Title:

Inferring drought and heat sensitivity across a Mediterranean forest region in southwest Western Australia: a comparison of approaches

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Abstract

Changes in climate trends and extreme climatic events are increasingly impacting on forests around the world. In order to better understand how and where major ecological and climatic changes will affect our forested ecosystems, tools based on landscape sensitivity analysis need to be developed to help inform sustainable forest management.

This study was undertaken in the Northern Jarrah Forest (NJF) region in the Mediterranean climate of southwest Western Australia. Extreme drought and multiple heatwaves in 2010/11 resulted in large-scale tree canopy dieback in the NJF. In this study, we used Landsat satellite imagery to (i) accurately map the damaged areas, (ii) produce a damage probability model, and (iii) compare the model with a probability model derived from data collected through an airborne flight survey. We found that the Landsat-derived Normalized Difference Vegetation Index (NDVI) was a good indicator of drought/heat induced damage in the NJF region. Both probability models identified the same set of topography and climate-related factors for determining the probability of drought/heat damage within the landscape. Extrapolation of the Landsat satellite method-based model, however, produced a more deterministic and useful drought/heat damage sensitivity map for the NJF region. The techniques and tools developed, and applied, in this study can readily be transferred to other regions around the world and can assist in
the sustainable management and timely climate adaptation efforts to accommodate our
future forests.

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**Key words**

climate change; extreme events; remote sensing; Northern Jarrah Forest; tree canopy
dieback and damage; NDVI; Landsat and airplane data; tree damage; forest collapse;
management tools; bias sensitivity analysis; spatial extrapolation; manual delineation

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Introduction

Declines in forest health and resilience have been increasingly reported around the world (Allen et al., 2010; Peng et al., 2011; Anderegg et al., 2013; Reyer et al., 2015). In many instances, changes in climate trends and/or extreme climatic events have been earmarked as significant contributors to the observed tree health declines and mortality (Allen et al., 2010; Carnicer et al., 2011; Peng et al., 2011; Brouwers et al., 2012; Anderegg et al., 2013; Brouwers et al., 2013; Williams et al., 2013; Matusick et al., 2014). Consequently, forest ecosystems may undergo significant changes in species composition (Barbeta et al., 2013; Ruiz-Benito et al., 2013; Williams et al., 2013), with dominant canopy trees being replaced by more resilient individuals and/or species (Cavin et al., 2013; Rigling et al., 2013), and changes in forest structure (Matusick et al., 2013). The rate of the climatic changes and the increasing frequency of extreme events, however, is such that many species might not have the ability to adapt, which could result in the loss of biodiversity (Mantyka-Pringle et al., 2011) and potentially a reduction in the carbon storage potential of forests (Arnone III et al., 2008; Huang and Anderegg, 2012).

There is an increasing need to develop robust tools and techniques at the landscape-scale that can be used in climate change adaptation and mitigation efforts and the sustainable management of forested ecosystems (Lindner et al., 2010). Extrapolation of findings from small local to large regional scales, however, remains an ongoing challenge (Wu and Hobbs, 2002; Miller et al., 2004; Turner, 2005; Wu et al., 2006; Wu, 2013).
Advances have been made in this field of research (Miller et al., 2004; Turner, 2005; Wu et al., 2006), including a suite of modelling techniques such as multilevel statistical models that are now widely used in landscape ecological studies (Wu et al., 2006). Opportunities for validation, and the evaluation, of these models developed at local scales and their suitability for extrapolation across regional scales are, however, often lacking (Li and Wu, 2006). Transparent model evaluation processes are therefore needed for building confidence in spatial models, and to determine their applicability for the development of predictive tools to assist in regional forest management (Brouwers et al., 2010). This study aims to address these issues.

Many studies have used remote sensing (RS) approaches to map damage from extreme climatic events across forested landscapes, for instance, using satellite imagery to map hurricane (Wang et al., 2010) and ice storm damage (Stueve et al., 2007; Shi et al., 2013), and using aircraft acquired imagery to map drought/heat (Brouwers et al., 2013; Matusick et al., 2013) and frost damage (Matusick et al., 2014). Determining where, and how, these types of events will impact on forest ecosystems in the future is an ongoing challenge (Allen et al., 2010; Medlyn et al., 2011).

