bnhcrc.com.au

DETECTING THE EFFECTS OF PRESCRIBED BURNING USING GENERALISED ADDITIVE MODELLING

Milestone 2.3.3 Calibration of water and carbon model using field/existing data

Mengran Yu, David Pepper, Tina Bell, Malcolm Possell
The University of Sydney

Version	Release history	Date
1.0	Initial release of document	15/05/2020

Publisher:
Bushfire and Natural Hazards CRC

May 2020

Citation: Yu M, Pepper D, Bell T, Possell M (2020) Detecting the effects of prescribed burning using generalised additive modelling, Bushfire and Natural Hazards CRC, Melbourne

Cover: Fire trail allowing access to field sites in the Blue Mountains. Source: Danica Parnell

TABLE OF CONTENTS

ABSTRACT

Data collected from 52 plots from sites in Victoria and New South Wales were used to test whether a simple modelling technique – a generalised additive model (GAM) – could be used in conjunction with satellite imagery to detect the effect of prescribed burning on the hydrological cycle. Evapotranspiration (ET) was selected as the strongest indicator of a change in forest hydrology given the direct effect of removal of vegetation with fuel reduction burning. Variables included in the ET GAM were site details (location, elevation, aspect, slope), soil properties (total carbon and nitrogen), climate (short-term and long-term rainfall, maximum and minimum daily temperature, solar radiation) and the enhanced vegetation index (EVI), a commonly used spectral product derived from satellite imagery. These variables were used to develop GAMs using sites in each state and combined together. Results from this modelling suggested a change in ET due to prescribed burning was more obvious for sites in Victoria than in NSW. Vegetation (EVI) and climatic variables (solar radiation, df5 and df95) were the best predictors for changes in ET due to prescribed burning activities. Soil (C:N) and terrain variables (slope, aspect, elevation) were not important factors for detecting change in ET. Limitations due to temporal and spatial differences in sampling unburnt and burnt plots and future potential for this method are discussed.

END USER STATEMENT

Dr Felipe Aires, *NSW National Parks and Wildlife Service*

Landscape management agencies using prescribed fires as a management tool are required to monitor the impacts of hazard reduction programs on the environment. The effects of hazard reduction on hydrology are not fully understood and modelling studies are currently limited and/or require a broad range of variables to explain any changes seen in the landscape.

This report demonstrates that site-based data can be combined with estimates of evapotranspiration from publicly available satellite imagery as a viable modelling option for landscapes managers to monitor the impact of hazard reduction programs on the hydrological cycle of treated forests.

These results add important knowledge to the evidence-based approach needed by agencies to improve the way they monitor the impacts of hazard reduction. There is potential to utilise this knowledge to reduce the amount of staff necessary to collect data from the field to monitor any post-fire changes in hydrology and save important resources that can be reallocated to other functions.

INTRODUCTION

As a consequence of global climate change, the frequency, timing and extent of bushfires are expected to increase and, in response, research into the consequences of fire on forest ecosystems has been intensified. One of the major concerns in Australia and elsewhere is the impact of fire on the hydrological cycle (Montes-Helu *et al*., 2009; Lane *et al*., 2010; Feikema *et al*., 2011; Smith *et al*., 2011; Glenn *et al*., 2013; Langhans *et al*., 2016). An immediate result of bushfire is the reduction of aboveground vegetation which affects the evapotranspiration (ET) component of the hydrological cycle. There are a number of hydrological studies that have investigated the effect of unplanned fire in forests and many of these have focused on changes in ET (Montes-Helu *et al*., 2009; Glenn *et al*., 2013). However, studies investigating changes in ET due to prescribed fires (also referred to as controlled or planned fires) are limited. Prescribed fires are used to mitigate the risk of bushfire by decreasing fuel loads in forested areas. Such fires are generally less severe than bushfires and mostly affect the litter layer and understorey vegetation (Cawson *et al*., 2012). As a result, they are likely to have different, and presumably lesser, effects on post-fire hydrology compared to bushfires. A better understanding of the impacts of prescribed fire on forest hydrology will test this assumption and will be useful knowledge to have for decision making in forest management. An effective way to investigate potential effects of prescribed fire on ecosystem functioning, including hydrological cycling, is through testing and high-quality modelling.

1.1 METHODS FOR ESTIMATING EVAPOTRANSPIRATION

Estimating forest ET can be difficult as it is influenced by various environment and terrain factors. One of the more traditional methods used for estimation of ET is the 'water balance' equation, where precipitation, groundwater storage, inflow, and outflow are required for estimating ET (Pereira *et al*., 1999). More recently, other measurement methods and tools have been developed, such as flux tower methods (Rana and Katerji, 2000), scintillometry to measure energy and water balances (Lenters *et al*., 2011), surface renewal methods using micrometeorology (Drexler *et al*., 2004) and monitoring of diurnal fluctuations in groundwater (Mould *et al*., 2010). However, these methods rely almost exclusively on use of hydrological data collected from the field. These data are often difficult and expensive to obtain, particularly for studies that require long term data for modelling purposes. For this reason, the use of remotely sensed data for estimation ET has increased and is becoming more and more sophisticated.

Given that plant transpiration usually accounts for 80% or more of ET, data describing foliage density is often used in estimation of ET (Glenn *et al*., 2007). Along with data that can be used to estimate ET directly, a range of vegetation indices can be used as parameters in empirically-based hydrological models. Estimating foliage density using vegetation indices obtained from satellite imagery is one of the most well-developed remote sensing tools available (Pettorelli *et al*., 2005; Xue and Su, 2017). One of the most commonly used vegetation indices is the Normalised Difference Vegetation Index (NDVI) which is calculated based on reflectance values of near infrared and red bands of satellite images.

An inherent limitation of the NDVI is the influence of background colour (e.g. soil, shade from canopy trees, cloud cover). For example, values of NDVI can vary with soil type (Huete, 1988). Numerous other vegetation indices have been developed to account for this problem (Xue and Su, 2017). The Enhanced Vegetation Index (EVI) (Huete *et al*., 2002) is widely used and several studies (e.g. Nagler *et al*., 2005, Rahman *et al*., 2005, Yang *et al*., 2006) have demonstrated better predictions of ET than when using NDVI. The EVI uses the blue band of satellite images to correct background effects and, consequently, it may have a more direct relationship with leaf area index (LAI) to provide better predictions of ET (Glenn *et al*., 2007). Further details about EVI are provided in the methods section.

Variations in weather such as rainfall and temperature are driving parameters for changes in ET (Hutley *et al*., 2001). As such, studies predicting ET using remotely sensed vegetation indices often include observed weather data. For example, Nagler *et al*. (2005) predicted ET using EVI together with precipitation and maximum daily temperature for a site located in the western United States. Eight out of nine sites showed a strong correlation between ET and EVI, and a strong correlation between ET and maximum temperature was also found. It was also shown that sites at lower elevations had peak ET earlier in the year (i.e. June or July) than sites at higher elevations (peaked in August or September) indicating the relative importance of landscape positioning. Similarly, Liu *et al*. (2012) demonstrated the importance of site location when investigating the sensitivity of ET to climate variation using more than 650 sites in China. Along the same line of investigation, Gao *et al*. (2008) found the greatest sensitivity of ET for climate variables in a forested site in Korea was due to elevation for sites on south-facing sites but not for north-facing sites.

