uncertainties on δX, δY and δZ, the result, R, is the sum or difference of the quantities (Taylor, 1982). From this, the uncertainty on δR can be calculated as:

$$\begin{aligned} R &= X + Y - Z \\ aR &\approx aX + aY + aZ \\ aR &= \sqrt{(aX)^2 + (aY)^2 + (aZ)^2} \end{aligned} \quad (3)$$

From Equation 3, the calculated error of the scales combined is 0.141421 g (0.014142 t ha^{-1}), and values smaller than this were removed from the dataset to ensure the removal of any measurement error. Outliers in the datasets were also removed, using the absolute deviation around the median as a more robust method of dispersion (Leys *et al.*, 2013).

2.6 MODELLING TOTAL BIOMASS AND CARBON CONTENT OF SURFACE FUEL

To model biomass and C content of surface fuels, a mixture design was used, where the influence of individual components on a response surface can be evaluated (Eide and Johnsen, 1998; Lawson and Wilden, 2015). For each site, the proportions of the total fuel load (t ha^{-1}) for each of the three litter fractions was used as an independent factor (x1, x2, and x3; where x represents a litter fraction;

Figure 1), and the corresponding total fuel load (t ha^{-1}) or C content for each fuel load (t C ha^{-1}) was used as the dependent factor. The model used was a generalised blending mixture (GBM) model and is described by Equation 4 (Brown *et al*., 2015):

$$E[y] = \sum_{i=1}^{q} \beta_i x_i + \sum_{i<j} \beta_{ij} x_i x_j + \sum_{i<j<k} \beta_{ijk} x_i x_j x_k + \cdots \quad (4)$$

Where [*y*] is the response of interest that is dependent on the proportions of the mixture (q) components (x). The components x_i, x_j, x_k are fixed in relative proportions to allow the linear blending effect of one or more components on the response surface to be described. These components are indicative of mixture proportions which, must equal one. 1<i, i<j, i<j<k characterises the response surface contrastingly enough to the effect of x_i, x_j, x_k. β_{ij} and β_{ijk} are parameters for values of parameters s_{ij}, s_{ijk}, $_{ij}$, $_{ijk}$, which are the values that define the form of the model terms. The joint effect of x_i, x_j and x_k is governed by s_{ijk}, $_{ijk}$, $_{jki}$, $_{kij}$, and corresponding β_{ijk}. s_{ijk} controls the blending effects between x_i, x_j and x_k and the remaining mixture, analogous to s_{ij}. Contrasting effects may be seen where x_i, x_j and x_k remain fixed in relative proportions.

In the second and third sums, there are q_2 and q_3 terms respectively. Equation 4 is a complex model that can be used to establish a broad range of joint effects with more included terms. As this model is a nonlinear function of parameters, when parameters are specified ($_{ij}$, $_{ji}$, s_{ij}, $_{ijk}$, $_{ijk}$ and s_{ijk}), the remaining parameters of Equation 4 become trivial and will therefore result in a linear response surface (Brown *et al*., 2015). To determine the best fitting equation, Akaike information criterion (AIC) was used as a measure of the relative quality of the response surface for a given set of data in relation to other models (Akaike, 1974; Brown *et al*., 2015). When the samples size is small, as was the case in this study, a correction can be made (AICc) to avoid overfitting. The model fittings were done for data collected from burnt and unburnt sites within each of the three study locations.

Data were randomly assigned into an 80%:20% split for training and testing, respectively, of the response surface model. A simulated response surface was fitted to the training data using a GBM model (Brown *et al*., 2015) and a polynomial equation for that response was generated by running the GBM model with varying numbers of terms included in the response surface equation.

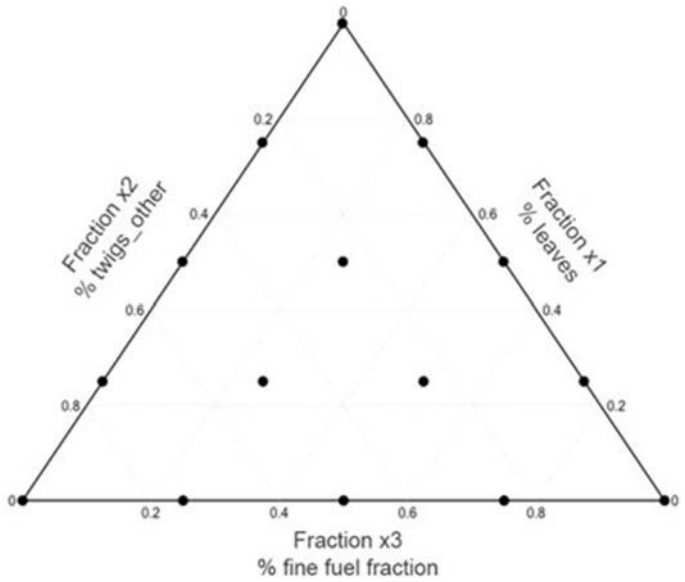

Figure 1. Example mixture design for modelling the relationship between the percentages of the fuel load (t ha^{-1}) for three fuel fractions and their corresponding total fuel load (t ha^{-1}; circles). The design allows the relationship between each individual composition and mixes among each other to be visualised and allow the fitting of a response surface that can be used to provide an estimate of carbon and biomass (t ha^{-1}). This design was generated using 'Mixexp' package on R studio (R Core Team, 2014).

Using the 'Metrics' package on R studio, evaluations were made for each of the model fits to determine how the 20% test data and mixed forest (MF) data fitted to the model generated from the 80% training data model (Hammer *et al.*, 2018). Bias is a calculation in this package that computes the average amount by which 'actual' is greater than the prediction data. Mean absolute error (MAE) is the average absolute difference between two numeric vectors, in this instance, 'actual' data and prediction data.

3. RESULTS AND DISCUSSION

3.1 MODEL DEVELOPMENT

Carbon and biomass models were initially developed for each state, presented previously (Milestones 2.1.3, 2.2.2, 2.3.2 and 2.4.3, and provided here in Appendix 7.1), then a single model was developed for dry sclerophyll forests in south eastern Australia. Further development of the existing models presented here, describe our efforts to refine model resolution.

In past iterations of our models, the default value for resolution was set to 0.5, which was deemed to be adequate for the GBM model method for the case study presented by Brown *et al*. (2015). In our study, the resolution was trialled and tested on 0.1, 0.05 and 0.01 refinements to increase the number of iterations for model fitting to potentially increase the accuracy of the predictions. As a benchmark, the original GBM model method had 648 iterations based on a resolution of 0.5. Running the models at 0.1 resolution required approximately 72,000 iterations and, at a resolution of 0.01, required approximately 72 million iterations. Running the model at a resolution of 0.01 was suboptimal, with respect to computational time and gains in accuracy, compared with models run at a resolution of 0.1. It would also run the risk of overfitting the dataset by increasing the number of parameters and increase model complexity but reduce its ability to make predictions of other datasets. Consequently, a resolution of 0.1 was chosen for developing the models presented.

3.1.1 Model choices

The data from each of the three locations studied – the ACT, NSW and Victoria – were combined to create the 'All states' model, developed with the greatest number of data points. This was done to investigate whether the combined data could provide more accurate estimates of surface fuel biomass and C than models derived from data for each state. As all of the sites surveyed were classed as dry sclerophyll forests, the amalgamation of the three states into the all states models was a rational approach. Comparisons of models developed from data from individual states and combined data (for both C and biomass) showed an increase in the spread of data points in the GBM modelling space. This in turn also increased the estimation capabilities of the prediction models for both C and biomass.

In this report we have presented an 'All states' model (ASA) using all of the data from all sites sampled. This model combined the data from plots located in both burnt and unburnt sites. We have also presented alternative models developed using data from plots sampled in burnt (ASB) and unburnt (ASUB) sites. The premise of having an ASA model was so that practitioners would only need to refer to one model for estimating biomass and a second one for estimating C content, and to be able to use the same tool before and after prescribed burning. However, the potential to under- or overestimate biomass or C in both unburnt and burnt locations does not allow the one model to be used reliably across all dry sclerophyll sites occurring in south eastern Australia (Parnell *et al.*, 2019).

3.1.2 Dealing with variability in the data

Outliers were removed in all datasets to improve the accuracy of the models. No data points were removed after accounting for measurement errors as all samples were above the threshold (i.e. 0.014 g experimental error). Outliers were identified and removed using the median absolute deviation. This resulted in the elimination of 24, nine and six datapoints from the biomass datasets for burnt, unburnt and all data, respectively. Similarly, 25, 11 and seven samples were removed from the C datasets for burnt, unburnt and all data, respectively. These values represent a very small proportion of datapoints in the whole dataset (n = 456). Although the variability in the datasets were reduced by removing outliers, data can also be normalised in this way to become useful for modelling processes (Grubbs, 2012; Zimek and Filzmoser, 2018).

The variability in biomass and in C in surface fuels represented in our datasets from burnt sites may be related to the nature in which they were burnt. Prescribed burns are often patchy due to low intensity fires and the conditions under which they are applied, and it is generally expected that between 50-90% of the planned area is burnt (Tolhurst, 2007). Sites in NSW had, on average, 6.3 t ha^{-1} surface fuel remaining after prescribed burning while sites in Victoria has closer to 2.2 t ha^{-1}. On average, 41%, 42% and 15% of surface fuel remained after prescribed burns at sites in the ACT, NSW and Victoria, respectively, implying that prescribed burns in Victoria were more effective for removal of surface fuel. The general variability inherent in forests, including fire history, may also play a role, with site conditions (topography, elevation, soil type, climate) influencing forest productivity and fire intensity and spread. Timing of sample collection can also introduce variability, possibly reducing the accuracy of modelling efforts. As an indicator of this, sites in Victoria sampled one week after prescribed burning had surface fuels composed of 0.66 t ha^{-1} leaves, whereas sites in NSW and the ACT sampled two to four weeks after prescribed burns had 0.91 t ha^{-1} leaves. Overestimation of the fine fuel fraction in surface fuel (based on dry weight) may have been due to the presence of inorganic and organic materials such as sand and, although we have not presented adjusted data here (i.e. taking into account the inadvertent addition of inorganic components in litter samples) this capacity (i.e. developing models based on adjusted values) could be added as required.

3.1.3 Biomass

There were differences in total biomass before and after prescribed burning at all sites (Table 2). Fine fuel and the fraction containing other materials (fruit, flowers, bark) were the least affected by prescribed burning compared to leaves and twigs (Table 2). When data from all sites were pooled, the range in the proportions of the different fractions that made up the total fuel load was smaller for samples from the unburnt sites compared to those from the burnt sites.

Model development using 80% of the data

All data from burnt and unburnt sites were randomly split into two groups. These groups consisted of 80% of the total dataset used for model development (training) and 20% of the total dataset used for testing – a form of cross-validation. All of the GBM models that were generated had the lowest AICc

value and the best score (best fit) when the models had a minimum of three included terms and a maximum of 10 included terms. The general statistics associated with these models are presented in Table 3. Of the three models produced ('all data', 'burnt' and 'unburnt'), the models for unburnt samples had the highest R^2 values. The optimal statistical output for each of the models correlated with the lowest AICc scores (Table 3). Model coefficients estimates and 95% confidence intervals are presented in Table 4.

The models developed using 80% of the data combined from sites in all three states are presented in Figure 3. With the removal of 20% of the data, an uneven spread of data was still evident in the unburnt model (Figure 3c). When the model was constrained to fit the extent of the data, the estimate range for surface fuel biomass from unburnt sites was from 10.3-15.5 t ha^{-1} and 0-15.0 t ha^{-1} for burnt sites. The combined model (all data from burnt and unburnt sites) had an estimated biomass range of 1.0-14.5 t ha^{-1}.

Table 1. Biomass (mean ± standard deviation) for each of the surface fuel fractions and total biomass from each of the sites in the Australian Capital Territory (ACT), New South Wales (NSW) and Victoria (VIC) and test data from Arthursleigh (NSW) and Blue Mountains (NSW). N/A = data not available.

Variable	Site condition	Leaves	Twigs	Fine fuel	Other	Total
ACT	Unburnt	1.98 ± 0.76	2.68 ± 1.78	1.38 ± 1.94	3.09 ± 2.75	9.28 ± 4.65
	Burnt	0.72 ± 0.86	1.25 ± 1.78	0.38 ± 0.69	1.67 ± 2.65	3.80 ± 3.67
NSW	Unburnt	2.89 ± 0.84	2.94 ± 1.24	6.94 ± 4.26	2.40 ± 1.32	15.14 ± 8.15
	Burnt	0.91 ± 0.34	0.75 ± 0.39	4.12 ± 4.12	0.77 ± 0.53	6.31 ± 6.34
VIC	Unburnt	4.03 ± 7.97	6.15 ± 2.82	4.58 ± 2.35	N/A	14.76 ± 9.10
	Burnt	0.66 ± 0.55	1.55 ± 2.04	0.52 ± 1.10	N/A	2.23 ± 3.24
Blue Mountains	Unburnt	4.13 ± 3.26	4.19 ± 4.38	5.96 ± 4.18	1.57 ± 1.06	15.85 ± 11.84
Arthursleigh	Unburnt	1.19 ± 0.84	3.51 ± 2.87	6.78 ± 4.29	0.70 ± 0.53	12.17 ± 6.31

Table 2. General blending mixing (GBM) model inclusions, Akaike information criterion (AICc) scores and statistical information for estimations of biomass of surface fuels from sites in the Australian Capital Territory (ACT), New South Wales (NSW) and Victoria (VIC). The values represented are indicative of the best model chosen based on the number of inclusions. RSE = residual standard error (with degrees of freedom), R^2 = R-squared value, Adj R^2 = adjusted R-squared value, *F* = *F* statistic (with degrees of freedom), *P* = *P*-value.

Variable	GBM	AICc	RSE	R^2	Adj R^2	*F*	*P*
All	$GBM_{3,10}$	2264.71	5.41 (356)	0.80	0.79	197.50 (7, 365)	<0.001
Burnt	$GBM_{3,10}$	704.92	2.05 (157)	0.81	0.80	109.40 (6, 157)	<0.001
Unburnt	$GBM_{3,10}$	1053.27	4.55 (172)	0.91	0.91	290.50 (6, 172)	<0.001

A useful way of representing the fitted surface besides the contour plots generated (see Figure 3) is through using 'effects plots'. These plots display the predicted response along each component axis on the same graph, whereby the defined component axis for component x_i is a line which passes through the design centroid to the vertex where $x_i = 1.0$ (Cox, 1971; Cornell, 2002). Essentially, these plots examine the effect of each component on the response, often when there are more than three components in the mixture which cannot be displayed effectively on a contour plot.

A Cox direction effects plot was generated for all models, and an example is provided in Figure 2 for biomass data from burnt and unburnt sites. The effects plots for the model developed for the burnt plots demonstrated that, with a decrease in the amount of leaves (a decrease in x1, Figure 2), the relative increase in the biomass of twigs and other material (x2) and the fine fuel fraction (x3) was relatively the same. However, the effect of fine fuel is slightly greater than for twigs and other material when values deviate further from the centre of the matrix. In contrast, the model developed for the unburnt sites showed that twigs and other material had the greatest effect as the values deviate further from the centroid. The predicted response suggests that when there is a decrease in leaf biomass, there is little to no change in fine fuel biomass, but a distinct response in the biomass of twigs and other materials (x2 in Figure 2b).

Model validation against test data

The accuracy of the models was tested by examining their performance in making prediction against the 20% validation (test) data. The relationship between model predictions and actual data from the test dataset are presented in Figure 4. There were reasonably strong relationships between the model predictions and the test data for the models developed from all data combined (All states model) and data from the burnt sites (Burnt model) and an underprediction for the model using data from unburnt sites (Unburnt model). The statistics for the linear regression models and the model metrics used to further evaluate the overall fit of the models to the data are presented in Table 5.