Models derived from field, observation, and/or satellite data can assist in developing a better understanding of the sensitivity of forests to climate-driven change. For example, observed damage patterns caused by extreme climatic events can be related to landscape specific factors (e.g., topography and geology) (e.g., Stueve et al., 2007; Brouwers et al., 2013; Shi et al., 2013). From these relationships, models can be developed that can assist
with identifying areas within the wider landscape that are likely to undergo significant changes in the future (Brouwers et al., 2013). Particularly forests that are situated in areas that are projected to become more frequently exposed to extreme climatic events and that show a persistent change-trend in average climate can benefit from this approach (Brouwers et al., 2013).

Globally, Mediterranean climate regions cover approximately 1.3% of the terrestrial land surface (based on Köppen-Geiger climate classification (code Csa and Csb) following Peel et al. (2007)). Mediterranean regions have been undergoing significant climatic changes in the past and these changes are expected to continue into the future, including a higher frequency of extreme climatic events such as prolonged droughts and heat waves (CSIRO and BOM, 2007; CSIRO and BOM, 2008; Giorgi and Lionello, 2008; Klausmeyer and Shaw, 2009; IPCC, 2013). The drought and heatwaves that occurred across the Mediterranean southwest of Western Australia (SWWA) in 2010 and early-2011 (hereafter described as the ‘2010/11 drought/heat’) (BOM, 2011a; BOM, 2011b; Evans and Lyons, 2013), provided an unique opportunity to determine the importance of predisposing factors of the widespread tree dieback and mortality that was observed across the Northern Jarrah Forest (NJF) region (Brouwers et al., 2013; Matusick et al., 2013). Brouwers et al. (2013), utilising an airborne remote sensing approach (i.e., visual examination supported by georeferenced oblique photography from a plane), provided the first insights into which landscape related factors were likely predisposing trees to the observed crown dieback response. Where the NJF region is projected to experience more frequent and severe extreme climatic events (CSIRO and BOM, 2007; CSIRO and BOM,
2008), these landscape-related factors were used to develop a statistical model to serve as an indicative management tool for inferring climate change sensitivity across the NJF region. In response to these investigations, the Forest Management Branch of the Western Australia Department of Parks and Wildlife (DPaW) initiated a satellite remote sensing study to improve the model-based management tool that was developed by Brouwers et al. (2013). They used satellite remotely sensed data (i.e., Landsat satellite imagery) and a larger-scale forest sample area within the NJF region to map the extent of the tree dieback damage across the forest estate (FE, see Figure 1), and equally developed a statistical model for inferring climate change sensitivity. This work provided a rare opportunity to perform a comparative analysis of the airborne remote sensing approach conducted by Brouwers et al. (2013) and the satellite remote sensing approach conducted by DPaW. This study aimed (1) to develop a robust data processing and modelling strategy to accurately map the 2010/11 drought/heat affected areas across the NJF region using Landsat satellite imagery; (2) to develop an accurate statistical probability model for inferring combined drought and heat sensitivity across the region; and (3) to perform a comparative analysis of the Brouwers et al. 2013 airborne and the DPaW satellite method-based models for monitoring canopy damage and inferring combined drought and heat sensitivity. We conducted comparisons using statistical model goodness-of-fit tests and sample bias analysis, and in doing so, we provide useful tools to progress the sustainable management of our future forests in the face of progressive environmental change.
Methods

Study region and sample area

The Northern Jarrah Forest (NJF) region, as defined by the Interim Biogeographic Regionalisation of Australia (IBRA) (Australian Government, 2012), is located in the SWWA (Latitude 30° 45 - 33° 30'S and Longitude 115° 52 - 117° 5'E) (Figure 1). The region has a Mediterranean climate that is characterised by warm to hot, dry summers (average daily temperatures: 22-23 °C, average total rainfall: 40-55 mm) and mild to cool, wet winters (average daily temperatures: 10-12 °C, average total rainfall: 400-550 mm) (derived from gridded climatology for Australia (Jones et al., 2009)). The NJF region is characterised by a distinct ridge (i.e., scarp) along the western edge averaging 300 m in elevation. The native vegetation in the more densely forested and wetter western part of the NJF region predominantly consists of forest dominated by *Eucalyptus marginata* Sm. (jarrah) and to a lesser extent *Corymbia calophylla* (Lindl.) K.D.Hill & L.A.S.Johnson (marri). In the more fragmented forest and drier eastern side of the NJF region (Figure 1), a variety of more drought tolerant *Eucalyptus* species are common including *E. wandoo* Blakely (wandoor), *E. accedens* W.Fitzg. (powderbark wandoo), and *E. loxophleba* Benth. (York gum). See Brouwers et al. (2013) for a more details of the NJF region, its climate trends and projections, the geology, and the dominant vegetation.