In the study presented here, empirical data collected from sites in Victoria sampled before and after prescribed fire and from sites in New South Wales treated with prescribed burning and adjacent unburnt areas were used in combination with satellite-derived data to investigate the following:

- The effect of prescribed fire on ET in representative dry sclerophyll forests
- The sensitivity of ET to differences in climate and terrain (e.g. location, slope, aspect, elevation)
- The sensitivity of ET at a landscape-scale

2. METHODS

2.1 STUDY SITES

Field data were collected from sites located in NSW and Victoria (for site details see Gharun *et al*., 2015; Bell *et al*., 2018; 2020). Twenty-five pairs of plots ('burn' units) were identified in NSW where unburnt (control) plots were adjacent (within 50 m) to burnt plots. In each 22.5 m radius circular plot, four soil samples were taken, one each from the north, south, west, and east cardinal points. Samples from sites in Victoria were collected from plots (27 in total) from the same location before (within 2-3 months) and after (within 1 month) a prescribed fire.

In general, sites in Victoria had higher average annual rainfall (1096 and 946 mm, respectively) and lower daily solar radiation (15.5 and 16.2 MJ m^2, respectively). Sites in NSW were generally located at greater elevation (355 m above sea level (asl)), had steeper slopes (8.5°), and lower aspects (155°) compared to the sites in Victoria (127 m asl, slope of 3.4° and aspect of 174°). A detailed description of data collecting methods can be found in Gharun *et al*. (2018).

2.2 CHANGE DETECTION METHOD

2.2.1 Generalised Additive Model

Change detection compares differences of a point or points of reference in the landscape over time. Understanding the scope and magnitude of changes in the landscape is an important technique for understanding and managing interactions in the environment (Lu *et al*., 2004). Predicting changes in ET after fire involves using both spatial and temporal variables. The correlation between these data might be nonlinear while the dependency and spatial structure are still important (Bailey *et al*., 2005). For this reason, a generalised additive model (GAM) was used in this study. Generalised additive models can be used to combine smooth and linear relationships between covariant and predicted variables (Wood, 2017) and can therefore capture nonlinear patterns in the data.

A basic function of a GAM is shown in Equation (1):

$$l(g) \sim a_0 + f_1(x_1) + f_2(x_2) + \cdots + f_i(x_i) \qquad (1)$$

where the response variable $l(g)$ is predicted from the sum of several individual nonparametric smoothing functions $() + () + \cdots + f()$. In this format, , $\cdots$ are smoothing functions for variable x_1, $x_2 \ldots x_i$ (Wood, 2017). While all other inputs are treated as constants, each of the smoothing functions can be treated as the effect of the input.

The function $()$ is estimated from:

$$f_i(x_i) = \sum_{m=}^{M} b_m(x_i)P_m \qquad (2)$$

where $b_m()$ are the base functions and $(3_m$ are the parameters to be estimated (Wood, 2008).

In this study, $_1$, $_2$… $_i$ were the environmental and terrain variables that typically affect ET (e.g. rainfall, temperature, aspect and prescribed fire), , ⋯ indicate different relationships between ET and the input variables. The response variable, $l(g)$, is the satellite-observed ET value, it is formulated as the sum of the individual smoothing functions of input variables. The smoothing function of the GAM provides flexibility in the model to present different forms of correlations between ET and individual input variables despite them being non-linear or linearly related.

2.2.2 Covariates

To determine the GAM for predicting ET (ET GAM) and, hence, the effect that prescribed fire may have on ET, data collected from the field were used together with satellite data. These data were grouped into three major forms: field-collected data, climate data and vegetation indices.

Field collected variables

Field collected data are the initial and central link of this study. These data were either used directly as a variable to create the GAM or used as an indicator for obtaining information from satellite imagery. For sites in both NSW and Victoria, samples of the upper layer of soil (0-10 cm) were collected either from plots at time points pre-fire and post-fire (sites in Victoria) or from unburnt and burnt paired plots (sites in NSW). Nitrogen and carbon content were analysed (LECO elemental analyser, CNS 2000; LECO, St Joseph, MI) and the measured values used as a variable for predicting ET.

The locations (latitude and longitude) of all sites/plots were used to extract the corresponding terrain information including elevation (m asl), slope (°) and aspect (°). Digital Elevation Models (DEMs) derived from LiDAR 5 m grid of the sites/plots were acquired from Geoscience Australia (Geoscience Australia, 2015). Elevation, slope and aspect for each site/plot was then calculated in ArcGIS (version 10; Esri Australia Pty Ltd, Brisbane, Australia).

The information relating to location together with the timing of sampling and prescribed burning allowed extraction of climate data and vegetation indices relevant to the study period. For sites located in NSW (paired burnt and adjacent unburnt plots), two different locations were used for the same site to extract pre-fire and post-fire climate and topography data. Consequently, only the satellite images and climate data collected during the post-fire period were used. For the sites located in Victoria, data were collected from the same location but at two different times (pre- and post-prescribed fire).

Climate variables

For each of the study sites, climate variables for the corresponding date were assembled and included maximum daily temperature (T_{max}), minimum daily temperature (T_{min}), solar radiation and rainfall. The climate variables were obtained from SILO (Jeffrey *et al*., 2001), a gridded gauge-based climate data product with a spatial resolution of 0.05° × 0.05° (approximately 5 × 5 km) produced by the Queensland Climate Change Centre of Excellence (QCCCE; http://www.longpaddock.qld.gov.au/silo/). Data provided by SILO are extracted from daily climate data interpolated from point measurements made by the network of weather stations developed and maintained by the Bureau of Meteorology. Data from SILO is freely available and has been used extensively in hydrology studies based in Australia (Beesley *et al*., 2009). The climate conditions during the pre-fire and post-fire periods were extracted from the corresponding grid cell for each of the sites. Due to the close location of paired plots in sites in NSW (within 50 m), all of the control and burnt sites were found to be in the same grid cell, therefore, the same climate data were used.

In addition to rainfall data, two discount factor values (df5 and df95) were used to represent the antecedent condition of rainfall. Discount factor values are values calculated based on a weighted past rainfall value (Wang *et al*., 2011). If the rainfall to time *j* is $(?_m)_{?m?j}$, the DF factor value with discount factor d is calculated as:

$$DF(d) = \frac{\sum_{i-1} d^{\,1-i}\, d}{\sum_{i-1}{}^{1-i}} \qquad (3)$$

A weighting, d, was given to past rainfall values to calculate the sum of weighted past rainfall values. This weighted value diminishes with time at a defined (d) rate. A smaller value for d gives more weight to recently observed rainfall while a larger value for d is used to present longer term rainfall conditions (Wang *et al*., 2011). In this study, df5 was used to present short-term past rainfall and df95 was used to present long-term rainfall conditions. Rainfall data for the past 1000 days were used for calculating DF values.