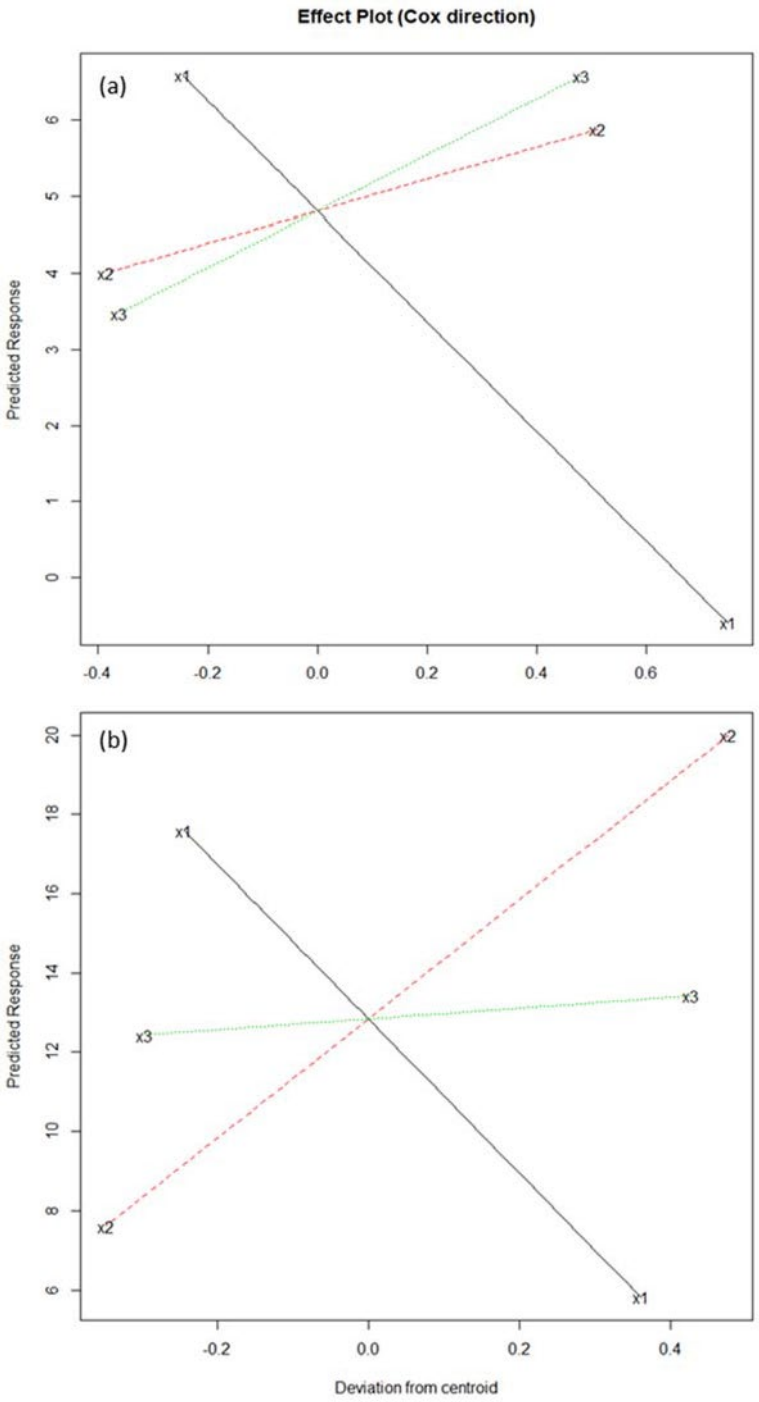

Figure 2. Examples of a Cox direction effects plot for biomass models for (a) burnt and (b) unburnt sites. The black line (x1) is leaves, red dashed line (x2) is twigs and other, and the green line (x3) is fine fuel.

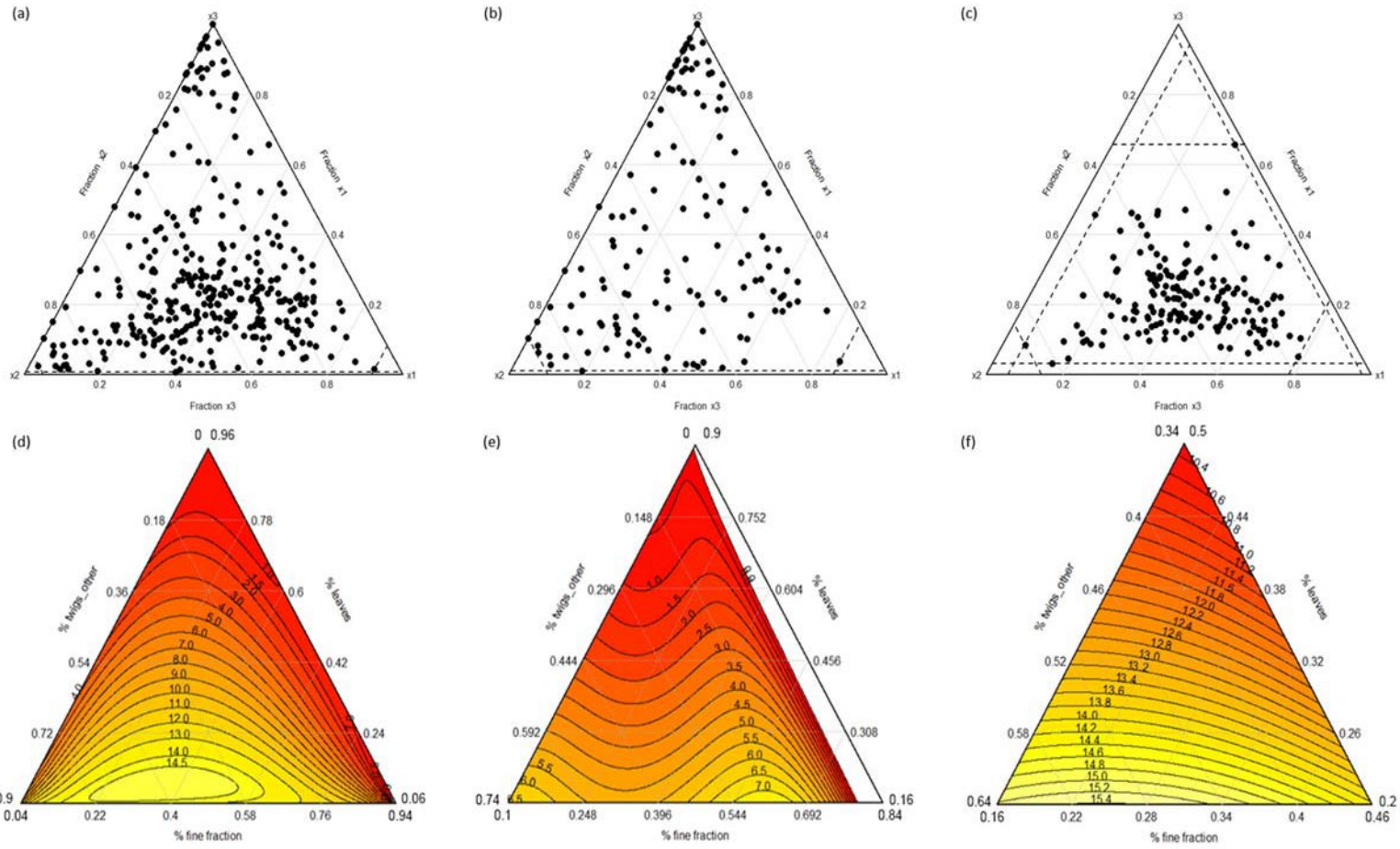

Figure 3. Biomass response surfaces developed using training data (80% data) from all sites in the Australian Capital Territory (ACT), New South Wales (NSW) and Victoria (VIC). (a, d) All data, (b, e) burnt or after prescribed burning, and (c, f) unburnt or before prescribed burning. Contours were modelled using a general blending model (GBM; Brown *et al*., 2015) with a minimum of three and a maximum of 10 terms included for each model. Panels (d), (e) and (f) represent the final biomass models generated, constrained to the limits presented in panels (a), (b) and (c).

Table 4. Statistical information for each of the 80% biomass models: all data from all sites (ASA), data from all burnt sites (ASB) and data from all unburnt sites (ASUB). Model coefficients, model estimates, Std Err = standard error, T = T value, PR(>|T|) = *P*-value for the T-test as the proportion of T distribution at that degrees of freedom which is greater than the absolute value of the T statistic, 95% CI = 95% confidence interval, *P* = *P*-value.

Coefficients	Estimate	Std Err	T	PR(>|T|)	95% CI	*P*
All data from all sites (ASA 80%)						
x1	1.10	0.88	1.26	0.21	-0.62 – 2.83	0.21
x2	-5.30	2.93	-1.81	0.07	-11.06 – 0.46	0.07
x3	-2.30	3.10	-0.74	0.46	-8.40 – 3.80	0.46
I(x1^0.5 * x2^2 * x3^1.3)	1824.01	908.86	2.01	0.05	36.60 – 3611.42	0.05
I(x1^0.5 * x3^1.7/(x1 + x3 + 0.001)^3)	7.89	1.61	4.90	1.46×10^{-6}	4.72 – 11.05	0
I(x1^0.5 * x2^1.9/(x1 + x2 + 0.001)^2.9)	15.97	4.49	3.56	0	7.14 – 24.793	0
I(x1^0.6 * x2^2.3 * x3^1.5)	-2753.11	1624.02	-1.70	0.09	-5946.99 – 440.78	0.09
Data from all burnt sites (ASB 80%)						
x1	0.72	0.35	2.02	0.05	0.01 – 1.42	0.05
x2	0.26	1.00	0.26	0.80	-1.72 – 2.23	0.80
x3	-10.65	3.65	-2.92	0	-17.86 – -3.44	0
I(x2^3 * x3^0.5/(x2 + x3 + 0.001)^1.1)	33.34	6.36	5.24	5.04×10^{-7}	20.78 – 45.91	0
I(x2^0.8 * x3^3/(x2 + x3 + 0.001)^2.3)	125.07	24.52	5.10	9.64×10^{-7}	76.64 – 173.51	0
I(x1^0.7 * x2^2.5 * x3^0.6)	58.84	28.12	2.09	0.04	3.29 – 114.39	0.04
Data from all unburnt sites (ASUB 80%)						
x1	52.62	10.59	4.97	1.62×10^{-6}	31.71 – 73.52	0
x2	22.35	2.45	9.12	$<2\times10^{-16}$	17.52 – 27.19	0
x3	53.00	12.92	4.10	6.29×10^{-5}	27.50 – 78.51	0
I(x1^1.9 * x2^0.5/(x1 + x2 + 0.001)^1.9)	-57.63	26.88	-2.14	0.03	-110.69 – -4.57	0.03
I(x1^0.9 * x2^0.6/(x1 + x2 + 0.001)^3)	245.59	69.32	3.54	0	108.77 – 382.42	0.01
I(x1^0.8 * x2^0.5/(x1 + x2 + 0.001)^2.7)	-253.35	72.69	-3.49	0	-396.84 – -109.87	0.01

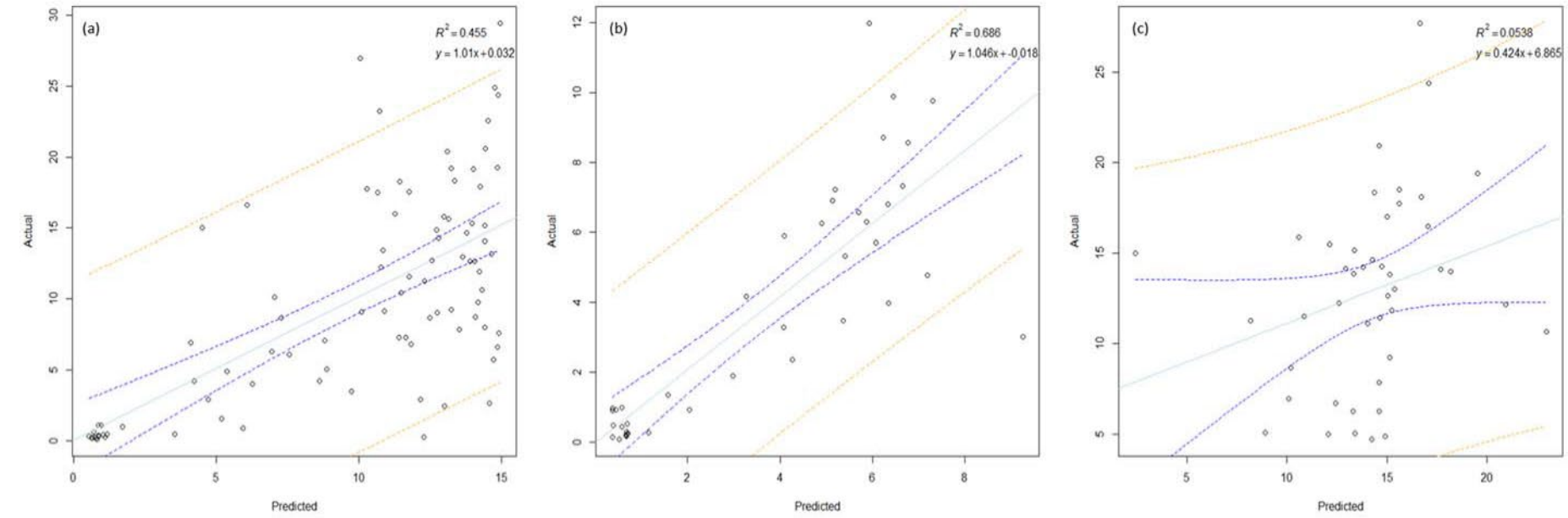

Figure 4. Linear regression plots for biomass of surface fuel showing the correlation between actual data and prediction generated from (a) all sites, (b) burnt sites and (c) unburnt sites. Dashed yellow lines represent the prediction intervals, dashed dark blue lines represent the confidence intervals and the solid light blue line represents the regression line.

Table 5. Statistical information and model metrics generated from the linear regression models. ASA = all data from all sites, ASB = data from all burnt sites, ASUB = data from all unburnt sites, RSE = residual standard error (with degrees of freedom), Adj R^2 = adjusted R^2 value, *F* = *F* statistic (with degrees of freedom), *P* = *P*-value, MAE = mean absolute error. Linear R^2 and zero R^2 (forced zero intercept) are taken from linear equations of the same data.

Variable	RSE	Adj R^2	*F*	*P*	MAE	Bias	Linear R^2	Zero R^2
ASA 20%	5.49 (89)	0.45	76.10 (1, 89)	<0.001	3.95	0.13	0.46	0.80
ASB 20%	1.91 (39)	0.69	88.24 (1, 39)	<0.001	1.26	0.14	0.69	0.86
ASUB 20%	5.11 (42)	0.05	3.44 (1, 42)	0.07	4.13	-1.31	0.05	0.85

3.1.4 Carbon

There were some differences in the C content of surface fuel both before and after prescribed burning at all sites (Table 6). Carbon was much lower in the leaf and twig fractions from sites in the ACT and those that were used to collect the test data (Blue Mountains and Arthursleigh) (Table 6). Carbon content of fine fuel was similar for all sites, ranging between 32 and 39% C.

Table 6. Carbon content (%; mean ± standard deviation) for each of the surface fuel layers and the total biomass from sites in the Australian Capital Territory (ACT), New South Wales (NSW), Victoria (VIC) and test data from Arthursleigh (NSW) and Blue Mountains (NSW). N/A = data not available.

Variable	Site condition	Leaves	Twigs	Fine Fuel	Other	Total
ACT	Unburnt	46.5 ± 2.2	44.2 ± 1.0	34.9 ± 8.7	40.4 ± 6.1	41.5 ± 7.0
	Burnt	47.3 ± 1.4	45.5 ± 1.8	32.2 ± 13.5	39.8 ± 11.3	41.1 ± 10.8
NSW	Unburnt	50.0 ± 1.3	47.1 ± 1.3	37.1 ± 5.2	38.0 ± 5.6	43.3 ± 9.9
	Burnt	51.1 ± 1.3	48.6 ± 2.8	36.9 ± 6.3	40.9 ± 8.4	44.1 ± 11.0
VIC	Unburnt	54.3 ± 2.1	49.4 ± 0.7	34.6 ± 8.2	N/A	46.1 ± 9.8
	Burnt	54.3 ± 2.2	49.4 ± 0.7	34.5 ± 8.4	N/A	46.1 ± 9.8
Blue Mountains	Unburnt	49.9 ± 9.7	41.6 ± 10.8	38.9 ± 14.1	41.5 ± 9.6	43.0 ± 11.9
Arthursleigh	Unburnt	47.5 ± 4.9	43.3 ± 8.9	35.6 ± 9.8	42.9 ± 8.9	42.3 ± 8.7

Model development using 80% of the data

All data relating to C content from burnt and unburnt sites were randomly split into two groups and used for testing, as described for the biomass data. The GBM models generated had the lowest AICc and the best score when the models had a minimum of three included terms and a maximum of 10 included terms (Table 7). As for the biomass models, C models derived from data from unburnt sites had the highest R^2 values (Table 7). The statistical information for all, burnt and unburnt GBM models and their coefficients are presented in Table 8.