#Figure 1 approximately here#
The forest estate (FE) that was used as the forest sample area in this study falls entirely within the boundaries of the NJF region (Figure 1). The FE is crown land held by the State of Western Australia that is managed by the DPaW, and mainly consists of jarrah and marri dominated forest. The major considerations for using the FE as the forest sample area were the availability of detailed spatial records of forest management, mining and fire incidence in this area. This provided the opportunity to avoid misclassification in the automated processing of drought/heat affected areas by excluding forest areas affected by these non-climatic factors. Furthermore, the larger extent of the FE forest sample, compared to the flight path (FLP) derived forest sample used in the Brouwers et al. 2013 study (see Figure 1), provided the opportunity to perform a comparative analysis between the results of both studies.

Landsat data processing and validation

The Landsat 5 Thematic Mapper imagery used in this study was downloaded from the United States Geological Survey (USGS) website (http://glovis.usgs.gov/) and included tiles from path 112, rows 82 and 83, captured on 18/01/11, 23/3/2011, and 08/04/11 (i.e., six image tiles in total). Later date images were not available and/or had too much cloud cover obscuring the area of interest. The first rains after the 2010/11 drought/heat event was recorded in April 2011, but average monthly rainfall was not achieved until June 2011 (Ruthrof et al., 2015).
To make the Landsat image tiles comparable for analysis, the following corrections were implemented. First, the images were standardised using the SUN_CORRECT software program that performs corrections for: (i) gain and offset (i.e., top of atmosphere), (ii) sun angle and distance, and the (iii) bi-directional reflectance distribution function (BRDF) correction (Wu and Danaher, 2001). The image tiles were further corrected for varying terrain illumination using the C-correct method (Wu et al., 2004). The image tiles were then mosaicked to form three seamless image datasets for January, March and April 2011. For this process, tile 112/82 was placed on top of tile 112/83, and any overlapping areas from tile 112/83 were erased to provide three seamless dataset.

To ensure the response of the drought/heat impacts on the vegetation was maximized, only the January and April Landsat 2011 images were used to map the tree dieback. Furthermore, to select the most accurate forest area for the analysis (i.e., forested areas primarily affected by the 2010/11 drought/heat), the following areas were removed from the imagery: (1) all areas outside the forest estate boundaries (Figure 1), (2) water bodies, (3) cloud in the Landsat images, (4) known areas of non-forest vegetation, (5) logging areas, (6) mining areas, and (7) areas affected by fire. Datasets 5, 6, and 7 included areas that were affected between 18 January and 8 April 2011 by the described non-drought disturbances. Datasets 1, 2, 4, 5, 6, and 7 were derived from official digital datasets provided and used by DPaW, and dataset 3 was derived by visual analysis of the Landsat images and manual delineation.
In the effort to accurately map the areas affected by the extreme climatic conditions of 2010/11 across the FE (Aim 1), two vegetation indices (i.e., NDVI and i35), which are described below, were used. The digital information of the processed Landsat images was used to calculate these indices and produce a total of four vegetation index value maps (two each for January and April). The red (B3) and near-infrared (B4) bands were used to calculate the ‘greenness’ index: Normalized Difference Vegetation Index (NDVI) (formula: \( \frac{(B4 - B3)}{(B4 + B3)} \); range: -1 to 1, with 0 generally representing bare ground and 0.7 representing lush green vegetation). The red (B3) and middle-infrared (B5) bands were used to calculate a ‘cover’ index, i35, commonly used by the DPaW to detect vegetation cover change (formula: \( \frac{(B3 + B5)}{2} \); range: 1 – 255, with 20 generally representing dense vegetation and above 65 representing sparse or no vegetation). These two indices were chosen, because they were successfully used as change indicators in previous studies in similar environments: for NDVI see Freitas et al. (2005) and Boer et al. (2008), and for i35 see Allen and Beetson (1999), Wallace et al. (2006) and Robinson et al. (2012). The four index value maps were used to perform a change detection analysis, by simply deducting the January index values from the April values, creating two vegetation index change maps, one for NDVI and one for i35.