Vegetation indices

Vegetation indices for the sites were used to represent the change in vegetation cover due to prescribed fire. In this study, we used the National Aeronautics and Space Administration (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) product, and specifically, the enhanced vegetation index (EVI) 'MOD16A1' (Running *et al*., 2017). This product is available as an 8-day composite interval with a resolution of 500 m. The EVI was used instead of NDVI because, as mentioned, the latter is very sensitive to canopy background colour (Huete, 1988) and we wished to avoid introducing avoidable noise to our models. The EVI is developed with an improved vegetation monitoring method by de-coupling the background colour by using correction coefficients:

$$= \quad d \quad + \quad 1 \quad d \quad 2 \quad b \quad + \qquad (4)$$

where L is a canopy background adjustment term, C_1 and C_2 are the coefficients of the aerosol resistance term which uses the blue band to correct for aerosol influences in the red band (Huete *et al*., 2002).

Predicted changes in ET derived from the ET GAM are reported as 'kg m² 8-d'. The ET for each pixel is a sum of 8 days of composite imagery supplied for the MODIS products (i.e. EVI) as a means to remove artefacts and atmospheric effects.

For each pair of the study sites in NSW, two EVI values for were extracted from the same satellite image for unburnt (control) and burnt plots. For plots in sites in Victoria, both pre-fire and post-fire images were used to extract EVI values for the two periods.

3. RESULTS AND DISCUSSION

Compared to ET values extracted from MODIS (ET_{MODIS}), a decrease in the modelled ET values (ET_{GAM}) was found for sites in both NSW and Victoria (Table 1). The maximum ET_{GAM} value for sites in NSW was reduced from 21.0 to 19.5 kg m² 8-d and the median value was reduced to 1.1 kg m² 8-d after prescribed fire. The change in ET_{GAM} for sites in Victoria due to prescribed burning was more obvious with a reduction in the maximum value of 13.9 kg m² 8-d alongside considerable decreases in median (39 to 11.1 kg m² 8-d) and minimum (33.2 to 8.1 kg m² 8-d) values.

3.1 EXPLORATORY DATA ANALYSIS

Overall, the number of observed values was similar for sites in NSW and Victoria, however, due to the close spatial location of some of the plots several had the same climate and ET_{MODIS} values (Table 2). As a result, only 8-9 unique values were available as climate input variables for sites in NSW and 11-14 were available for sites in Victoria. This affected the degrees of freedom of the GAM model and possibly influenced the sensitivity level of the response variable. The close location of some plots also affected ET_{MODIS} observations, particularly for some plots in sites in NSW because they were located in the same pixel of the satellite image and the same value was assigned to both burnt and unburnt plots. However, such spatial resolution constraints cuts both ways, e.g. for plots slightly further apart or positioned just in the next pixel, and the results of GAM modelling carry such inherent constraint and were interpreted as such.

3.2 GENERALISED ADDITIVE MODELLING

Selected predictor variables in the ET_{model} showed significant correlations (Table 3). Despite the effect of close locations of the unburnt and burnt plots, a significant effect of fire was still found for all of the models developed. None of the models predicted terrain or soil parameters to be a significant factor for ET estimation. The model for NSW did not predict EVI or short-term rainfall (df5) to be significant predictors for ET while the ET_{model} value for Victoria plots was not affected by df5 or T_{max}. However, when the observations from NSW and Victoria were combined (ALL model), all the climate inputs together with EVI were required for predicting ET.

Overall, model predictions for the effect of prescribed fire on ET_{GAM} show high adjusted R^2 values (Table 4). The model predictions for sites in NSW had a low adjusted R^2 value (0.82) compared to model predictions for sites in Victoria (0.95), while the combined model had an adjusted R^2 value of 0.92.

Table 1. Summary of input data used for modelling. Sites in NSW had 25 observations for each variable and sites from Victoria had 27 observations for unburnt sites (sampled prior to prescribed burning) and 24 observations for burnt sites (the same sites sampled after prescribed burning). max = maximum, min = minimum, ET = evapotranspiration, T_{max} = maximum daily temperature, T_{min} = minimum daily temperature, EVI = enhanced vegetation index.

	NSW						Victoria					
Variable	**Unburnt**			**Burnt**			**Unburnt**			**Burnt**		
	Max	**Median**	**Min**	**Max**	**Median**	**Min**	**Max**	**Median**	**Min**	**Max**	**Median**	**Min**
ET (kg m^2 8-d)	21.0	18.5	7.6	19.5	17.4	7.4	44.6	39.0	33.2	30.7	11.1	8.1
Nitrogen (%)	0.08	0.06	0.04	0.10	0.06	0.04	0.54	0.21	0.10	0.43	0.20	0.12
Carbon (%)	3.49	2.18	1.16	3.92	2.36	1.36	11.75	6.52	2.48	12.44	6.22	3.63
Aspect (°)	355	122	0	347	140	3	330	175	12	330	194	12
Slope (°)	26.4	6.4	0.8	20.4	6.6	1.2	7.9	2.5	0.6	7.9	2.5	0.9
Elevation (m)	664	430	35	684	441	42	271	113	55	271	115	55
T_{max} (°C)	25	21	18	25	21	18	29	21	21	30	23	13
T_{min} (°C)	12	11	7	12	11	7	17	16	10	13	9	7
Solar radiation (MJ m^2)	19	18	9	19	18	9	26	20	14	24	12	8
df95 (mm)	1.53	1.02	0.25	1.53	1.02	0.25	2.76	1.79	1.17	4.94	2.38	1.40
df5 (mm)	1.00	0.53	0.01	1.00	0.53	0.01	3.33	0.87	0	5.13	0	0
EVI	0.41	0.33	0.27	0.42	0.29	0.24	0.86	0.74	0.65	0.89	0.81	0.74

Table 2. The number of unique variables used as input data for generalised additive modelling. ET = evapotranspiration, EVI, enhanced vegetation index; df5 and df95, discount factor value at the 5 and 95% confidence intervals; t_{max}, maximum temperature; t_{min}, minimum temperature.

	Time	ET (kg m^2 8-d)	Nitrogen (%)	Carbon (%)	Slope (°)	Aspect (°)	Elevation (m)	EVI	Solar radiation (MJ m^2)	df95 (mm)	df5 (mm)	T_{max} (°C)	T_{min} (°C)
NSW	**Pre-fire**	20	25	25	25	25	25	25	9	9	8	9	8
	Post-fire	19	25	25	25	25	25	23	9	9	8	9	8
	All	35	50	50	50	50	50	48	9	9	8	9	8
Victoria	**Pre-fire**	25	27	27	27	27	27	27	6	6	7	5	5
	Post-fire	23	24	24	24	24	24	24	8	8	8	8	7
	All	48	51	51	51	51	51	51	10	14	15	11	11

Table 3. Blue shaded boxes indicate selected predictors for generalised additive models developed for predicting evapotranspiration. C:N = carbon to nitrogen ratio, EVI = enhanced vegetation index, df5 and df95 = discount factor values at 5 and 95% confidence intervals, respectively, t_{max} = maximum daily temperature, t_{min} = minimum daily temperature.