Table 7. General blending mixing (GBM) model inclusions, Akaike information criterion (AICc) scores and statistical information for estimations of biomass of surface fuels from sites in the Australian Capital Territory (ACT), New South Wales (NSW) and Victoria (VIC). The values represented are indicative of the best model chosen based on the number of inclusions. RSE = residual standard error (with degrees of freedom), R^2 = R-squared value, Adj R^2 = adjusted R-squared value, *F* = *F* statistic (with degrees of freedom), *P* = *P*-value.

Variable	GBM	AICc	RSE	R^2	Adj R^2	*F*	*P*
All	$GBM_{3,10}$	909.89	2.67 (347)	0.80	0.79	153.1 (9, 347)	<0.001
Burnt	$GBM_{3,10}$	779.29	0.91 (158)	0.81	0.81	115.2 (6, 158)	<0.001
Unburnt	$GBM_{3,10}$	809.69	2.45 (166)	0.89	0.89	174.6 (8, 166)	<0.001

After constraining the data to their respective limits (Figure 5a, b, c), GBM models using 80% of the data were developed for all site data, and data for burnt and unburnt sites (Figure 5d, e, f). The C content for surface fuel samples from unburnt sites ranged from 5.4-7.8 t C ha^{-1} and from 0-3.7 t C ha^{-1} for surface fuel samples collected from burnt sites. Predictions from the GBM model developed using all of the data combined ranged from 0-8.0 t C ha^{-1} (Figure 5d).

Model validation against test data

The accuracy of the C models was tested by examining their performance in making prediction against the 20% validation (test) data. The relationship between model predictions and actual data from the test dataset are depicted in Figure 6, and their associated statistical information and model metrics are presented in Table 9. Unlike the biomass models, the C predictions were slightly better for the model developed using all of the data, with an adjusted R^2 value of 0.54 (0.45 for biomass). In contrast, the biomass model predictions were better for data from burnt sites (R^2 values of 0.69 and 0.51 for biomass and C predictions, respectively) (Table 9). However, predictions using data from unburnt sites were weak for both C and biomass, with R^2 values of -0.02 and 0.05, respectively. The model developed using data from unburnt sites greatly underpredicted C pools in surface fuel with a negative value of -10 t C ha^{-1}, when according to the actual dataset, 14 t C ha^{-1} was expected (Figure 6c). Forcing the intercept of the linear regression to zero improved the model (R^2 value 0.64, Table 9) and removed the nonsensical estimates and error terms produced when including the -10 t C ha^{-1} prediction in the regression model.

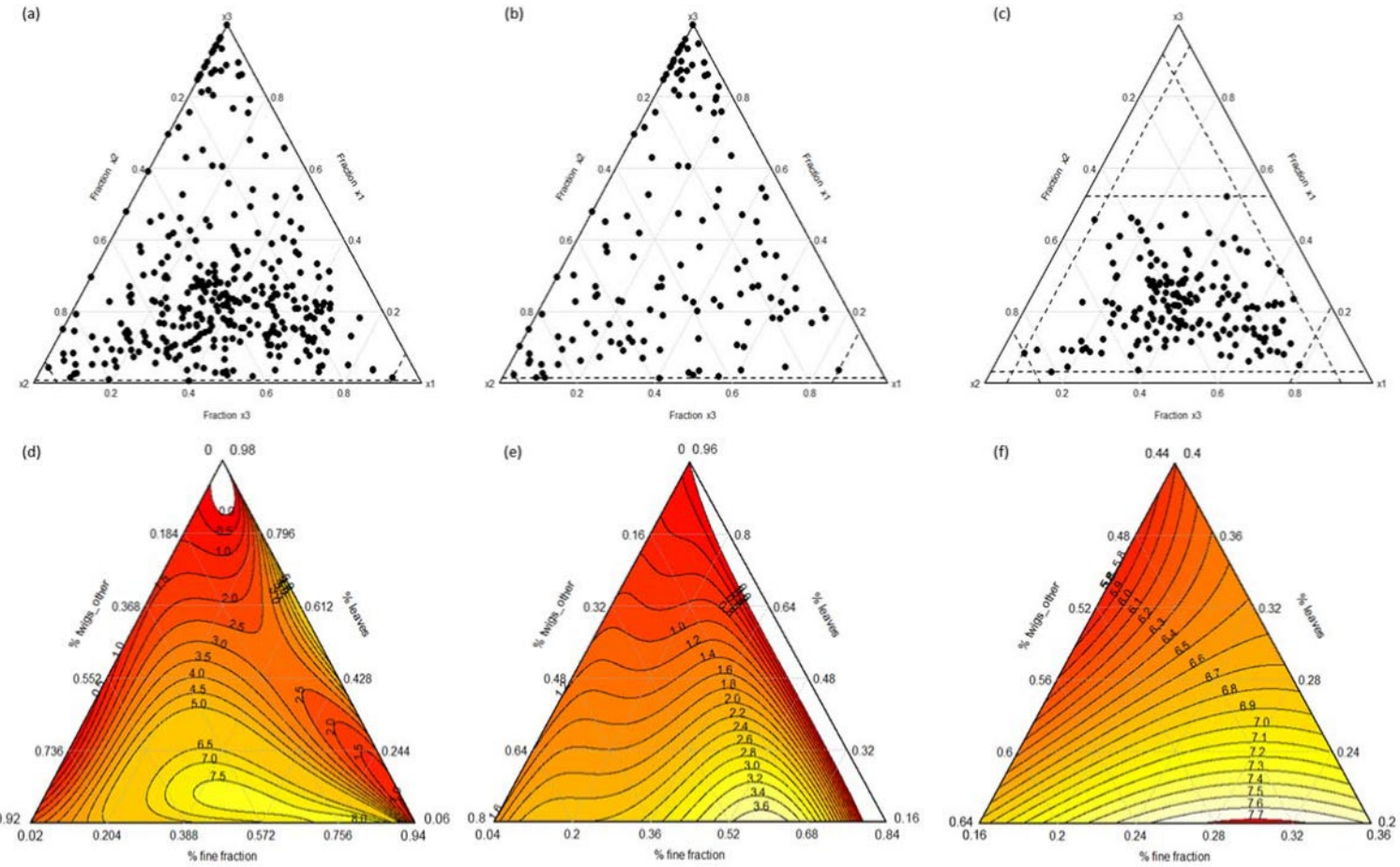

Figure 5. Carbon response surfaces developed using training data (80% data) from all sites in the Australian Capital Territory (ACT), New South Wales (NSW) and Victoria (VIC). (a, d) All data, (b, e) burnt or after prescribed burning, and (c, f) unburnt or before prescribed burning. Contours were modelled using a general blending model (GBM; Brown *et al*., 2015) with a minimum of three and a maximum of 10 terms included for each model. Panels (d), (e) and (f) represent the final carbon models generated, constrained to the limits presented in panels (a), (b) and (c).

Table 8. Statistical Information for each of the 80% biomass models: all data from all sites (ASA), data from all burnt sites (ASB) and data from all unburnt sites (ASUB). Model coefficients, model estimates, Std Err = standard error, T = T value, PR(>|T|) = *P*-value for the T-test as the proportion of T distribution at that degrees of freedom which is greater than the absolute value of the T statistic, 95% CI = 95% confidence interval, *P* = *P*-value.

Coefficients	Estimate	Std Err	T	PR(>|T|)	95% CI	*P*
All data from all sites (ASA 80%)						
x1	-0.10	0.47	-0.21	0.83	-1.03 – 0.83	0.83
x2	3.11	1.11	2.81	0.01	0.93 – 5.30	0.01
x3	1.04	2.76	0.38	0.71	-4.38 – 6.46	0.71
I(x1^0.8 * x2^2.5 * x3^1.9)	126.01	278.70	0.45	0.65	-422.15 – 674.17	0.65
I(x1^0.5 * x2^1.7/(x1 + x2 + 0.001)^3)	3.03	1.85	1.64	0.10	-0.60 – 6.66	0.10
I(x1^1 * x2^3/(x1 + x2 + 0.001)^0)	-100.38	29.04	-3.46	0.00	-157.50 – -43.26	0
I(x1^3 * x3^1.9/(x1 + x3 + 0.001)^0)	150.10	52.07	2.88	0.00	47.68 – 252.51	0
I(x1^0.8 * x2^2.3/(x1 + x2 + 0.001)^3)	39.47	15.95	2.48	0.01	8.11 – 70.84	0.01
I(x2^0.8 * x3^2.4/(x2 + x3 + 0.001)^3)	13.88	9.17	-1.51	0.13	-31.92 – 4.16	0.13
Data from all burnt sites (ASB 80%)						
x1	0.25	0.15	1.66	0.10	-0.05 – 0.55	0.10
x2	0.27	0.32	0.84	0.41	-0.37 – 0.90	0.41
x3	-8.26	1.98	-4.16	5.19×10^{-5}	-12.18 – -4.34	0
I(x2^0.5 * x3^0.8/(x2 + x3 + 0.001)^0)	28.33	4.68	6.05	1.02×10^{-8}	19.08 – 37.58	0
I(x2^2.5 * x3^1.8/(x2 + x3 + 0.001)^2.9)	-84.94	21.24	-4.00	9.74×10^{-5}	-126.89 – -42.99	0
I(x1^0.7 * x3^3/(x1 + x3 + 0.001)^1.7)	10.05	6.39	1.57	0.12	-2.58 – 22.68	0.12
Data from all unburnt sites (ASUB 80%)						
x1	-25.87	12.87	-2.01	0.05	-51.28 – -0.46	0.05
x2	1.08	4.84	0.22	0.82	-8.48 – 10.64	0.82
x3	-30.23	21.23	-1.42	0.16	-72.13 – 11.68	0.16
I(x1^0.5 * x2^2.5/(x1 + x2 + 0.001)^2.9)	157.09	64.93	2.42	0.02	28.90 – 285.28	0.02
I(x2^0.8 * x3^3/(x2 + x3 + 0.001)^2.8)	-28.39	31.11	-0.91	0.36	-89.82 – 33.04	0.36
I(x1^2.5 * x2^0.8 * x3^0.7)	420.62	226.33	1.86	0.06	-26.24 – 867.48	0.07
I(x1^1.9 * x2^0.5/(x1 + x2 + 0.001)^3)	56.04	24.55	2.28	0.02	7.57 – 104.51	0.02
I(x1^0.5 * x2^2.1/(x1 + x2 + 0.001)^1.2)	-123.92	71.28	-1.74	0.08	-264.65 – 16.82	0.08

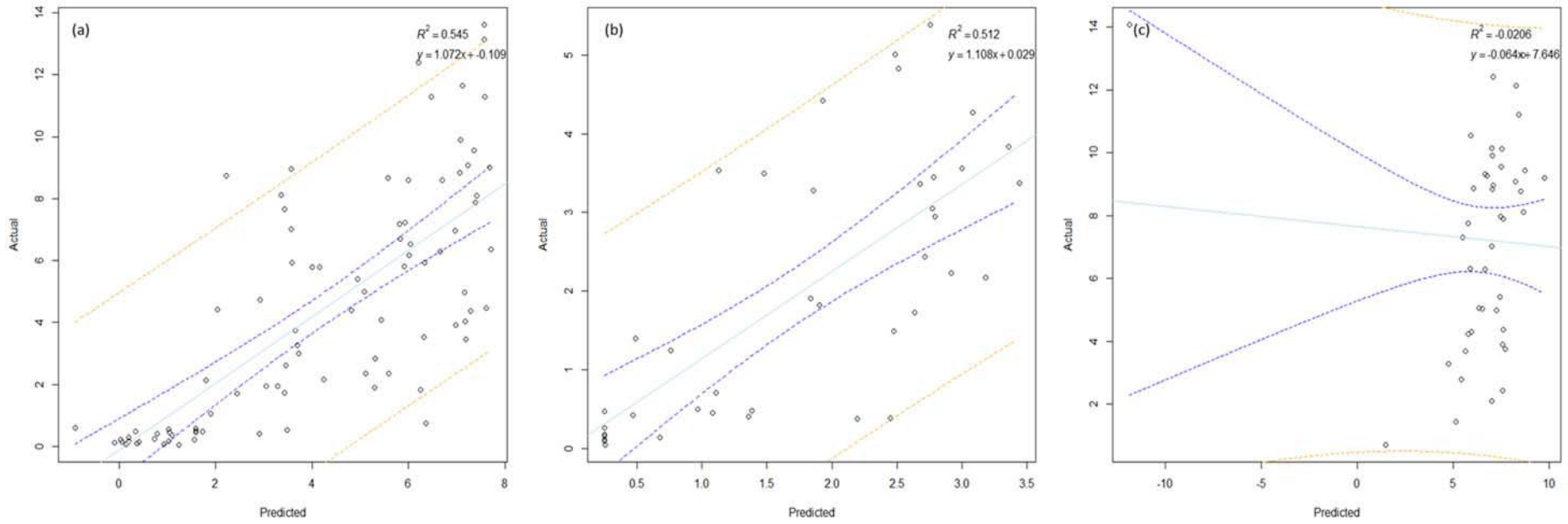

Figure 6. Linear regression plots for carbon in surface fuel showing the correlation between actual data and prediction generated from (a) all sites, (b) burnt sites and (c) unburnt sites. Dashed yellow lines represent the prediction intervals, dashed dark blue lines represent the confidence intervals and the solid light blue line represents the regression line.

Table 9. Statistical information and model metrics generated from the linear regression models. ASA = all data from all sites, ASB = data from all burnt sites, ASUB = data from all unburnt sites, RSE = residual standard error (with degrees of freedom), Adj R^2 = adjusted R^2 value, *F* = *F* statistic (with degrees of freedom), *P* = *P*-value, MAE = mean absolute error. Linear R^2 and zero R^2 (forced zero intercept) are taken from linear equations of the same data.

Variable	RSE	Adj R^2	*F*	*P*	MAE	Bias	Linear R^2	Zero R^2
ASA 20%	2.50 (87)	0.54	106.3 (1, 87)	<0.001	1.86	0.19	0.55	0.81
ASB 20%	1.16 (39)	0.51	43.04 (1, 39)	<0.001	0.83	0.22	0.51	0.80
ASUB 20%	3.36 (41)	-0.02	0.15 (1, 41)	0.70	2.77	0.77	-0.02	0.64

3.2 TOTAL BIOMASS AND TOTAL CARBON FUEL LOADS

The total biomass fuel load (TBFL) and total carbon fuel load (TCFL) was modelled using all data (ASA) and burnt (ASB) and unburnt (ASUB) data sets to better understand the relationships for biomass and C for each model developed (Figure 7). The average values for %C according to the models derived from ASA and ASUB data was 51 ± 1 %C and 47 ± 1 %C for the model developed using ASB data. These plots provide an estimate for total surface fuel biomass rather than providing an estimate based on the four fuel types incorporated in the GBM models (leaves, fine fuel, twigs and other). For example, using the all data model (ASA), if the total biomass fuel load was 21 t ha^{-1}, it is expected that there would be between 5-14 t C ha^{-1} (Figure 7a). The large range for this estimate is likely to be due to individual site differences, whether the site is burnt or unburnt, or the varying proportions of each surface fuel component. Furthermore, this range may over- or underpredict estimates according to the prediction interval line (Figure 7). For example, according to predictions made using the ASA model, if there is 26 t ha^{-1} of surface fuel, there is a considerably higher prediction for C (i.e. 21 t C ha^{-1}) than for 30 t ha^{-1} (5 t C ha^{-1}) (Figure 7a).