To evaluate the accuracy of the two indices in predicting areas where tree dieback due to the 2010/11 drought and heat occurred, 18 change maps were created (i.e., nine per index) that each represented negative change based on different threshold levels of changes in the index values. For NDVI, nine maps were created indicating a negative change in NDVI value with thresholds ranging from >0.07 (= map no. 7) negative change
in NDVI to $>0.15$ (= map no. 15) negative change. For i35, the same procedure was undertaken to create nine maps indicating a negative change in i35 value with thresholds ranging from $>3$ (= map no. 7) negative change in i35 to $>11$ (= map no. 15) negative change. To reduce the effects of the potential misclassifications of the damaged areas on the statistical analysis, only areas that were larger than 4 adjoining pixels ($>3,600 \text{ m}^2$) were included in the change maps. This strategy was adopted to find the optimum threshold level for each vegetation index that then could be used for comparing the performance of both indices and to determine the most accurate map for indicating areas where tree dieback occurred across the forest.

The accuracy assessment was undertaken using the 18 change maps (i.e., nine maps for each index, ranging from no. 7-15) and 35 validation sites representing on-ground delineations of affected forest areas (Average size: 45,420 m$^2$; size range: 3,719 - 142,059 m$^2$). The visually distinct boundaries between affected (i.e., brown/red) and unaffected (i.e., green) overstorey canopies (Matusick et al., 2013) were used by the ground surveyors to differentiate between affected and unaffected forest areas. The validation sites were recorded and delineated between 14/6/2011 – 22/11/2011 by walking around the distinctly affected forest patches with a differential GPS (Pathfinder Pro XRS receiver, Trimble Navigation Ltd., Sunnyvale, CA, USA). Contingency tables were developed for each of the 18 change maps including counts of whether or not the map accurately predicted the location of affected and unaffected forest areas. To represent the unaffected forest area, a 42.5 m (= diagonal of a 30x30m Landsat pixel) wide buffer at a distance of 42.5 m from the edge of each of the 35 validations sites was
created. For this accuracy assessment, the 35 delineations representing affected and
unaffected forest were used by overlaying them on top of each of the 18 change maps.
The number of intersections between the affected and unaffected area samples with the
predicted affected areas of the individual change maps were counted and put into 18
contingency tables. From these contingency tables, the percentage of agreement (i.e.
observed agreement) was calculated and plotted, and Chi-square (Kappa statistic) tests
were performed to assess the best-fitting predictive map.

The change map that was found to have the highest agreement with the validation dataset
was used to perform a landscape-scale assessment investigating the relationships between
the predicted dieback areas and landscape-related factors focussing on (i) geology, (ii)
topography, and (iii) climate. A presence-absence (i.e., affected vs. unaffected) analysis
was conducted similar to the one described in Brouwers et al. (2013). In this case, the
centre point of the affected areas, as predicted by the change map with the highest
agreement, was used as the ‘affected sample’ \(n = 944\). A random point sample within
the boundaries of the surrounding unaffected FE forest region (= total FE area minus the
predicted affected areas, water bodies, clouds, known areas of non-forest vegetation,
logging areas, mining areas, and areas affected by fire) was used as the ‘unaffected
sample’ \(n = 988\). Both these point samples were used to extract relevant landscape
related values from various datasets. These variables included topographic position
variables, i.e., elevation, slope, aspect, slope position, distance to valley, distance to
ridge, distance to rock, and distance to drainage as well as climatology including 30-year
average rainfall and temperature, and 30-year average seasonal temperature variables
(see further Table 1 in Brouwers et al. (2013) for more details). Additional to these variables, the climatology variables were expanded including 30-year average rainfall and minimum/maximum temperatures for the four separate seasons (i.e., summer (Dec - Feb), autumn (Mar - May), winter (Jun - August) and spring (Sep - Nov)). Furthermore, the variable ‘Soil type’, which was found by Brouwers et al. (2013) to be of potential importance in determining where in the landscape tree dieback had occurred, was converted into a continuous variable for inclusion in the logistic regression analysis. Based on the expert interpretation of the specific soil properties described in the ‘Soil-landscape’ dataset (see further Table 1 in Brouwers et al. (2013) for more details) following Harper et al. (2005), individual soil types were converted into a % of suitability for tree growth. This suitability estimate was based on general soil related limitations for growth of deep-rooted perennial plants, including presence of deep sandy profiles, salinity levels, presence of impenetrable rock layers at less than 2 m depth, and waterlogging potential (see further Harper et al. (2005)). Furthermore, slope angle, slope aspect, and latitude were used to generate layers representing the heat index (Parker, 1988; Enright et al., 1994) and incident radiation and heat load index (McCune and Keon, 2002) for the southern hemisphere NJF region. These indices represent a value for the level of sun exposure based on the underlying topography of the landscape. Finally, to compare the extreme weather impacts for the affected and unaffected forest samples used, differences for rainfall and temperature values calculated from the 30-year (1981-2010) averages and 2010/11 were compared.