	Fire	Solar radiation (MJ m^2)	C:N	Slope (°)	Aspect (°)	Elevation (m)	EVI	df95 (mm)	df5 (mm)	T_{max} (°C)	T_{min} (°C)
NSW											
Victoria											
All sites											

The validity of the assumptions of the ET GAM models and the adequacy of the model fit were tested using graphical techniques (Figures 1-3). In all three models (NSW, Victoria and All sites), the model adequacy was examined using the quantile-quantile plot for deviance residuals in the model. The closeness of the data to a 1:1 line for NSW, Victoria and all states models indicates the models in all cases were adequate to describe ET (panel (a), Figures 1-3). Model adequacy was also examined using the residuals of the model fits (panel (b), Figures 1-3). The residuals were randomly distributed, and no obvious trend was observed indicating that the variance in the models were consistent across all estimations of ET. Histograms of residuals (panel (c), Figures 1-3) were normally distributed indicating that the assumption of randomisation was met. Lastly, there were no obvious outliers in the observed versus predicted value plot (panel (d), Figures 1-3).

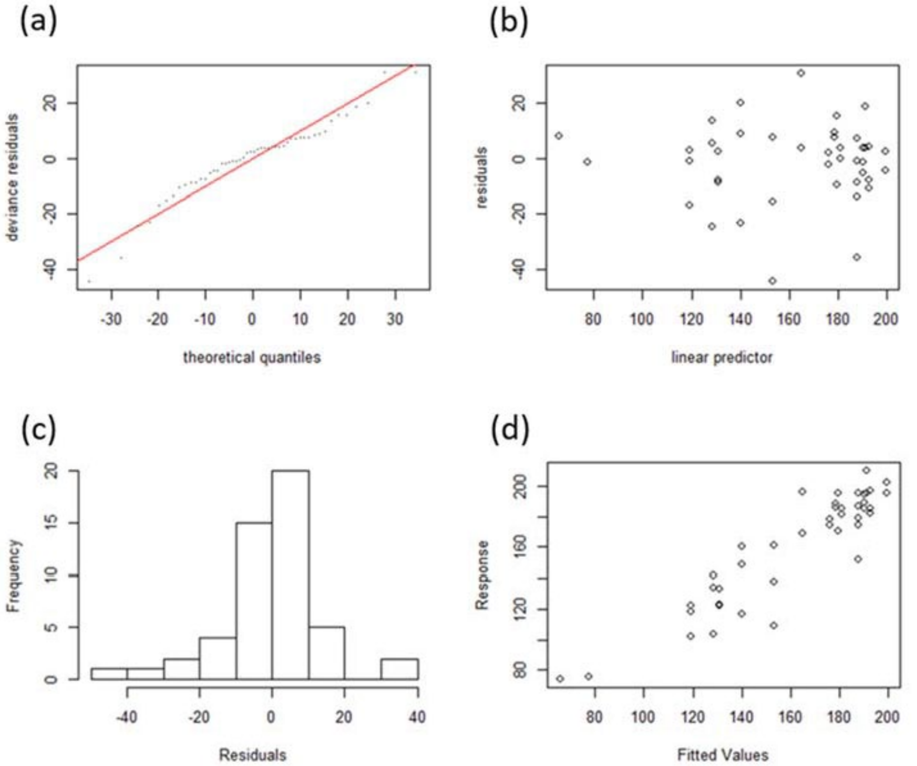

Figure 1. Diagnostics of the fitted generalised additive model (GAM) for sites in NSW; (a) quantile-quantile plot for deviance residuals, (b) residuals of the model fits, (c) histograms of the residuals, and (d) modelled versus observed evapotranspiration values. The closer the data is to the red line in (a), the closer to normality are the data.

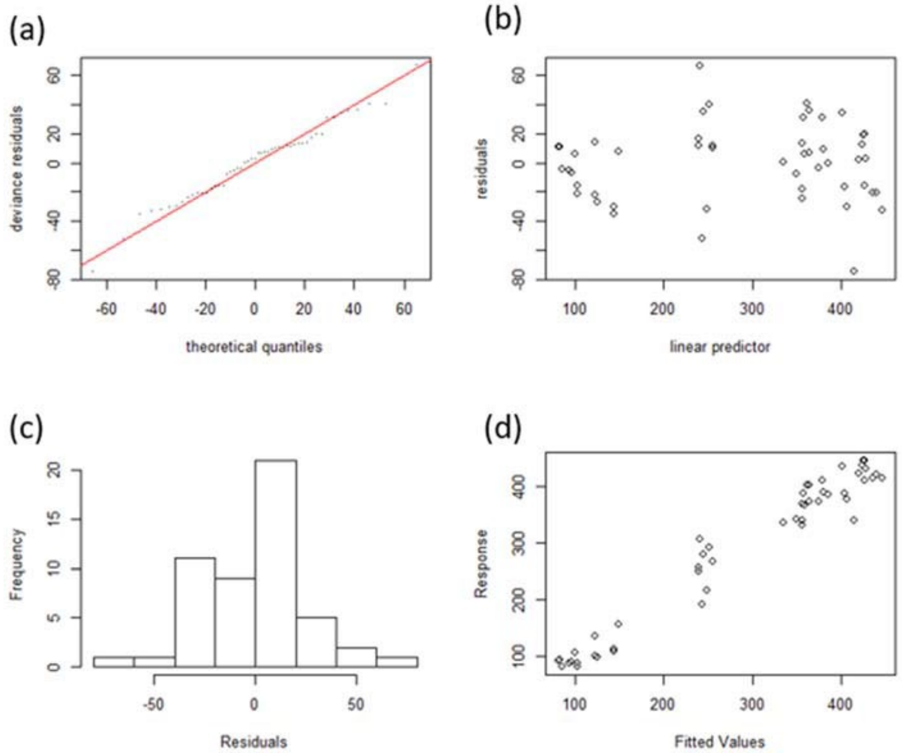

Figure 2. Diagnostics of the fitted generalised additive model (GAM) for sites in Victoria; (a) quantile-quantile plot for deviance residuals, (b) residuals of the model fits, (c) histograms of the residuals, and (d) modelled versus observed evapotranspiration values. The closer the data is to the red line in (a), the closer to normality are the data.