3.3 MODEL VALIDATION USING INDEPENDENT SITES

Although there was a reasonably strong relationship between the 20% validation (testing) and 80% training datasets for biomass and C, validation of the data and the models was also compared to data from three independent sites. Validation data from the independent sites are referred to as the 'mixed forest' (MF) dataset.

3.3.1 Biomass

The models developed using the 80% training data were used to generate predictions of biomass against the MF data (Figure 8) and the associated model metrics from these predictions are presented in Table 10. Although the all data model (ASA) had the lowest mean absolute error (5.1 t ha^{-1}), the best model for predicting the MF data was the unburnt data model (ASUB (Table 10). This was expected as the MF dataset contained samples only from unburnt sites. The model based on samples from burnt sites had the greatest mean absolute error (6.17 t ha^{-1}) and, as such, was the least reliable model (Table 10a).

3.3.2 Carbon

In contrast to the biomass models, C was best predicted when using the burnt model (ASB) compared to models using all data combined (ASA) and data from unburnt sites (ASUB) (Figure 9). Models developed using data from burnt sites (ASB) had the greatest error values (MAE) in the MF dataset (4.00 t C ha^{-1}; Table 10b) compared to the combined data from all sites (ASA; 2.89 t C ha^{-1}). Despite this, ASB was the better model for predicting C in the MF dataset.

Table 10. Model metrics generated from the mixed forest (MF) data and 80% biomass linear regression models of actual and predicted data for (a) biomass and (b) carbon. ASA = all data from all sites, ASB = data from all burnt sites, ASUB = data from all unburnt sites, RSE = residual standard error (with degrees of freedom), Adj R^2 = adjusted R^2 value, *F* = *F* statistic (with degrees of freedom), *P* = *P*-value, MAE = mean absolute error. Linear R^2 and zero R^2 (forced zero intercept) are taken from linear equations of the same data.

Variable	RSE	Adj R^2	*F*	*P*	MAE	Bias	Linear R^2	Zero R^2
(a) *Biomass*								
ASA vs MF	6.09 (55)	0.03	2.67 (1, 55)	0.11	5.09	-0.28	0.03	0.80
ASB vs MF	6.13 (55)	0.02	1.87 (1, 55)	0.18	7.07	6.51	0.02	0.78
ASUB vs MF	6.06 (55)	0.04	3.22 (1, 55)	0.08	6.17	-4.01	0.04	0.80
(b) *Carbon*								
ASA vs MF	3.39 (54)	0.01	1.54 (1, 54)	0.22	2.89	0.64	0.01	0.77
ASB vs MF	3.32 (54)	0.05	3.84 (1, 54)	0.06	4.00	3.75	0.05	0.79
ASUB vs MF	3.42 (54)	-0.01	0.33 (1, 54)	0.57	3.07	-0.39	-0.01	0.74

3.3.3 Model predictions

The validation data were initially selected to test the extremes of the models using two forms of dry sclerophyll forest with low productivity; Stringybark Forest and Grassy Box Woodland (Arthursleigh), and dry sclerophyll forest with high productivity (Blue Mountains). When these data were used to validate the models, it was evident that they under- and overpredicted values for biomass and C (Table 10). The ASA data had the best predictive capacity with only small underpredictions (average bias, -0.28) and an associated MAE of 5.1 t ha^{-1}. In contrast, predictions using the ASB model had an average bias of 6.51 (overprediction) and a higher MAE (7.1 t ha^{-1}). For C in surface fuels, the ASUB model was the only model that underpredicted (average bias -0.39) with a MAE of 3.07 t C ha^{-1}. The ASB model overpredicted C values by 4.0 t C ha^{-1} and had a MAE of 3.75 t C ha^{-1}. These results indicate that the models are still somewhat unreliable, particularly for predictions related to surface fuels from burnt sites. As the samples from burnt sites in the Blue Mountains were collected 10 years post-fire they could potentially be classified as unburnt allowing recalibration of the ASUB model.

So, why do the models perform poorly when used against independent datasets? Initially, we used a form of cross validation, taking 20% of the original data, to test models developed with the remaining 80% of the data. This reduces

the risk of overfitting the models and thereby reducing the complexity of the models. However, the testing data is assumed to be approximately typical of the data that the models will evaluate because it is randomly selected from the same pool of data as the training data. In order to examine the broader applicability of the models we tested them against the MF dataset, which is not necessarily typical of the model training data. The poor performance against MF data indicates that the models are not yet universal. Improvements to the model-data fits can simply be made by including more training data from non-typical sites. Another approach to improve performance and reduce errors is to fit models to datasets where large or unequal variances in biomass or carbon values are reduced or equalised by statistical means. A common method is to use data transformations, such as a log-transform, that can address several issues related to regression modelling. However, the choice of transformation depends on several data considerations e.g. a log transform cannot be used on zero data, and it must be readily invertible i.e. be easily transformed back to normal values, so that the results can be interpreted. Further research is required to examine whether this approach is feasible and still provide a tool that is straightforward to use and understand.

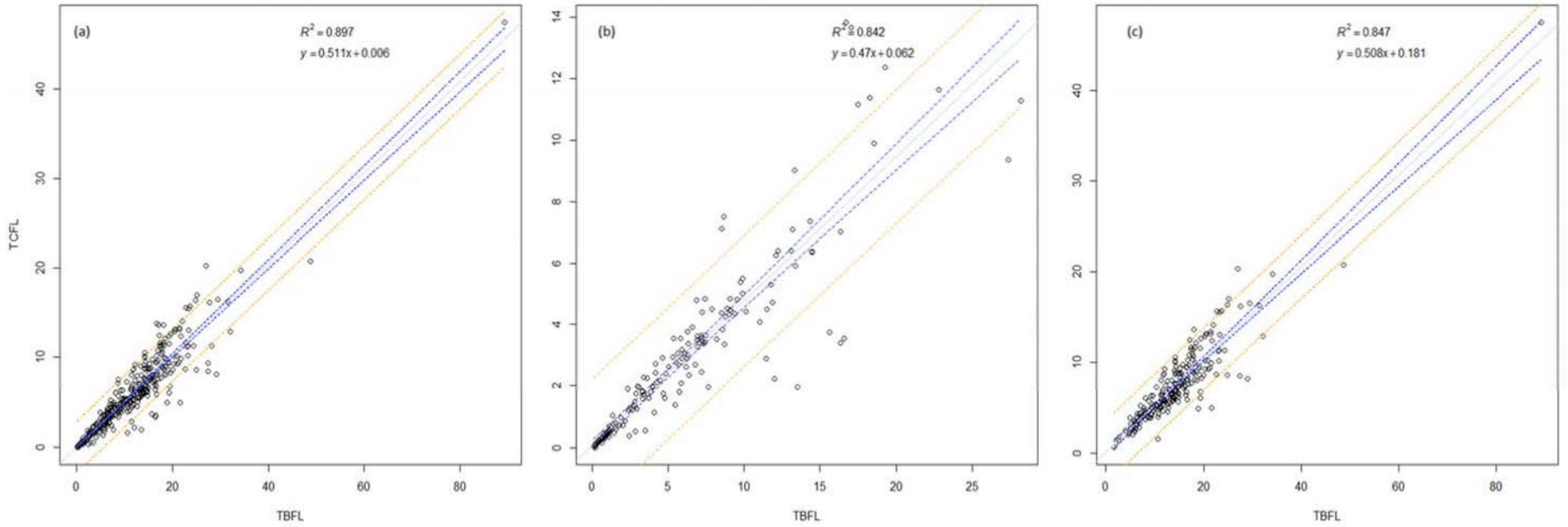

Figure 7. The relationship between total biomass fuel load (TBFL) and total carbon fuel load (TCFL) for (a) all data, (b) data from burnt sites and (c) unburnt sites. Dashed yellow lines represent the prediction intervals, dashed dark blue lines represent the confidence intervals and the solid light blue line represents the regression line.

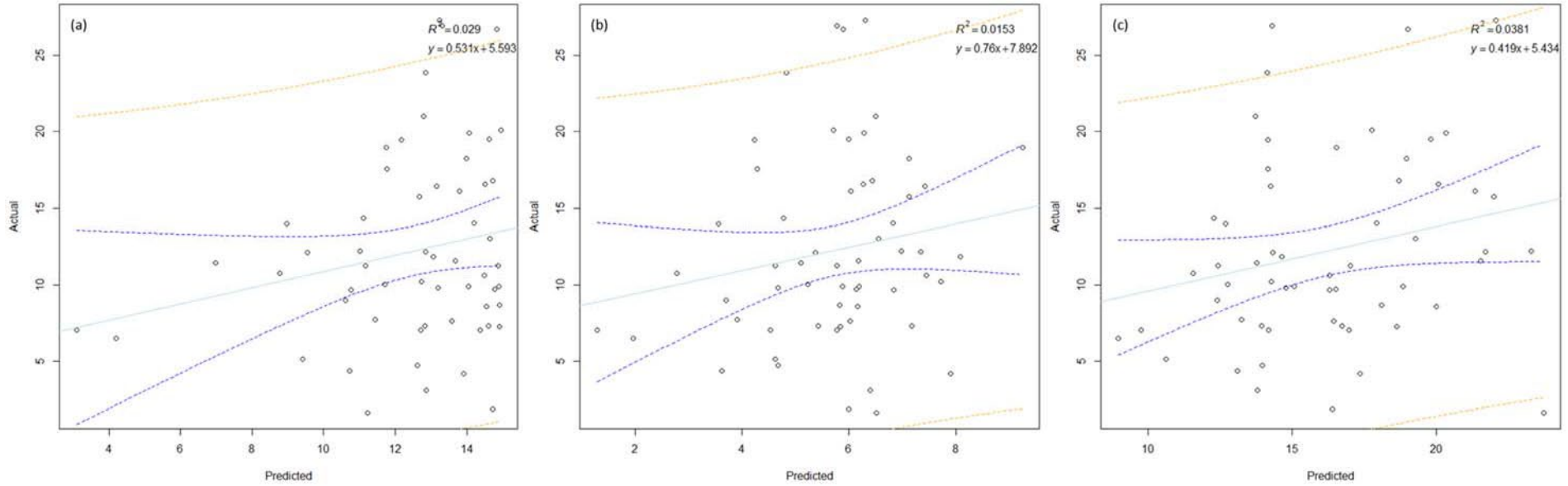

Figure 8. Linear regression plots for biomass of surface fuel showing the correlation between actual data and prediction data generated from mixed forest data and 80% models derived from (a) all sites, (b) burnt sites and (c) unburnt sites. Dashed yellow lines represent the prediction intervals, dashed dark blue lines represent the confidence intervals and the solid light blue line represents the regression line.

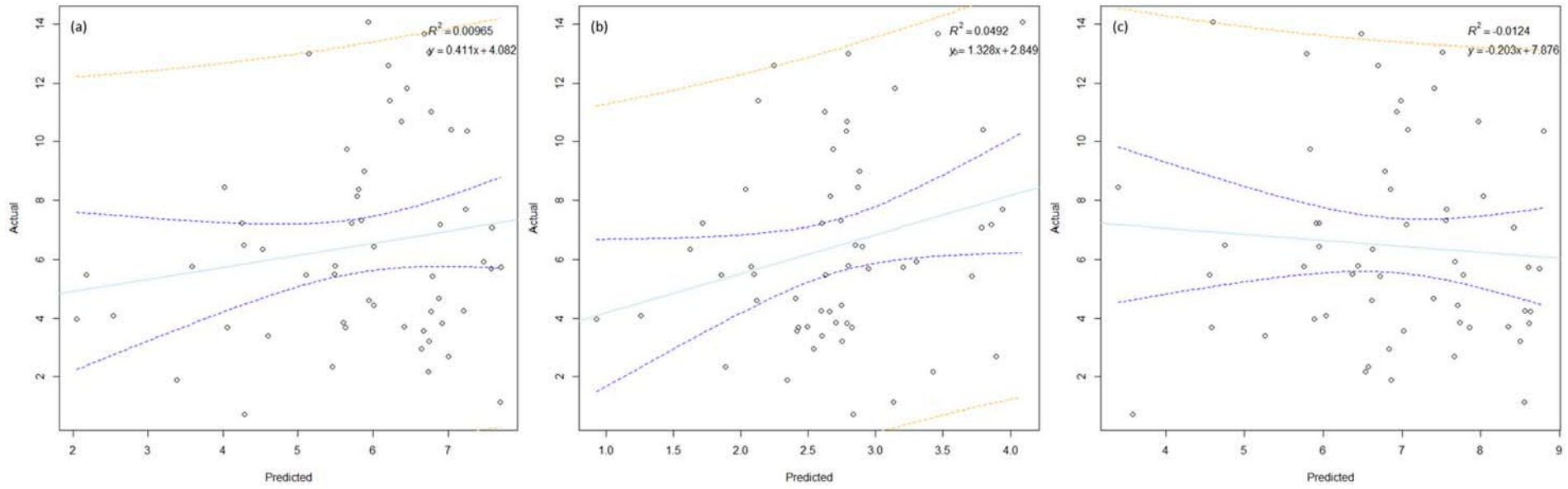

Figure 9. Linear regression plots for carbon in surface fuel showing the correlation between actual data and prediction data generated from mixed forest data and 80% models derived from (a) all sites, (b) burnt sites and (c) unburnt sites. Dashed yellow lines represent the prediction intervals, dashed dark blue lines represent the confidence intervals and the solid light blue line represents the regression line.

4. CONCLUSION

The ability to model changes in biomass and the C content of individual fractions in surface fuel layers is important for increasing accuracies in estimating C loss due to combustion during prescribed burning. Current models for biomass have prediction errors of 5.1 (all data from all sites; ASA), 6.2 (data from all unburnt sites; ASUB) and 7.1 t ha^{-1} (data from all burnt sites; ASB). Models for C have prediction errors of 2.9 (ASA), 3.1 (ASUB) and 4.0 t C ha^{-1} (ASB).

Testing and validating predictive models for biomass and carbon (C) content of surface fuel created with independent site data (MF; mixed forest), indicated that further testing and modelling with more sites would be beneficial. Including the MF data into the 'all states' ('Universal') models, and further validation of the data with new sites, could improve GBM development. Additional data to test the models presented in this report further may include recently surveyed plots in the Blue Mountains, where data were collected in the same way as for sites in Victoria, NSW and the ACT.

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7. APPENDIX

7.1 MODEL DEVELOPMENT FOR INDIVIDUAL STATES

7.1.1 Biomass

Original models

Table A1. Statistical information for 80% biomass models developed using all data from burnt and unburnt sites (A) in New South Wales (NSW), Victoria (VIC) and the Australian Capital Territory (ACT). Model coefficients, model estimates, Std Err = standard error, T = T value, PR(>|T|) = *P*-value for the T-test as the proportion of T distribution at that degrees of freedom which is greater than the absolute value of the T statistic, 95% CI = 95% confidence interval, *P* = *P*-value.