Data processing and statistical analyses
All image processing and spatial analyses steps were undertaken using ERDAS ER Mapper 2011 (Intergraph Corporation, Madison, AL, USA) and ArcGIS 10 software (ESRI, Redlands, CA, USA). To investigate the configuration of the affected and unaffected sites within the forest sample area, a cluster analysis was performed using the Average nearest neighbor tool available in the ArcGIS Spatial statistics toolbox.

All other statistical analyses were performed using R (version 2.15.1, www.r-project.org). The continuous variables were found to be non-normally distributed and were individually analysed using independent 2-group Mann-Whitney-Wilcoxon tests. To develop an accurate statistical model for inferring combined drought and heat sensitivity across the region (Aim 2), the continuous variables were used to develop probability models by performing logistic regression and model selection analyses following Logan (2010). Model selection steps and criteria included: (i) investigation for multicollinearity between variables and subsequent variable selection based on Akaike information criterion for finite sample sizes ($AIC_c$), (ii) significance tests of parameters (model parameter estimates, $z$-statistic), (iii) model goodness-of-fit tests based on model residuals (le Cessie-van Houwelingen normal test, Pearson Chi-square $P$-value, dispersion estimation), (iv) variable goodness-of-fit tests based on residuals (log odds ratio linearity, influence measures Cook’s distance), and (v) model comparison based on $AIC_c$ and $R^2$ values. Models meeting all selection criteria were ultimately ranked based on best performance in the goodness-of-fit tests and the $R^2$ values.
To perform a comparative analysis of the Brouwers et al. 2013 airborne and the DPaW satellite method-based models and their applicability for inferring drought and heat sensitivity across the NJF region (Aim 3), the following steps were undertaken. First, the similarities and differences of both remote sensing approaches were assessed based on the fit of the logistic regression models developed in both approaches (i.e., the model selection criteria and $R^2$ values), and the importance of the landscape related predictor variables included in the models. Second, the differences between the model outcomes were compared for the entire NJF region using probability maps. For each approach, probability maps were created by inputting the logistic regression equation (Equation 1) and the related model estimates ($\beta_0$ and $\beta_i$) and variable values ($x_i$) of the best models in the Raster calculator tool in ArcGIS 10 (ESRI, Redlands, CA, USA).

\textbf{Equation 1} Logistic regression equation.

\[ y(x_i) = \frac{e^{\beta_0 + \beta_1 x_1 + \ldots + \beta_i x_i}}{1 + e^{\beta_0 + \beta_1 x_1 + \ldots + \beta_i x_i}} \]  

Finally a sample bias analysis was undertaken following Pressey et al. (2000) and Andrew et al. (2011). We used this analysis in a novel way to evaluate the effects of forest sample area size on the outcomes of the landscape assessments presented here and in Brouwers et al. (2013). In this case, the forest sample area used in this study (i.e., forest estate (FE)) and in Brouwers et al. (2013) (i.e., flight path (FLP)), was compared with the forested area of the entire NJF region (dark + darkest grey, Figure 1). For this purpose, the frequency distribution of values for the landscape factors that were found to be important in the logistic regression analysis were compared for each forest sample area.
and the entire forested NJF region. The bias was calculated by taking the median value of
the frequency distribution of each forest sample and the entire forested NJF region and
expressing these as the percentage of the full range of values represented by the NJF
region. The percentage bias was then calculated by deducting the median percentage for
the NJF region with the median percentage of each forest sample area (Pressey et al.,
2000). Bias values were used to compare the level of over or underestimation of the
individual samples in relation to the NJF region, and to infer the effects this might have
had on using the individual logistic models for creating the drought/heat damage
probability maps. Based on these combined comparative analyses, the usefulness of both
remote sensing approaches for inferring combined drought and heat sensitivity across the
NJF region was assessed.