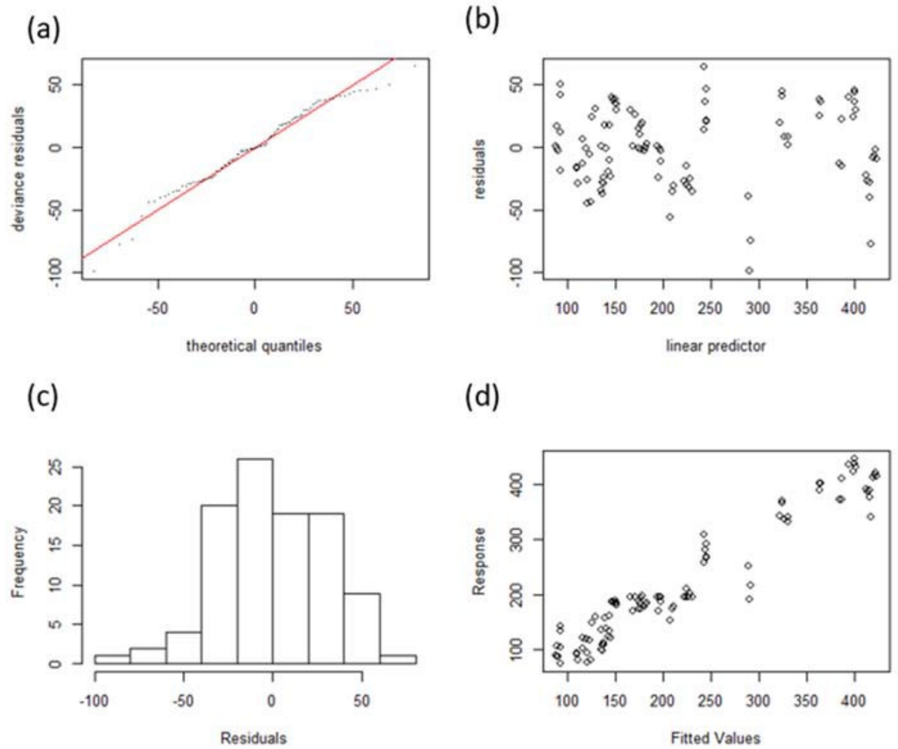

Figure 3. Diagnostics of the fitted generalized additive model (GAM) for an 'All states' model (i.e. for sites in NSW and Victoria); (a) quantile-quantile plot for deviance residuals, (b) residuals of the model fits, (c) histograms of the residuals, and (d) modelled versus observed evapotranspiration values. The closer the data is to the red line in (a), the closer to normality are the data.

3.3 THE EFFECT OF PRESCRIBED FIRE AND OTHER VARIABLES

The coefficients for the fire factors in the model indicate that the effect of prescribed fire on satellite observed ET (ET_{MODIS}) was 9.6 times greater for sites sampled in Victoria (111.76) compared to sites sampled in NSW (11.68). This suggests that prescribed fire in Victoria has a greater effect on post-fire ET change. However, it may also be caused in part by the combined effects of different fire intensity among sites, the use of different collection methods (i.e. the same plot sampled before and after for Victoria versus control and burnt plots adjacent to each other for NSW), and differences in satellite imagery.

The partial response curves for the different ET models are shown in Figures 4-6. The models for sites in both NSW and Victoria show a positive correlation between ET_{MODIS} and solar radiation (Figure 4a and 5a) and a negative correlation between ET and long-term rainfall (df95) (Figure 4b and 5c). The model for sites in NSW also had a negative effect for T_{max} (Figure 4c) while the model for sites in Victoria indicated EVI as a significant, positively correlated predictor of ET (Figure 5b). When the observed values from both states were combined, the model predicted a strong correlation of ET_{MODIS} with solar radiation (Figure 6a), recent rainfall (df5) (Figure 6b) and EVI (Figure 6c). Long-tern rainfall (df95) was predicted to have a negative effect on ET while other predictors were positively correlated.

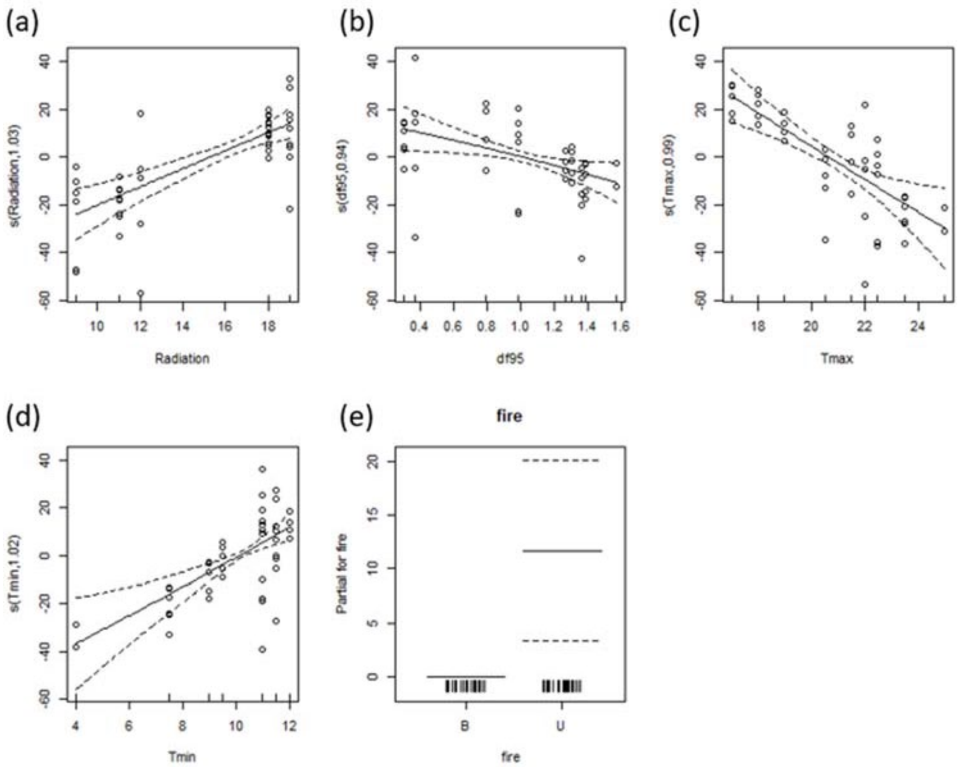

Figure 4. Partial response curves for evapotranspiration (ET) for variables included in the generalised additive model for sites sampled in NSW; (a) solar radiation (MJ m^2), (b) discount value for precipitation at the 95% confidence interval (df95, mm), (c) maximum daily temperature (T_{max}, °C), (d) minimum daily temperature (T_{min}, °C), and (e) presence of prescribed fire at a site where B = burnt, U = unburnt.