Coefficients	Estimate	Std Err	T	PR(>|T|)	95% CI	*P*
NSWA						
x1	1.83	1.94	0.94	0.35	-2.00 – 5.66	0.35
x2	-14.63	6.32	-2.32	0.02	-27.11 – 2.15	0.02
x3	-7.93	6.31	-1.26	0.21	-20.40 – 4.55	0.21
I(x1^0.7 * x2^2.4 * x3^2.5)	4072.11	1312.97	3.10	0	1477.08 – 6667.14	0
I(x1^0.5 * x3^1.5/(x1 + x3 + 0.001)^2.6)	100.98	31.83	3.17	0	38.08 – 163.88	0
I(x1^0.5 * x2^2.2/(x1 + x2 + 0.001)^3)	54.42	16.20	3.36	0	22.40 – 86.43	0
I(x1^3 * x3^1.6/(x1 + x3 + 0.001)^0)	247.73	98.26	2.52	0.01	53.53 – 441.93	0.01
I(x1^0.7 * x3^1.7/(x1 + x3 + 0.001)^3)	-116.22	41.83	-2.78	0.01	-198.89 – -33.55	0.01
I(x2^1.1 * x3^1.5/(x2 + x3 + 0.001)^0.6)	-123.98	57.63	-2.15	0.03	-237.88 – -10.07	0.03
VICA						
x1	0.24	0.82	0.30	0.77	-1.39 – 1.88	0.77
x2	46.84	28.67	1.63	0.10	-9.91 – 103.59	0.11
x3	7.97	6.09	1.31	0.19	-4.08 – 20.02	0.19
I(x2^1.3 * x3^0.5/(x2 + x3 + 0.001)^0.6)	-35.38	48.89	-0.72	0.47	-132.154 – 61.39	0.47
I(x1^0.7 * x2^1.2/(x1 + x2 + 0.001)^3)	50.64	13.59	3.73	0	23.73 – 77.55	0
I(x1^2.5 * x2^2.5 * x3^0.9)	7220.78	2783.74	2.59	0.01	1710.98 – 12730.59	0.01
I(x1^0.6 * x2^0.9/(x1 + x2 + 0.001)^2.3)	-52.02	18.64	-2.79	0.01	-88.92 – -15.12	0.01
I(x1^1.9 * x2^2.6/(x1 + x2 + 0.001)^0)	-719.35	456.72	-1.58	0.12	-1623.33 – 184.63	0.12
ACTA						
x1	-0.67	4.98	-0.14	0.89	-10.61 – 9.26	0.89
x2	-1.72	4.68	-0.37	0.71	-11.07 – 7.63	0.71
x3	10.47	3.48	3.01	0	3.53 – 17.41	0
I(x1^0.5 * x3^1.5/(x1 + x3 + 0.001)^3)	-4.87	16.87	-0.29	0.77	-4.87 – -38.53	0.77
I(x1^1.7 * x3^1.3/(x1 + x3 + 0.001)^3)	-214.96	84.15	-2.56	0.01	-382.92 – -47.00	0.01
I(x1^1 * x2^0.5 * x3^0.6)	168.42	81.81	2.06	0.04	5.12 – 331.72	0.04
I(x1^0.7 * x3^1.3/(x1 + x3 + 0.001)^3)	34.03	22.21	1.53	0.13	-10.31 – 78.37	0.13

Table A2. General blending mixing (GBM) inclusions, Akaike information criterion (AICc) scores and statistical information for estimations of biomass in surface fuels using all data from burnt and unburnt sites (A) in New South Wales (NSW), Victoria (VIC) and the Australian Capital Territory (ACT). The values represented are indicative of the best model chosen based on the number of inclusions. RSE = residual standard error (with degrees of freedom), R^2 = R-squared value, Adj R^2 = adjusted R-squared value, *F* = *F* statistic (with degrees of freedom), *P* = *P*-value.

Variable	GBM	AICc	RSE	R^2	Adj R^2	*F*	*P*
NSWA	$GBM_{3,10}$	987.05	5.73 (145)	0.79	0.77	58.93 (9, 145)	<0.001
VICA	$GBM_{3,10}$	764.06	2.83 (124)	0.93	0.93	204.40 (8, 124)	<0.001
ACTA	$GBM_{3,10}$	695.39	5.78 (67)	0.81	0.79	40.65 (7, 67)	<0.001

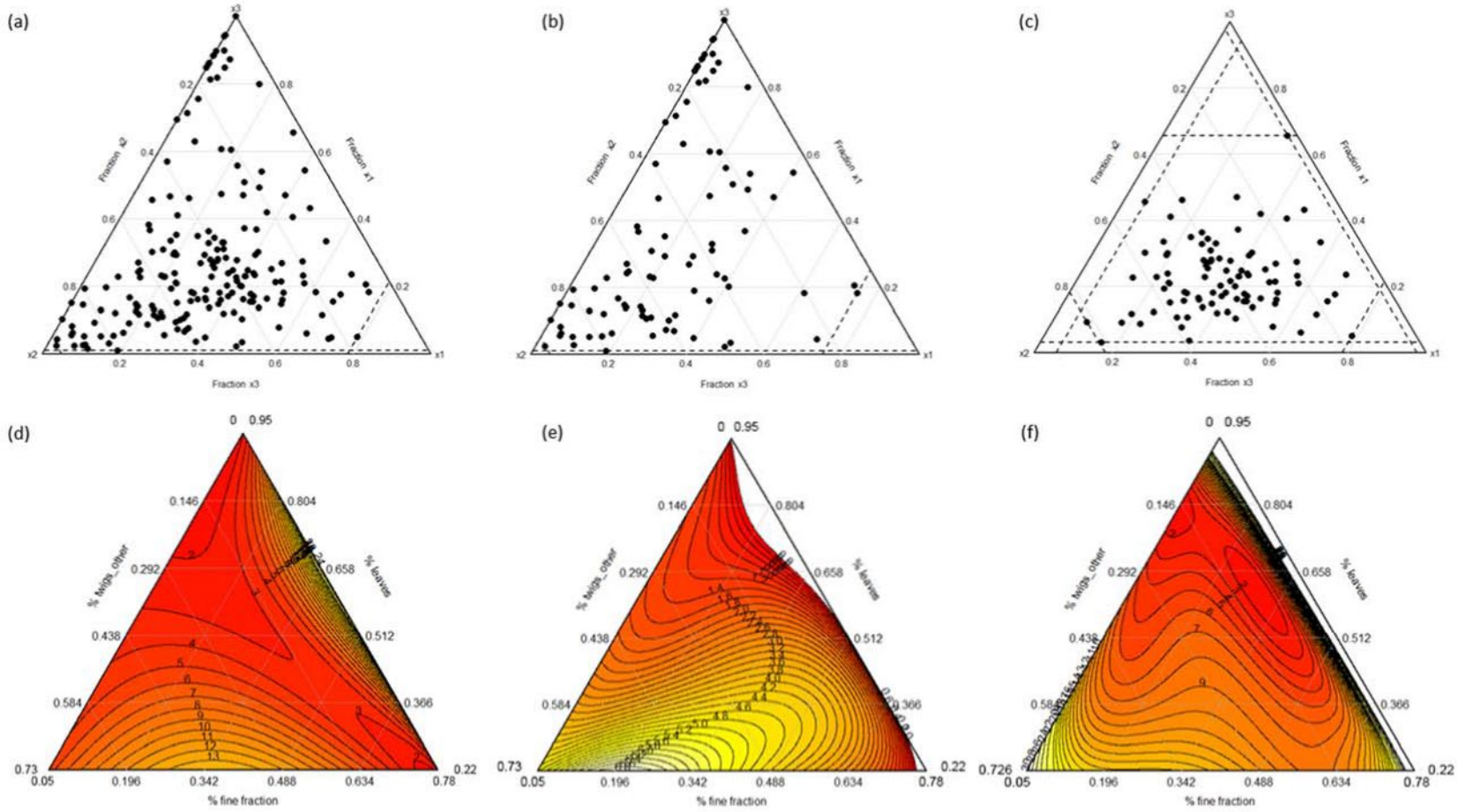


Figure A1. Biomass response surfaces developed using data from News South Wales. (a, d) All data from burnt and unburnt sites, (b, e) data from burnt sites and (c, f) data from unburnt sites. Contours were modelled using a general blending model (GBM; Brown et al., 2015) with a minimum of three and a maximum of 10 terms included for each model. Panels (d), (e) and (f) represent the final biomass models generated, constrained to the limits presented in panels (a), (b) and (c).

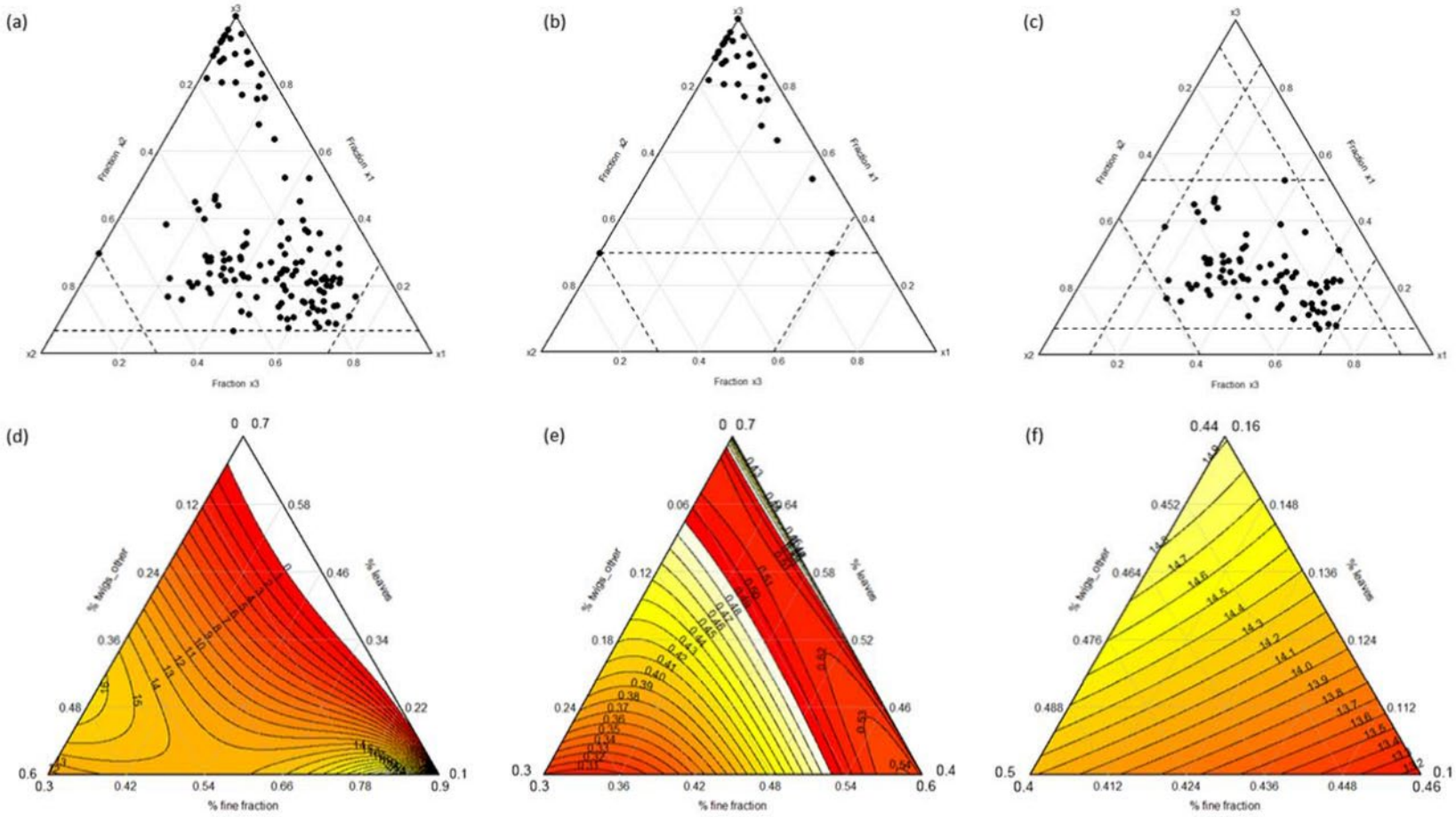


Figure A2. Biomass response surfaces developed using data from Victoria. (a, d) All data from burnt and unburnt sites, (b, e) data from burnt sites and (c, f) data from unburnt sites. Contours were modelled using a general blending model (GBM; Brown *et al.*, 2015) with a minimum of three and a maximum of 10 terms included for each model. Panels (d), (e) and (f) represent the final biomass models generated, constrained to the limits presented in panels (a), (b) and (c).

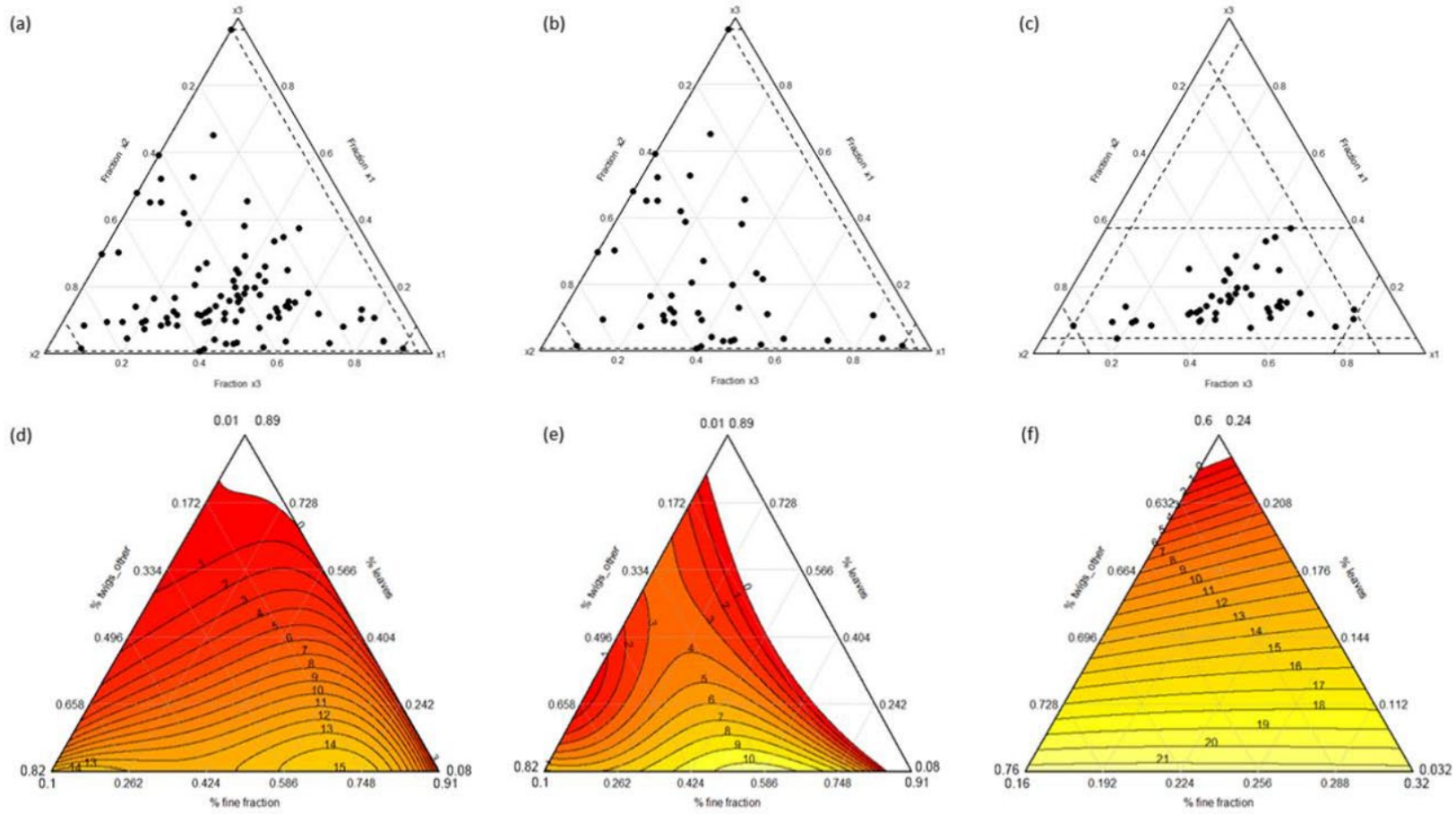


Figure A3. Biomass response surfaces developed using data from the Australian Capital Territory. (a, d) All data from burnt and unburnt sites, (b, e) data from burnt sites and (c, f) data from unburnt sites. Contours were modelled using a general blending model (GBM; Brown *et al*., 2015) with a minimum of three and a maximum of 10 terms included for each model. Panels (d), (e) and (f) represent the final biomass models generated, constrained to the limits presented in panels (a), (b) and (c).