Results

Map Selection

The accuracy assessment of the change maps that were created for each vegetation index
found that the map representing a negative change of >0.10 in NDVI (i.e., NDVI change
map no. 10, see Figure 2), most accurately matched the on-ground delineations of
affected areas and the surrounding unaffected forest (Observed agreement: 83\%, Cohen’s
kappa: Z = 5.498, P = <0.001, Estimate = 0.66, indicating ‘Substantial agreement’
following Landis and Koch (1977)). Negative changes in NDVI from 0.10 and up were
therefore assumed to most accurately identify areas of tree dieback in the NJF. NDVI
change map no. 10 was consequently used for further analysis. Based on this map, the amount of area that suffered tree dieback during the 2010/11 drought and heat event was estimated to be 2,244 ha for the FE area (Figure 3). When extrapolating, this translates in approximately 4,711 ha of damaged forest across the NJF region, of which most has likely been permanently changed based on the tree mortality rate of 26% reported in Matusick et al. 2013.

Site sample configuration

The affected sites were found to be clustered within the FE forest sample area (Nearest Neighbor Ratio: 0.541, $z = -28.789$, $P < 0.001$, $n = 944$), indicating a spatial correlation between affected areas. The unaffected sites were found to display a dispersed pattern within the FE forest sample area (Nearest Neighbor Ratio: 1.185, $z = 11.581$, $P < 0.001$, $n = 988$), indicating an unbiased sample and representation of the unaffected FE forest area.

Climatic conditions in 2010/11
The extreme 2010/11 drought/heat weather conditions that were experienced were comparable for the affected and unaffected sites across the FE forest sample ($n = 1932$; affected: 944, unaffected: 988). In both cases, total and seasonal rainfall was reduced by 46% in 2010/11 compared to the 30-year average (1981-2010) of 966 mm and 853 mm for affected and unaffected areas, respectively. Higher average temperatures and the extreme heat experienced during the summer of 2010/11 were also comparable across the sites. Affected and unaffected sites experienced an increase in average temperatures of 2.7 and 2.5% compared to the 1981-2010 30-year average of 16.7 and 16.6 °C, respectively. Indicating the extreme hot weather conditions during the 2010/11 summer, maximum temperatures experienced at affected and unaffected sites showed increases of 5.3 and 4.7% in average maximum daily summer temperatures compared to the 30-year average daily summer maxima of 29.9 and 30.3 °C, respectively. Additionally, minimum daily summer temperatures were found to be 11.6 and 11.5% higher compared to the 30-year average daily summer minima of 14.9 and 14.7 °C for affected and unaffected sites, respectively, indicating the lesser cooling of the atmosphere during the night in the summer of 2010/11.

Landscape variable relationships

The additional seasonal climatology and soil suitability variables as well as the incident radiation, heat load, and heat index did not significantly improve the models. The best
performing (i.e., best-fit) model, based on performance comparison of the goodness-of-fit
tests and the highest $R^2$ value, included the landscape related variables: elevation, slope,
distance to rock (i.e., Euclidean distance from an affected site to the nearest rocky
outcrop in the landscape), and 30 year averages for rainfall and temperature (Table 1).
This model was found to include the same explanatory variables as the best-fit model
found in Brouwers et al. (2013). This indicates the suitability of this set of landscape
related variables (see Table 1) as predictors of drought/heat sensitivity in the NJF region.

Differences between the best-fit Table 1 and the best-fit model found in Brouwers et al.
(2013) were primarily the higher explanatory power of the Table 1 satellite method-based
model compared to the airborne method-based model ($R^2 = 0.35$ vs. 0.15, respectively;
Table 1 and see Table 4 in Brouwers et al. (2013)), and the order of importance of the
explanatory variables within these models. The order of importance of the explanatory
variables in the Table 1 model was, from high to low; average rainfall (explaining 15% of
the variation in the dataset ($R^2 = 0.15$)), slope, distance to rock, average temperature, and
elevation. For the Brouwers et al. (2013) model this order was, from high to low; distance
to rock, average rainfall, elevation, slope, and average temperature (see Table 4 in
Brouwers et al. (2013)).