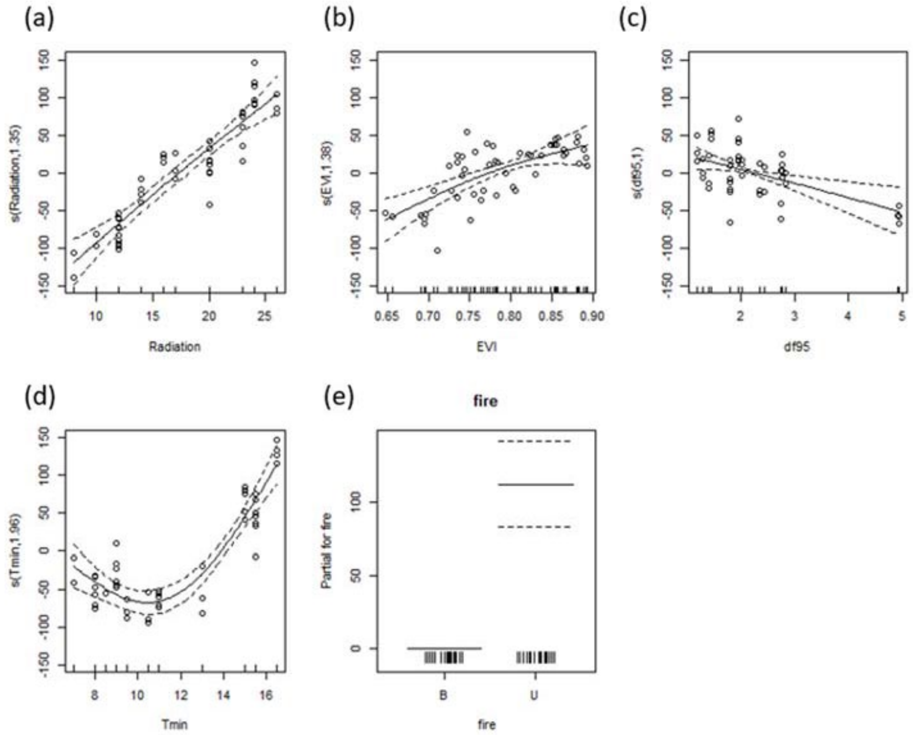

Figure 5. Partial response curves for evapotranspiration (ET) for variables included in the generalised additive model for sites sampled in Victoria; (a) solar radiation (MJ m2), (b) enhanced vegetation index (EVI), (C) discount value for precipitation at the 95% confidence interval (df95, mm), (d) minimum daily temperature (T_{min}, °C), and (e) presence of prescribed fire at a site where B = burnt, U = unburnt.

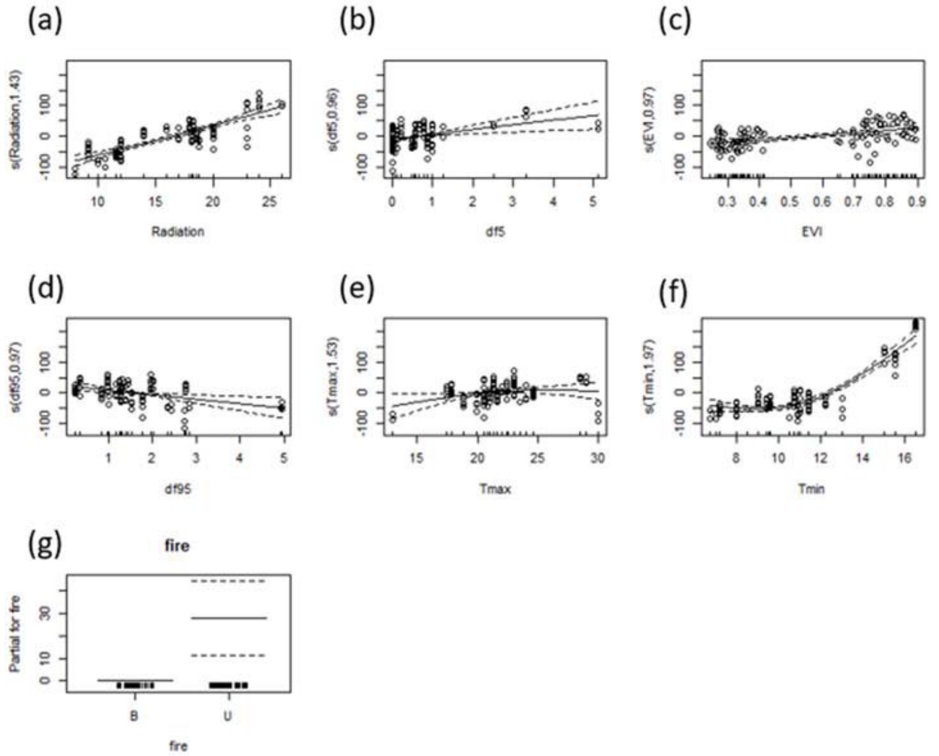

Figure 6. Partial response curves for evapotranspiration (ET) for variables included in the generalised additive model for all sites; (a) solar radiation (MJ m2), (b) discount value for precipitation at the 5% confidence interval df5, mm), (c) enhanced vegetation index (EVI), (d) discount value for precipitation at the 95% confidence interval (df95, mm) (e) maximum daily temperature (T_{max}, °C), (f) minimum daily temperature (T_{min}, °C), and (g) presence of prescribed fire at a site where B = burnt, U = unburnt.

To further investigate the effect of location, the data collected from the field, together with derived climate and vegetation variables were plotted on maps to allow visual investigation of spatial patterns. This step was particularly important for sites in NSW because pre-fire and post-fire data were collected at the same time but from different locations. In this instance, the effect of location on differences in ET can possibly be misinterpreted as the effect of a prescribed fire. Two examples of these maps for sites in NSW are provided in Figure 7 and for sites in Victoria in Figure 8.

The elevation of sites in NSW was lower near the coast (dark blue) and for northerly sites (mid-blue) and greater towards the south west corner (light blue, Figure 7a). Long-term rainfall (df95) showed a similar pattern with rainfall increasing towards the southwest corner (lighter blue, Figure 7b). This distribution reflects the use of gridded climate data (SILO) in the model. The observations from sites in Victoria appeared to be more randomly distributed (Figure 8). No obvious patterns or similarities were observed for other variables in either state.

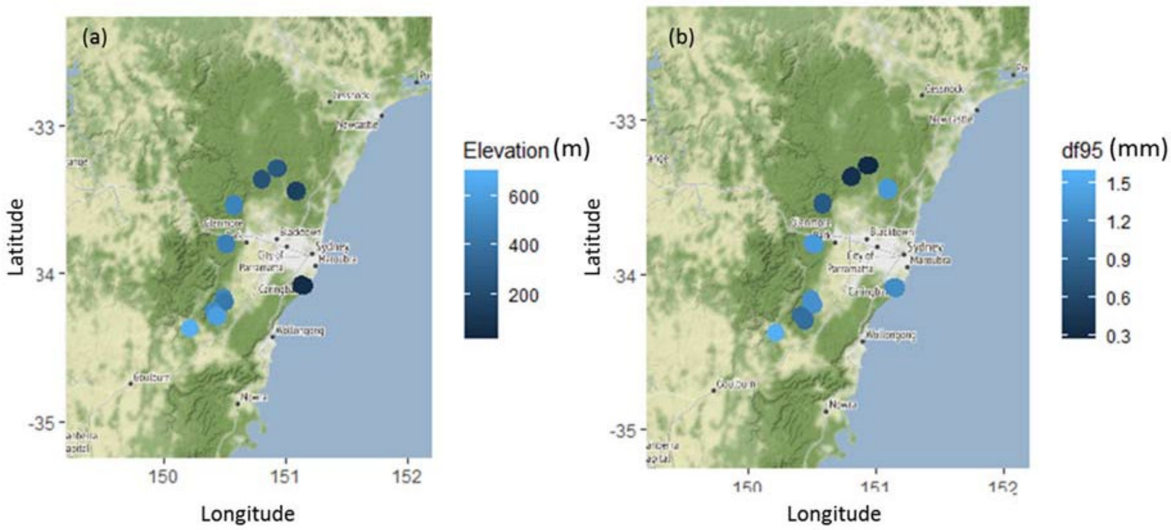

Figure 7: Examples of spatial distribution of (a) elevation above sea level (m) and (b) discount value for precipitation at the 95% confidence interval (df95, mm) for sites sampled in NSW.