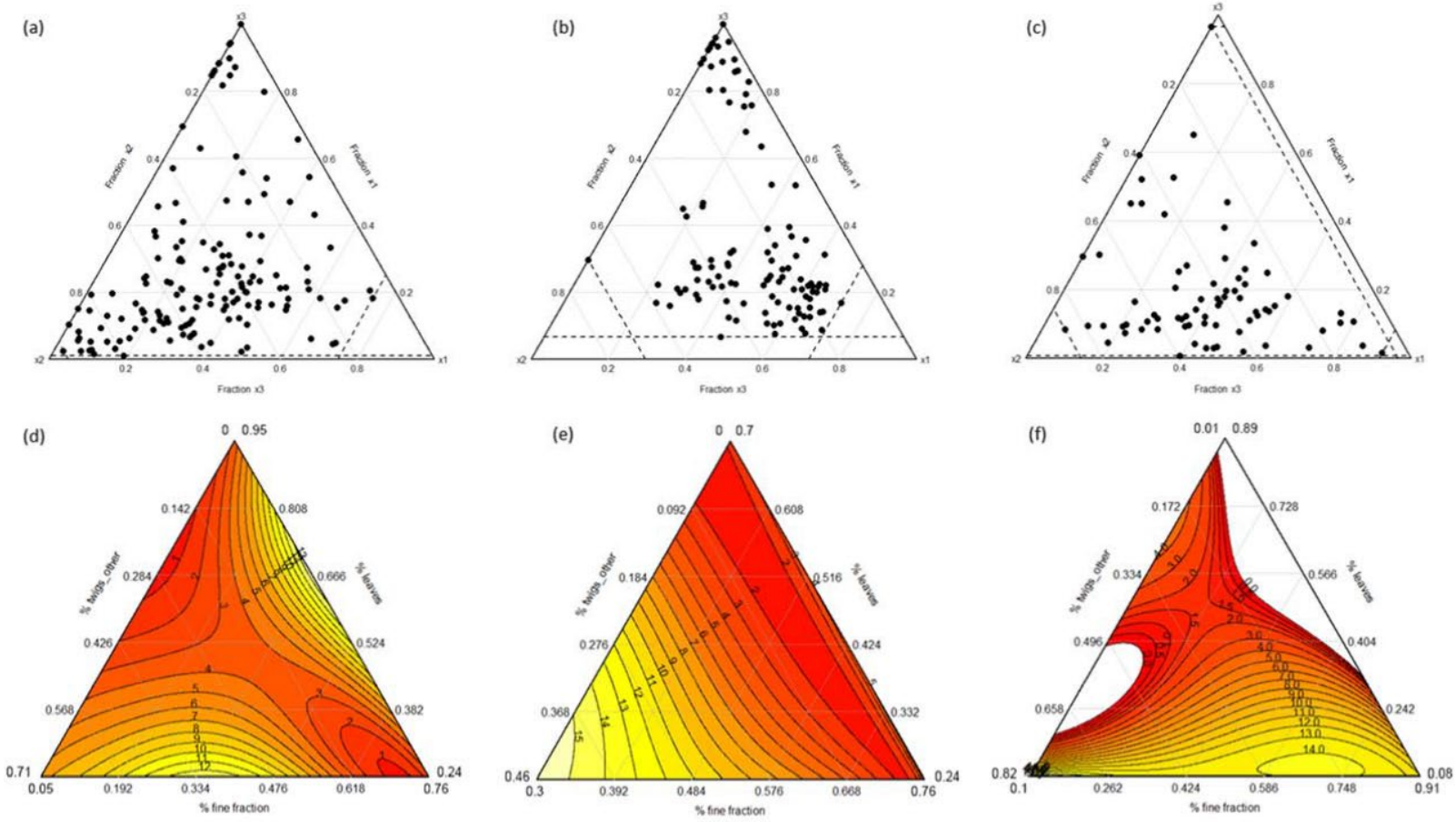


Figure A4. Biomass response surfaces developed using 80% data from (a, d) News South Wales, (b, e) Victoria, and (c, f) the Australian Capital Territory. Contours were modelled using a general blending model (GBM; Brown *et al*., 2015) with a minimum of three and a maximum of 10 terms included for each model. Panels (d), (e) and (f) represent the final biomass models generated, constrained to the limits presented in panels (a), (b) and (c).

80% models versus 20% model validation

Table A3. Statistical information and model metrics generated from the linear regression models for biomass data from sites in New South Wales (NSW), Victoria (VIC) and the Australian Capital Territory (ACT). RSE = residual standard error (with degrees of freedom), Adj R^2 = adjusted R^2 value, *F* = F statistic (with degrees of freedom), *P* = *P*-value, MAE = mean absolute error. Linear R^2 and zero R^2 (forced zero intercept) are taken from linear equations of the same data.

Variable	RSE	Adj R^2	*F*	*P*	MAE	Bias	Linear R^2	Zero R^2
NSWA 20%	5.24 (36)	0.36	22.16 (1, 36)	<0.001	3.73	1.75	0.36	0.81
VICA 20%	2.57 (31)	0.88	231.30 (1, 31)	<0.001	1.99	0.78	0.88	0.95
ACTA 20%	5.07 (17)	0.18	5.01 (1, 17)	0.04	5.11	0.06	0.18	0.16

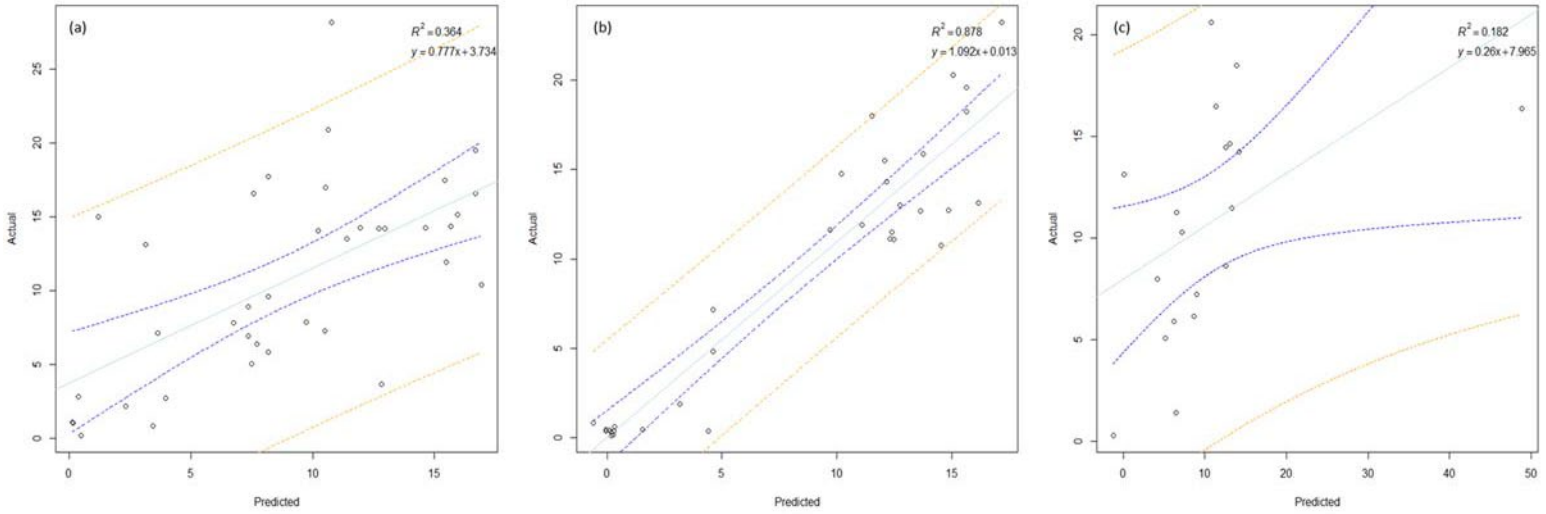


Figure A5. Linear regression plots for biomass of surface fuel showing the correlation between actual data and prediction generated from all data collected from (a) New South Wales (NSWA), (b) Victoria (VICA) and (c) the Australian Capital Territory (ACTA). Dashed yellow lines represent the prediction intervals, dashed dark blue lines represent the confidence intervals and the solid light blue line represents the regression line.

7.1.2 Carbon

Original models

TABLE A4. Statistical information for 80% carbon models developed using all data from burnt and unburnt sites (A) in New South Wales (NSW), Victoria (VIC) and the Australian Capital Territory (ACT). Model coefficients, model estimates, Std Err = standard error, T = T value, PR(>|T|) = *P*-value for the T-test as the proportion of T distribution at that degrees of freedom which is greater than the absolute value of the T statistic, 95% CI = 95% confidence interval, *P* = *P*-value.

Coefficients	Estimate	Std Err	T	PR(>|T|)	95% CI	*P*
NSWA						
x1	0.19	0.85	0.22	0.82	-1.50 – 1.87	0.83
x2	1.78	0.97	1.84	0.07	-0.13 – 3.69	0.07
x3	37.07	8.10	4.58	1.01×10^{-5}	21.06 – 53.08	0
I(x1^0.7 * x2^2.1 * x3^2.5)	7750.49	2231.56	3.47	0	3339.89 – 12161.08	0
I(x2^1.7 * x3^2.3/(x2 + x3 + 0.001)^3)	-334.77	75.50	-4.43	1.81×10^{-5}	-483.99 – -185.55	0
I(x1^0.6 * x3^3/(x1 + x3 + 0.001))	-171.36	42.75	-4.01	9.74×10^{-5}	-255.86 – -86.87	0
I(x1^0.6 * x2^2.1 * x3^2.3)	-3397.83	1492.06	-2.28	0.02	-448.83 – -2.28	0.02
VICA						
x1	8.09×10^{-2}	3.72×10^{-1}	0.22	0.83	-0.66 – 0.82	0.83
x2	-1.86×10^{-1}	7.14	-2.56	0.01	-32.40 – -4.12	0.01
x3	3.19	7.44×10^{-1}	4.28	3.61×10^{-5}	1.71 – 4.66	0
I(x1^0.5 * x2^3/(x1 + x2 + 0.001)^0)	-1.15×10^{-2}	1.40×10^{-1}	-8.25	1.76×10^{-13}	-142.77 – -87.55	0
I(x1^0.5 * x2^1.7/(x1 + x2 + 0.001)^1.3)	1.16×10^{-2}	1.97×10^{-1}	5.91	2.95×10^{-8}	77.44 – 155.34	0
I(x1^1 * x2^1.9 * x3^2.5)	-1.55×10^{-3}	3.62×10^{-2}	-4.30	3.42×10^{-5}	-2269.93 – -838.58	0
ACTA						
x1	0.63	2.04	0.31	0.76	-3.44 – 4.71	0.76
x2	-0.28	3.59	-0.08	0.94	-7.46 – 6.90	0.94
x3	-11.58	8.30	-1.40	0.18	-28.15 – -4.99	0.17
I(x1^0.5 * x3^3/(x1 + x3 + 0.001)^2.9)	65.11	18.77	3.47	0	27.64 – 102.59	0
I(x2^0.8 * x3^3/(x2 + x3 + 0.001)^1.3)	1257.09	642.44	1.96	0.05	-25.58 – 2539.76	0.06
I(x1^0.5 * x3^0.7/(x1 + x3 + 0.001)^1.5)	4.49	5.18	0.87	0.39	-5.86 – 14.83	0.39
I(x1^1.3 * x3^3/(x1 + x3 + 0.001)^1.0)	-627.77	277.09	-2.27	0.02	-1181.00 – -74.56	0.03
I(x2^0.8 * x3^2.9/(x2 + x3 + 0.001)^0.5)	-1158.04	653.69	-1.77	0.08	-2463.17 – 147.093	0.08

TABLE A5 General blending mixing (GBM) inclusions, Akaike information criterion (AICc) scores and statistical information for estimations of carbon in surface fuels using all data from burnt and unburnt sites (A) in New South Wales (NSW), Victoria (VIC) and the Australian Capital Territory (ACT). The values represented are indicative of the best model chosen based on the number of inclusions. RSE = residual standard error (with degrees of freedom), R^2 = R-squared value, Adj R^2 = adjusted R-squared value, *F* = *F* statistic (with degrees of freedom), *P* = *P*-value.

Variable	GBM	AICc	RSE	R^2	Adj R^2	F	P
NSWA	$GBM_{3,10}$	783.53	3.08 (145)	0.78	0.77	72.50 (7, 145)	<0.001
VICA	$GBM_{3,10}$	468.14	1.38 (126)	0.92	0.91	235.40 (6, 126)	<0.001
ACTA	$GBM_{3,10}$	368.96	2.69 (66)	0.84	0.82	41.79 (8, 66)	<0.001

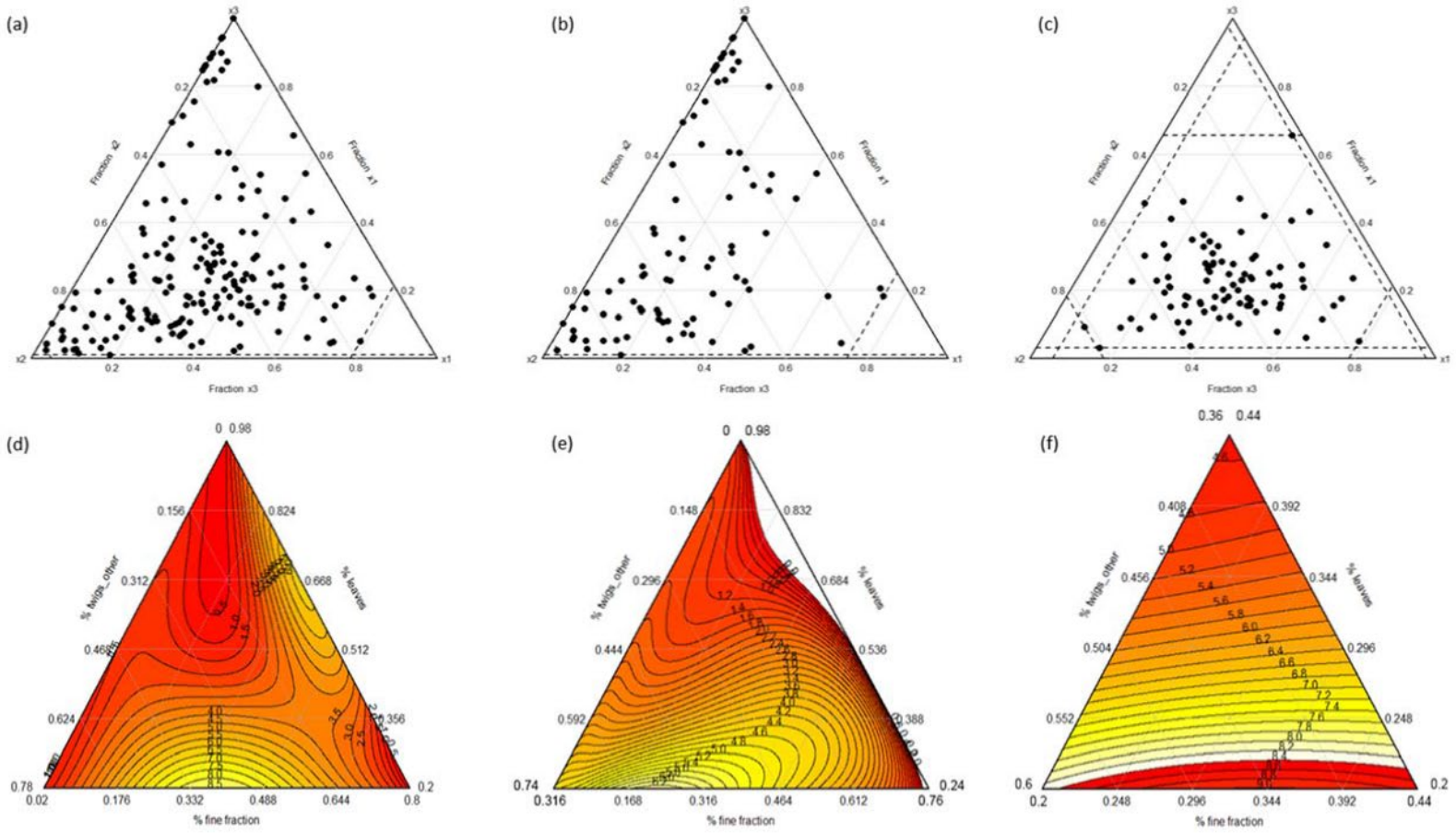


Figure A6. Carbon response surfaces developed using data from News South Wales. (a, d) All data from burnt and unburnt sites, (b, e) data from burnt sites and (c, f) data from unburnt sites. Contours were modelled using a general blending model (GBM; Brown *et al*., 2015) with a minimum of three and a maximum of 10 terms included for each model. Panels (d), (e) and (f) represent the final biomass models generated, constrained to the limits presented in panels (a), (b) and (c).

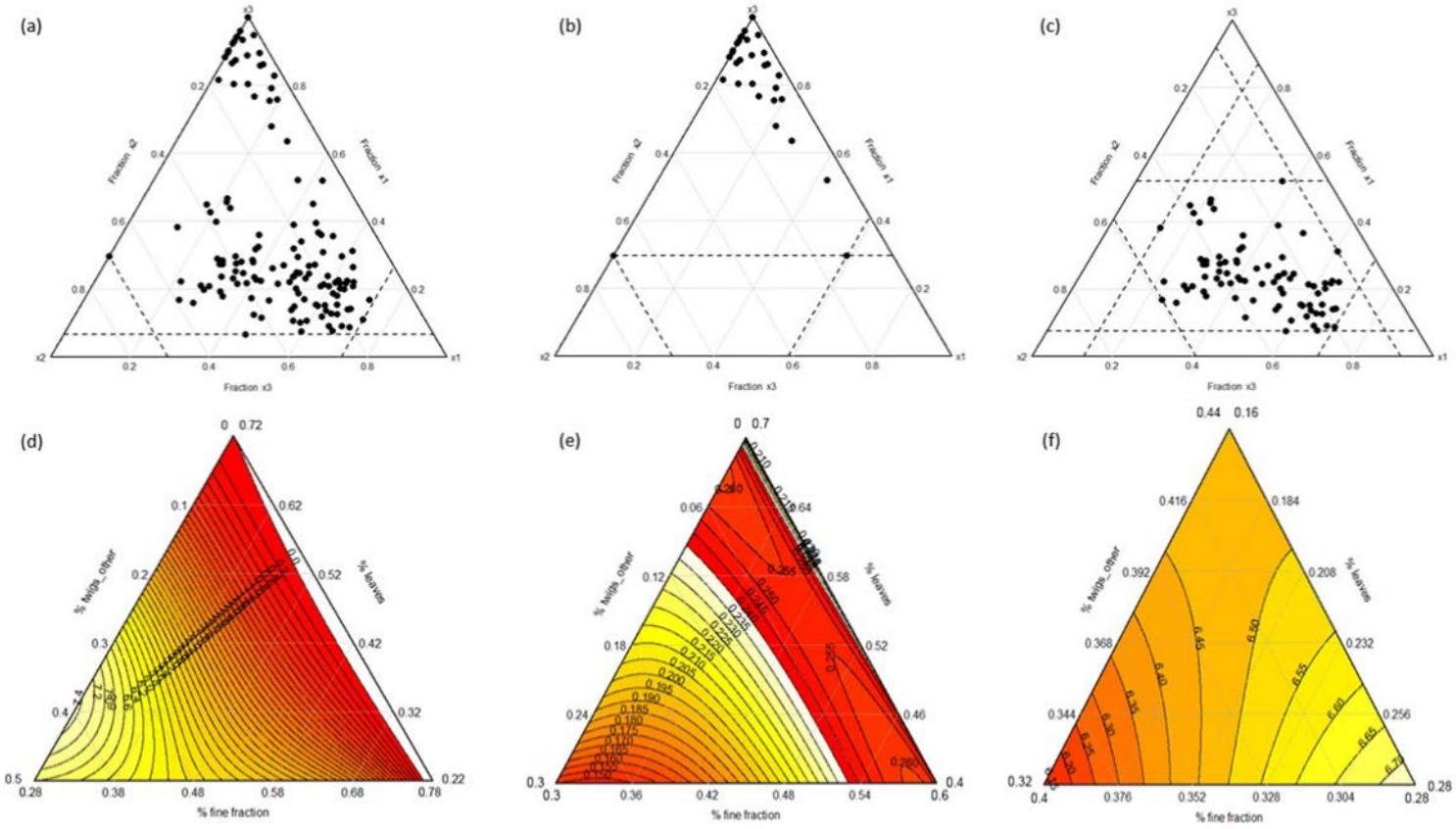


Figure A7. Carbon response surfaces developed using data from Victoria. (a, d) All data from burnt and unburnt sites, (b, e) data from burnt sites and (c, f) data from unburnt sites. Contours were modelled using a general blending model (GBM; Brown *et al.*, 2015) with a minimum of three and a maximum of 10 terms included for each model. Panels (d), (e) and (f) represent the final biomass models generated, constrained to the limits presented in panels (a), (b) and (c).

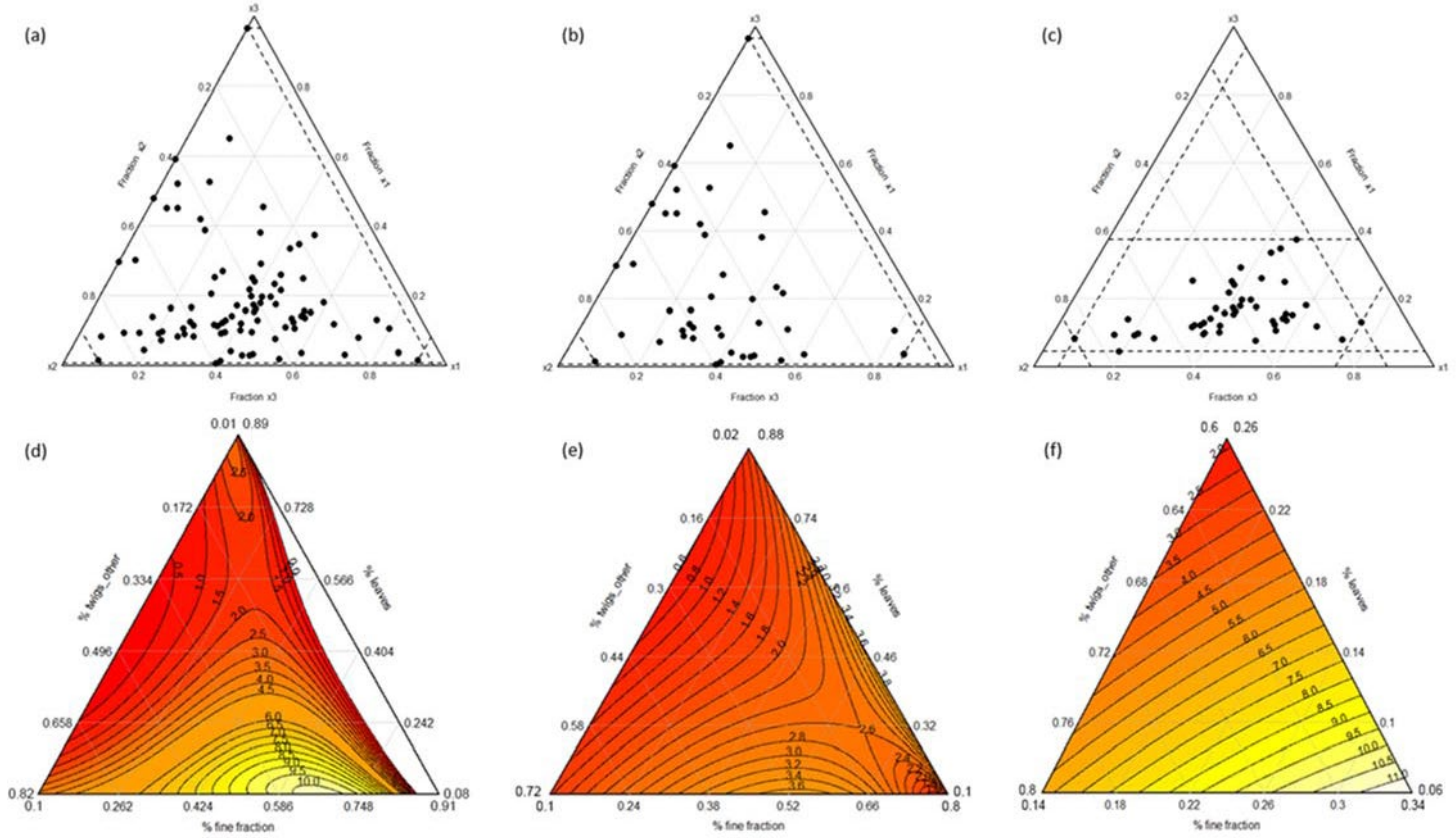


Figure A8. Carbon response surfaces developed using data from the Australian Capital Territory. (a, d) All data from burnt and unburnt sites, (b, e) data from burnt sites and (c, f) data from unburnt sites. Contours were modelled using a general blending model (GBM; Brown *et al*., 2015) with a minimum of three and a maximum of 10 terms included for each model. Panels (d), (e) and (f) represent the final biomass models generated, constrained to the limits presented in panels (a), (b) and (c).

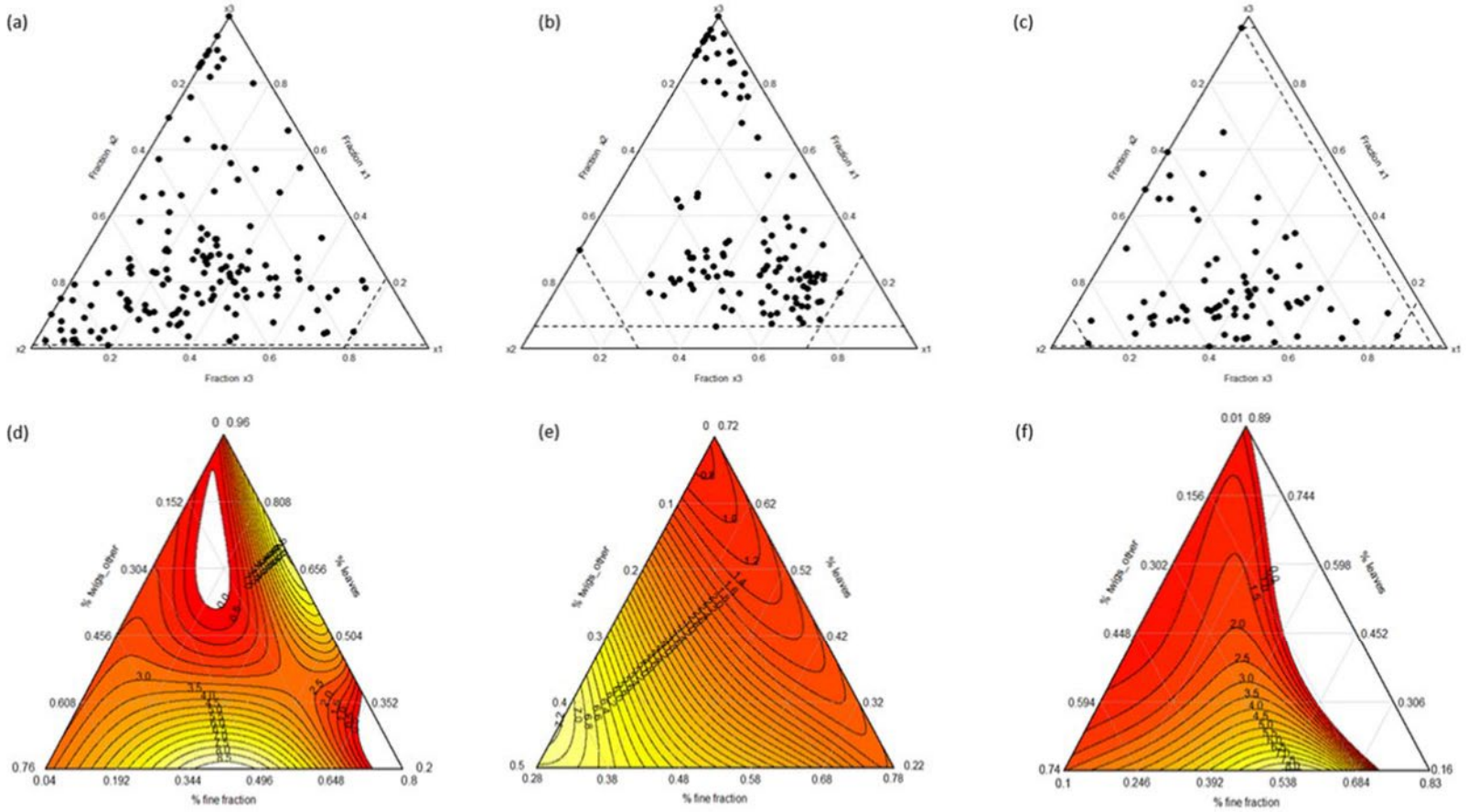


Figure A9. Carbon response surfaces developed using 80% data from (a, d) News South Wales, (b, e) Victoria, and (c, f) the Australian Capital Territory. Contours were modelled using a general blending model (GBM; Brown *et al*., 2015) with a minimum of three and a maximum of 10 terms included for each model. Panels (d), (e) and (f) represent the final biomass models generated, constrained to the limits presented in panels (a), (b) and (c).

80% models versus 20% model validation

Table A6. Statistical information and model metrics generated from the linear regression models for carbon data from sites in New South Wales (NSW), Victoria (VIC) and the Australian Capital Territory (ACT). RSE = residual standard error (with degrees of freedom), Adj R^2 = adjusted R^2 value, *F* = F statistic (with degrees of freedom), *P* = *P*-value, MAE = mean absolute error. Linear R^2 and zero R^2 (forced zero intercept) are taken from linear equations of the same data.

Variable	RSE	Adj R^2	*F*	*P*	MAE	Bias	Linear R^2	Zero R^2
NSWA 20%	3.15 (36)	0.26	14 (1, 36)	0.001	2.33	0.33	0.26	0.75
VICA 20%	1.57 (31)	0.80	125.6 (1, 31)	0.001	1.13	0.29	0.80	0.92
ACTA 20%	3.88 (16)	0.17	4.37 (1, 16)	0.05	2.91	1.35	0.17	0.72

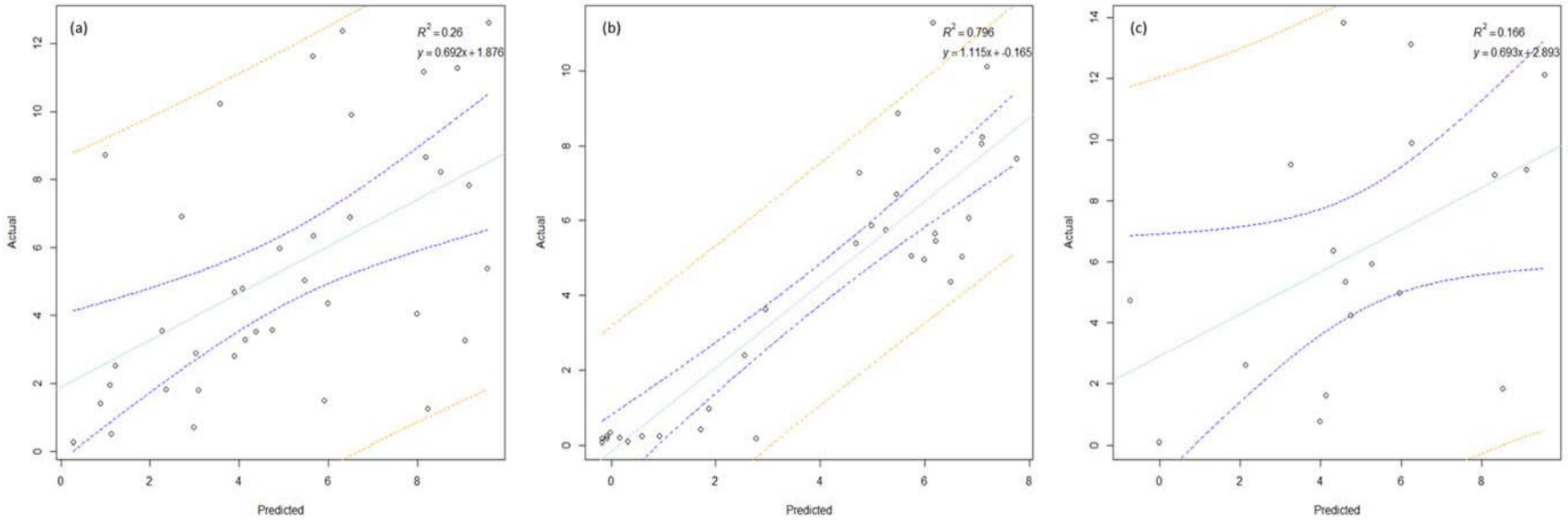


Figure A10. Linear regression plots for carbon in surface fuel showing the correlation between actual data and prediction generated from all data collected from (a) New South Wales (NSWA), (b) Victoria (VICA) and (c) the Australian Capital Territory (ACTA). Dashed yellow lines represent the prediction intervals, dashed dark blue lines represent the confidence intervals and the solid light blue line represents the regression line.