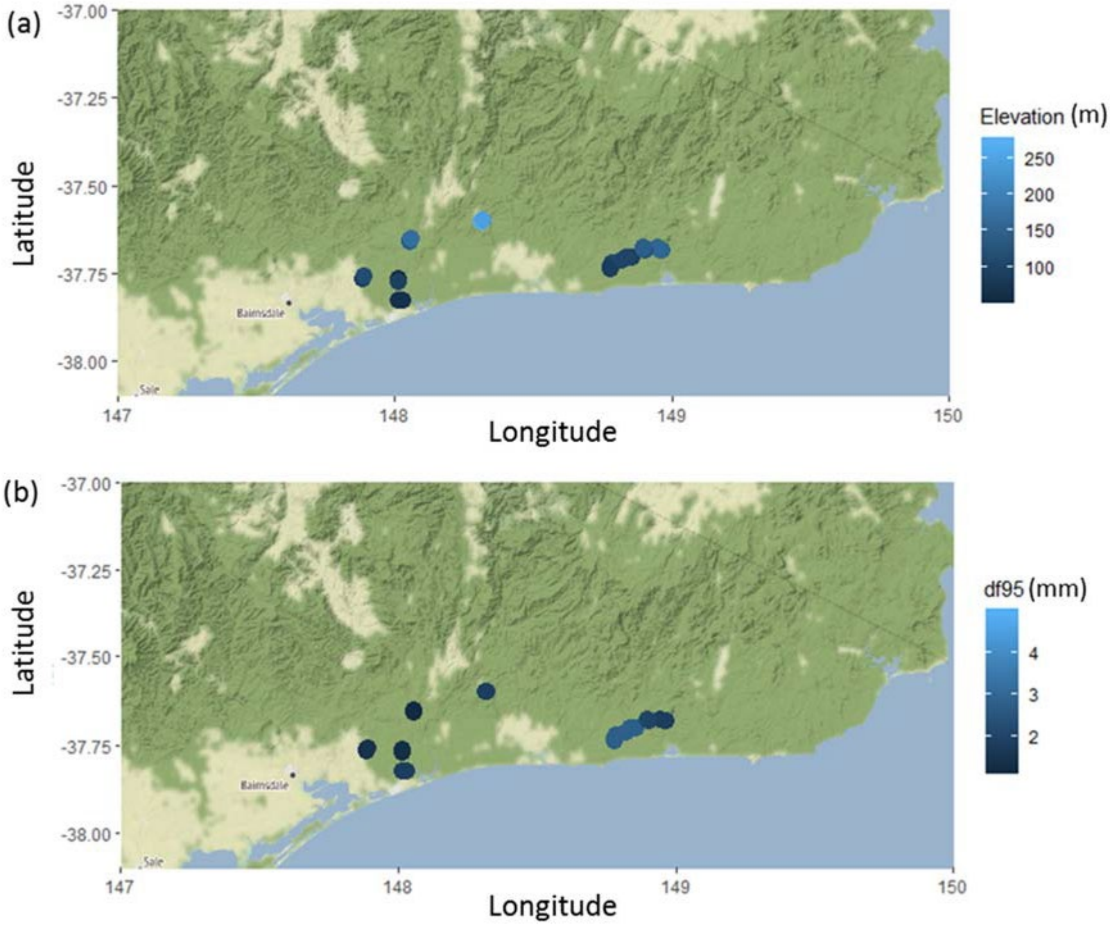

Figure 8: Examples of spatial distribution of (a) elevation above sea level (m), and (b) discount value for precipitation at the 95% confidence interval (df95, mm) for sites sampled in Victoria.

4. CONCLUSIONS AND NEXT STEPS

The use of satellite imagery combined with data collected from the field in a GAM showed that prescribed burning had an effect on ET in forested sites in NSW and Victoria. The change in ET due to prescribed burning was stronger for sites in Victoria than in NSW, however, this might be an effect of temporal and/or satellite differences not accounted for by GAMs. Vegetation (EVI) and climatic variables (solar radiation, df5 and df 95) were the best predictors for changes in ET with prescribed burning. None of the soil (C:N) or terrain variables (slope, aspect, elevation) were identified as being important factors for detecting change in ET.

Despite the promise shown by using this type of modelling approach, the analysis and comparison process was challenging because pre-fire and post-fire data were collected using different formats (before and after prescribed burning and in unburnt and burnt plots) and in different years. There were limitations to this study as no hydrological data was available for the sites which would have allowed changes to ET to be interpreted according to processes associated with the water cycle. If more accurate predictions and validation of ET are required additional data (e.g. streamflow, groundwater levels, water lost through evaporation) is still necessary despite the time and cost involved in collection of this type of information.

5. ACKNOWLEDGEMENTS

The authors would like to acknowledge Danica Parnell from The University of Sydney for formatting and editing this report and technical assistance. They would also like to acknowledge past members of the Fire Group from the University of Sydney for their help with collecting and collating field data.

5. REFERENCES

1. Bailey TC, Barcellos C, Krzanowski WJ (2005) Use of spatial factors in the analysis of heavy metals in sediments in a Brazilian coastal region. *Environmetrics: The Official Journal of the International Environmetrics Society* 16**,** 563-572.

2. Beesley C, Frost A, Zajaczkowski J (2009) A comparison of the BAWAP and SILO spatially interpolated daily rainfall datasets. 18th World IMACS/MODSIM Congress, Cairns, Australia, Citeseer, 13-17.

3. Bell T, Parnell D, Possell M (2018) Sampling and data analysis of field site in NSW, Bushfire and Natural Hazards CRC Milestone report, p. 23.

4. Bell T, Parnell D, Possell M (2020) Sampling and data analysis of field sites of 40 prescribed burns, Bushfire and Natural Hazards CRC Milestone report, p. 23.

5. Bond-Lamberty B, Peckham SD, Gower ST, Ewers BE (2009) Effects of fire on regional evapotranspiration in the central Canadian boreal forest. *Global Change Biology* 15**,** 1242-1254.