7.2 MODEL VALIDATION FOR INDIVIDUAL STATES

7.2.1 Biomass

Table A7. Statistical information and model metrics generated from the mixed forest (MF) data and 80% biomass linear regression models for biomass data from sites in New South Wales (NSW), Victoria (VIC) and the Australian Capital Territory (ACT). RSE = residual standard error (with degrees of freedom), Adj R^2 = adjusted R^2 value, *F* = F statistic (with degrees of freedom), *P* = *P*-value, MAE = mean absolute error. Linear R^2 and zero R^2 (forced zero intercept) are taken from linear equations of the same data.

Variable	RSE	Adj R^2	*F*	*P*	MAE	Bias	Linear R^2	Zero R^2
NSWA vs MF	6.18 (55)	0	0.98 (1, 55)	0.33	5.50	0.34	0	0.77
VICA vs MF	6.17 (55)	0	1.10 (1, 55)	0.30	6.22	-3.26	0	0.78
ACTA vs MF	6.12 (55)	0.02	2.00 (1, 55)	0.16	6.36	2.14	0.02	0.66

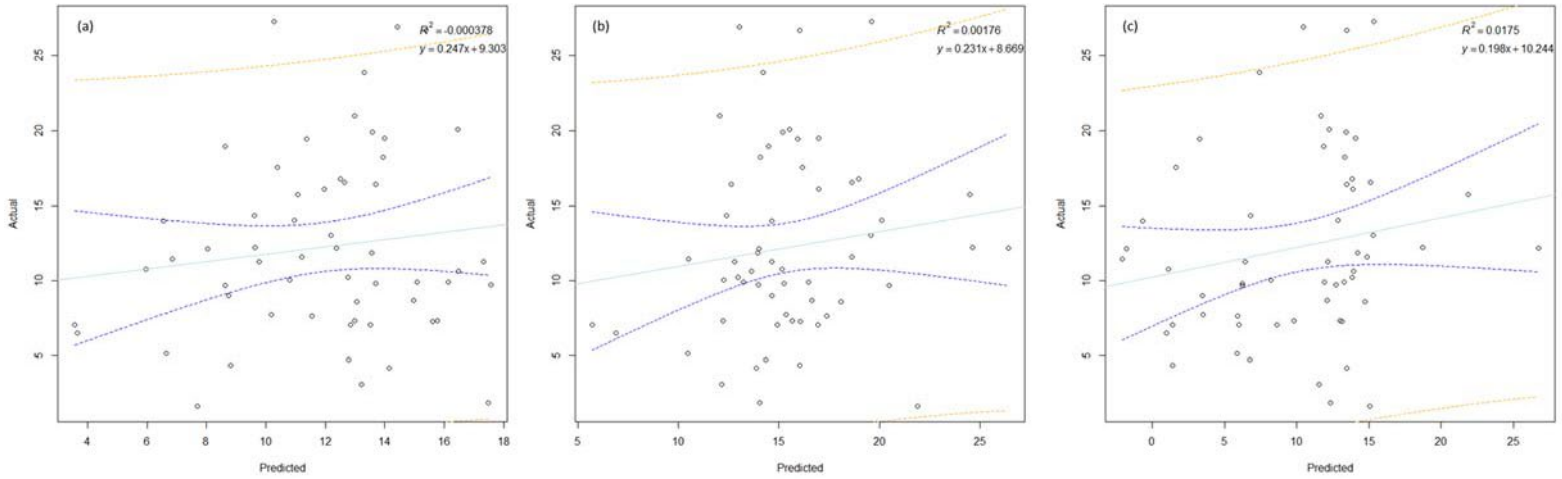


Figure A11. Linear regression plots for biomass of surface fuel showing the correlation between actual data and prediction generated from mixed forest data collected from (a) all sites, (b) burnt sites and (c) unburnt sites. Dashed yellow lines represent the prediction intervals, dashed dark blue lines represent the confidence intervals and the solid light blue line represents the regression line.

7.2.2 Carbon

Table A8. Statistical information and model metrics generated from the mixed forest (MF) data and 80% biomass linear regression models for carbon data from sites in New South Wales (NSW), Victoria (VIC) and the Australian Capital Territory (ACT). RSE = residual standard error (with degrees of freedom), Adj R^2 = adjusted R^2 value, *F* = F statistic (with degrees of freedom), *P* = *P*-value, MAE = mean absolute error. Linear R^2 and zero R^2 (forced zero intercept) are taken from linear equations of the same data.

Variable	RSE	Adj R^2	*F*	*P*	MAE	Bias	Linear R^2	Zero R^2
NSWA vs MF	3.41 (54)	0	0.92 (1, 54)	0.34	3.20	0.35	0	0.73
VICA vs MF	3.41 (54)	0	0.93 (1, 54)	0.34	3.93	2.61	0	0.45
ACTA vs MF	3.34 (54)	0.04	3.24 (1, 54)	0.08	3.07	1.23	0.04	0.73

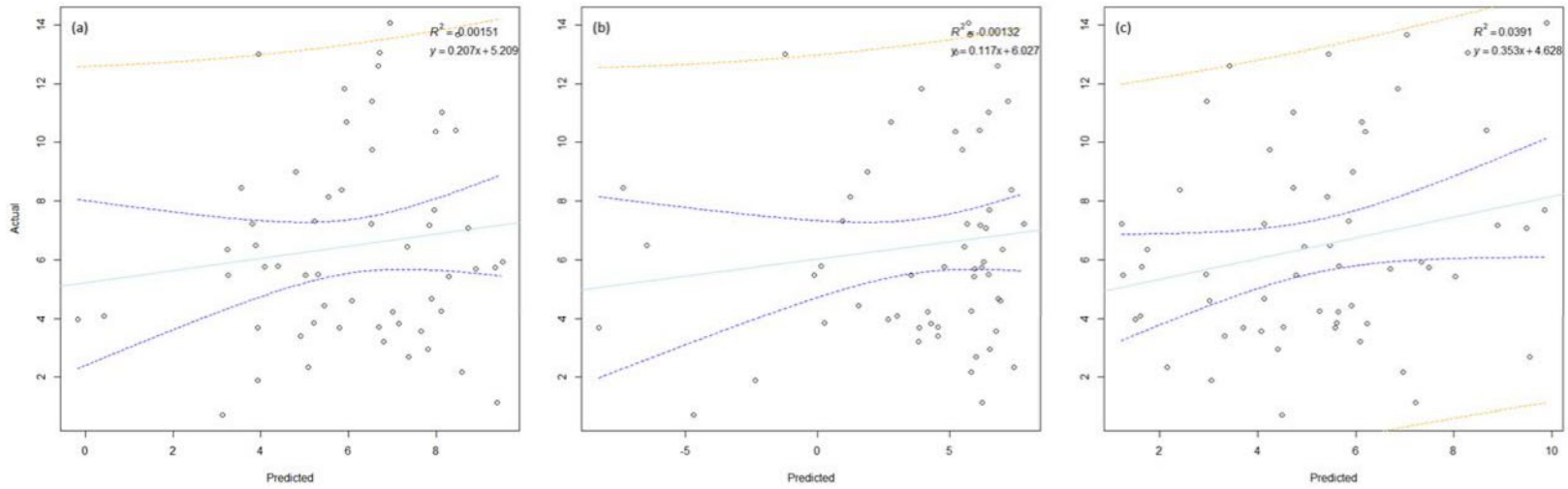
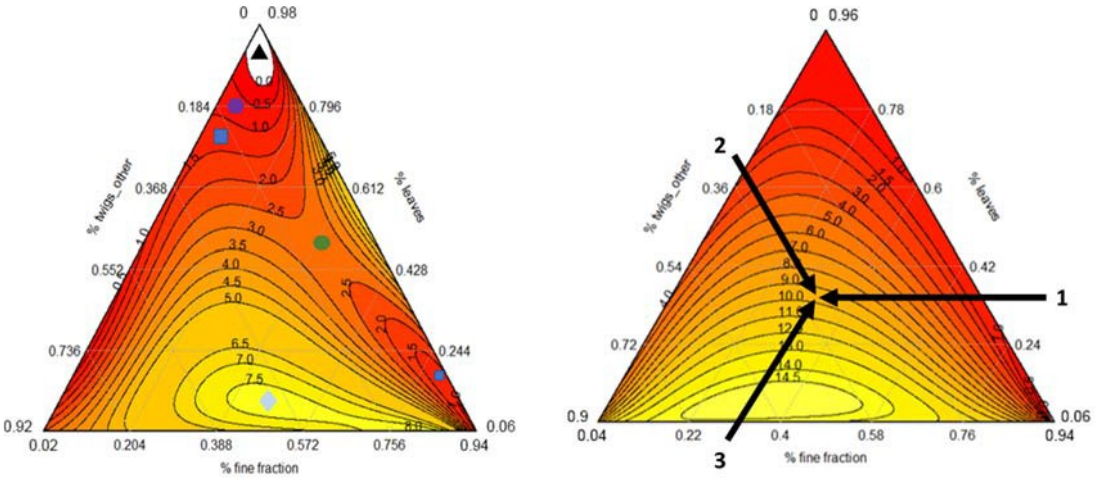


Figure A12. Linear regression plots for carbon in surface fuel showing the correlation between actual data and prediction generated from mixed forest data collected from (a) all sites, (b) burnt sites and (c) unburnt sites. Dashed yellow lines represent the prediction intervals, dashed dark blue lines represent the confidence intervals and the solid light blue line represents the regression line.

UNDERSTANDING THE MODEL – A USERS GUIDE

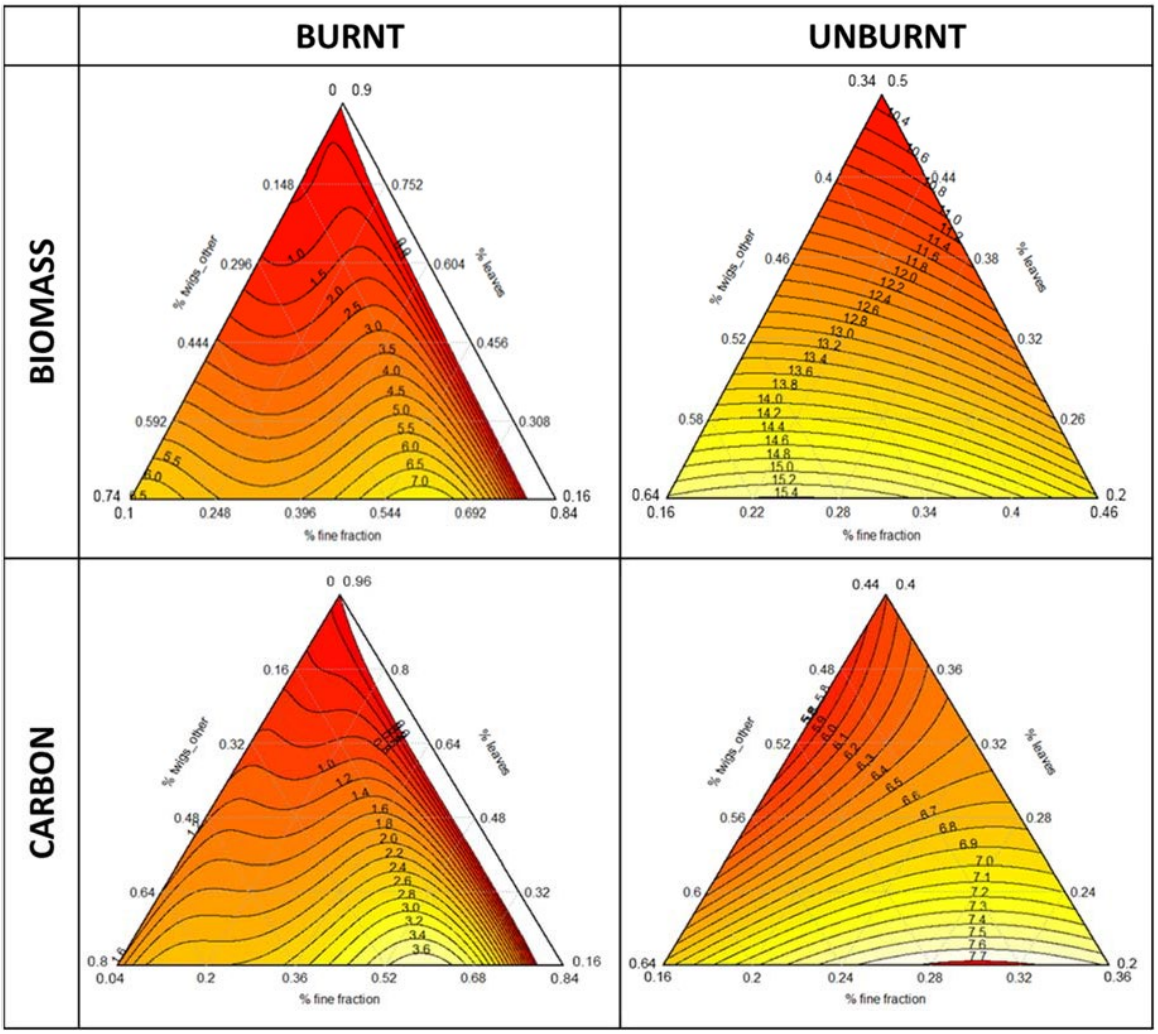
When using these models, it is important to notice the direction of the contours and their respective values. An example is shown below (left) using the all states, all sites (both burnt and unburnt data) biomass model. Contour values in these models correspond to a specific colour, a gradient of yellow (high values; e.g. blue diamond) through to red (low values; e.g. purple hexagon). When the yellow colour gradient has reached white in the middle, the colour scheme starts again at red. However, in these models, values less than 0 are removed and will show up as white (e.g. black triangle). There can be multiple contours in different locations with the same prediction values. In the example model, there are two blue squares located in two separate contours which both represent values between 1.0 to 1.5 t ha^{-1}. Similarly, there can also be an entire 'space' dedicated to one prediction value (e.g. a green circle is in one contour that represents the values between 2.5 and 3.0 t ha^{1}).



These models use estimates of proportions of the components of surface fuel collected within a defined area, such as a litter ring. For example, a sample collected in this way may contain 35% leaves, 25% fine fuel fraction (<9 mm) and 40% twigs and other components, such as bark and fruit. To calculate the respective carbon or biomass content of a sample of surface fuel, it is as simple as following the proportion percentages of each fraction in the mixture, until a middle point is reached.

In the carbon example model from all states all sites (above right), the proportion of leaves is determined first (35% or 0.37), as indicated by arrow 1, drawn parallel to % fine fraction (bottom axis). The proportion of twigs and other fraction is found next (30% or 0.30), represented by arrow 2, parallel to % leaves axis. The third and final component, the fine fuel fraction as indicated by arrow 3, parallel to % twigs and other, is found (23% or 0.23), and intersects with arrows 1 and 2.

Once the intersecting point has been reached, the contour that this point lies in represents the estimated amount of carbon or biomass content in tonnes per hectare. In this example, 35% leaves, 30% twigs and other and 35% fine fuel returns the estimate range of 9 to 10 t ha^{-1} of carbon in the surface fuel. The same method can be made to estimate total biomass of surface fuel and carbon loads prior to and after prescribed burns.


BURNT
UNBURNT
BIOMASS
CARBON
% twigs_other
% leaves
% fine fraction