6. Cawson J, Sheridan G, Smith H, Lane P (2012) Surface runoff and erosion after prescribed burning and the effect of different fire regimes in forests and shrublands: a review. *International Journal of Wildland Fire* 21**,** 857-872.

7. Drexler JZ, Snyder RL, Spano D, Paw U KT (2004) A review of models and micrometeorological methods used to estimate wetland evapotranspiration. *Hydrological Processes* 18**,** 2071-2101.

8. Feikema PM, Sheridan GJ, Argent RM, Lane PNJ, Grayson RB (2011) Estimating catchment-scale impacts of wildfire on sediment and nutrient loads using the E2 catchment modelling framework. *Environmental Modelling & Software* 26**,** 913-928.

9. Gao Y, Long D, Li ZL (2008) Estimation of daily actual evapotranspiration from remotely sensed data under complex terrain over the upper Chao river basin in North China. *International Journal of Remote Sensing* 29**,** 3295-3315.

10. Geoscience Australia (2015) Digital Elevation Model (DEM) of Australia derived from LiDAR 5 Metre Grid. Geoscience Australia, Canberra. http://pid.geoscience.gov.au/dataset/ga/89644

11. Gharun M, Possell M, Bell T (2015) Variability in soil and fuel properties at different spatial scales after prescribed burning. Bushfire and Natural Hazards CRC Milestone report, p. 19.

12. Gharun M, Possell M, Vervoort RW, Adams MA, Bell TL (2018) Can a growth model be used to describe forest carbon and water balance after fuel reduction burning in temperate forests? *Science of the Total Environment* 615**,** 1000-1009.

13. Glenn, E. P., Huete, A. R., Nagler, P. L., Hirschboeck, K. K. & Brown, P. 2007. Integrating remote sensing and ground methods to estimate evapotranspiration. *Critical Reviews in Plant Sciences,* 26**,** 139-168.

14. Glenn EP, Mexicano L, Garcia-Hernandez J, Nagler PL, Gomez-Sapiens MM, Tang D, Lomeli MA, Ramirez-Hernandez J, Zamora-Arroyo F (2013) Evapotranspiration and water balance of an anthropogenic coastal desert wetland: responses to fire, inflows and salinities. *Ecological Engineering* 59**,** 176-184.

15. Huete AR (1988) A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment* 25**,** 295-309.

16. Huete A, Didan K, Miura T, Rodriguez EP, Gao X, Ferreira LG (2002) Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment* 83**,** 195-213.

17. Hutley L, O'Grady A, Eamus D (2001) Monsoonal influences on evapotranspiration of savanna vegetation of northern Australia. *Oecologia* 126**,** 434-443.

18. Jeffrey SJ, Carter JO, Moodie KB, Beswick AR (2001) Using spatial interpolation to construct a comprehensive archive of Australian climate data. *Environmental Modelling & Software* 16**,** 309-330.

19. Lane PNJ, Feikema PM, Sherwin CB, Peel MC, Freebairn AC (2010) Modelling the long term water yield impact of wildfire and other forest disturbance in Eucalypt forests. *Environmental Modelling & Software* 25**,** 467-478.

20. Langhans C, Smith HG, Chong DM, Nyman P, Lane PNJ, Sheridan GJ (2016) A model for assessing water quality risk in catchments prone to wildfire. *Journal of Hydrology* 534**,** 407-426.

21. Lenters JD, Cutrell GJ, Istanbulluogl, E, Scott DT, Herrman KS, Irmak A, Eisenhauer D (2011) Seasonal energy and water balance of a *Phragmites australis*-dominated wetland in the Republican River basin of south-central Nebraska (USA). *Journal of Hydrology* 408**,** 19-34.

22. Liu C, Zhang D, Liu X, Zhao C (2012) Spatial and temporal change in the potential evapotranspiration sensitivity to meteorological factors in China (1960-2007). *Journal of Geographical Sciences* 22**,** 3-14.

23. Lu D, Mausel P, Brondízio E, Moran E (2004) Change detection techniques. International *Journal of Remote Sensing* 25, 2365-2407.

24. Montes-Helu M, Kolb T, Dore S, Sullivan B, Hart S, Koch G, Hungate BA (2009) Persistent effects of fire-induced vegetation change on energy partitioning and evapotranspiration in ponderosa pine forests. *Agricultural and Forest Meteorology* 149**,** 491-500.

25. Mould D, Frahm E, Salzmann T, Miegel K, Acreman M (2010) Evaluating the use of diurnal groundwater fluctuations for estimating evapotranspiration in wetland environments: case studies in southeast England and northeast Germany. *Ecohydrology* 3**,** 294-305.

26. Nagler PL, Cleverly J, Glenn E, Lampkin D, Huete A, Wan Z (2005) Predicting riparian evapotranspiration from MODIS vegetation indices and meteorological data. *Remote Sensing of Environment* 94**,** 17-30.

27. Pereira LS, Perrier A, Allen RG, Alves I (1999) Evapotranspiration: concepts and future trends. *Journal of Irrigation and Drainage Engineering* 125**,** 45-51.

28. Pettorelli N, Vik JO, Mysterud A, Gaillard J-M, Tucker CJ, Stenseth NC (2005) Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in Ecology and Evolution* 20**,** 503-510.

29. Rahman A, Sims D, Cordova V, El-Masri B (2005) Potential of MODIS EVI and surface temperature for directly estimating per-pixel ecosystem C fluxes. *Geophysical Research Letters* 32, L19404.

30. Rana G, Katerji N (2000) Measurement and estimation of actual evapotranspiration in the field under Mediterranean climate: a review. *European Journal of Agronomy* 13**,** 125-153.

31. Running S, Mu Q, Zhao M (2017) MOD16A2 MODIS/Terra Net Evapotranspiration 8 - Day L4 Global 500 m SIN Grid V006. Distributed by NASA EOSDIS Land Processes DAAC, https://doi.org/10.5067/MODIS/MOD16A2.006

32. Smith HG, Sheridan GJ, Lane PNJ, Nyman P, Haydon S (2011) Wildfire effects on water quality in forest catchments: A review with implications for water supply. *Journal of Hydrology* 396**,** 170-192.

33. Wang Y-G, Kuhnert P, Henderson B (2011) Load estimation with uncertainties from opportunistic sampling data–a semiparametric approach. *Journal of Hydrology* 396**,** 148-157.

34. Wood SN (2008) Fast stable direct fitting and smoothness selection for generalized additive models. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 70**,** 495-518.

35. Wood SN (2017) *Generalized Additive Models: An Introduction with R*. 2nd ed., Chapman and Hall/CRC, 476 p.

36. Xue J, Su B (2017) Significant remote sensing vegetation indices: a review of developments and applications. *Journal of Sensors* 2017, Article ID 1353691.

37. Yang F, White MA, Michaelis AR, Ichii K, Hashimoto H, Votava P, Zhu A-X, Nemani RR (2006) Prediction of continental-scale evapotranspiration by combining MODIS and AmeriFlux data through support vector machine. *IEEE Transactions on Geoscience and Remote Sensing* 44**,** 3452-3461.