#Figure 4a, b approximately here#

The probability map comparison shows that the satellite method-based model indicates
the sensitivity of areas within the landscape for drought/heat damage with a higher
certainty (i.e., more defined black/dark colouring indicates higher probability for damage) (Figure 4a, b). Compared to the airborne model-based map (Figure 4a), the satellite model-based map (Figure 4b) more clearly indicates and delineates the most sensitive areas in the NJF region, and more clearly shows the higher sensitivity of the western half compared to the eastern half of the NJF region. Because of this higher discriminative power, as an indicative management tool, the satellite model-based map (Figure 4b) is likely to be more valuable for directing targeted on-ground monitoring and management purposes.

Sample bias

The FLP : FE : NJF forest area ratio was 1 : 6.5 : 13.5. Overall, both forest samples represented the NJF region relatively well (bias < 0.02), displaying similar frequency curves for the individual topographical variables (Figure 5a, b). However, both forest samples displayed a larger bias towards the higher rainfall areas represented in the western part of the NJF region (bias > 0.09; Table 2). This is further highlighted in the poorer parallel fit shown by the frequency curves for average annual rainfall (Figure 5c). Nevertheless, compared to the FLP bias values, all FE values were closer to 0, indicating that the FE forest sample used in this study displayed an overall better representation of the NJF region compared to the FLP forest sample used in Brouwers et al. (2013) (Table 2).
Discussion

The differences between the airborne examination by plane and the Landsat satellite remote sensing approaches are diverse as indicated in our comparative study (Appendix 1). Nonetheless, both approaches demonstrated that they could be used to identify the likely predisposing landscape related factors where drought/heat damage occurred. For constructing an accurate predictive sensitivity model for the entire NJF region, however, we demonstrated through the adoption of a robust comparative analysis approach that the higher accuracy was achieved by using the Landsat satellite-derived dataset. The primary reason for achieving this higher accuracy was the opportunity to include a larger forest sample area when using Landsat satellite imagery compared to conducting an airborne monitoring survey by plane. The larger forest sample area resulted in a better representation of the important landscape-related characteristics of the NJF region, which translated into a higher accuracy of the model estimates and consequently a more useful indicative sensitivity map (Figure 4b).

An ongoing challenge in landscape ecological studies is to extrapolate results obtained at small spatial scales across the wider landscape (Wu and Hobbs, 2002; Miller et al., 2004; Wu et al., 2006). In our study, we developed a statistical model based on the FE forest sample area (darkest grey, Figure 1) and used this model to produce a sensitivity map for
the entire NJF region (Figure 4b). To compare this model and the model developed in Brouwers et al. (2013) and to justify extrapolation of our model results, we performed an effective and simple sample bias analysis following Pressey et al. (2000) looking at the potential influence of the spatial scale of the study samples that were used. This analysis revealed that the model developed with the larger FE forest sample area (~537,161 ha), more accurately represented the topography and climatology of the forested NJF region (~1,127,600 ha), resulting in a predictive sensitivity map with a higher discriminative ability (Figure 4b). This indicates that when considering extrapolation of modelling results, care should be taken whether the sample area is representative of the larger region of interest. The sample bias analysis we adopted could routinely be applied for determining an appropriate sample size for spatial studies that aim to provide tools for managers of large forested regions.

In our study, the model based on the FE sample showed the smallest bias values compared to the entire NJF region. However, the predictive map resulting from the extrapolation of the FE model across the entire NJF region needs to be interpreted with caution. The bias analysis clearly indicated that the FE sample overrepresented the wetter western side of the NJF region. The predictive map therefore is likely to underestimate the probability of damage in the fragmented forest in the drier eastern part of the NJF region (as is shown by no/low probability of damage in Figure 4b). Nonetheless, the damage probability map is still a useful management tool for indicating drought/heat damage vulnerability across the wetter and higher western scarp of the NJF region, and as
such can contribute to targeted climate change adaptation and mitigation actions in this highly vulnerable region.

Similar to work undertaken on bark-beetle damage (Meddens et al., 2013) and ice storm affected forests (Stueve et al., 2007), our study showed that Landsat satellite-derived NDVI can be used to identify areas where drought/heat damage occurred across the NJF region. The ‘greenness’ index NDVI outperformed the ‘cover’ index i35 in this case, which was most probably due to the damage symptoms and the time lapse between the images used in the change analysis. NDVI is specifically sensitive to picking up changes in ‘greenness’ of leaves (Tucker, 1979), which was an evident process that occurred across the NJF region in response to the drought and heat (Matusick et al., 2013). The lesser performance of i35 was likely due to the specific date of the Landsat images that were used in the change analysis. The April image revealed little significant structural changes as the affected trees were observed to be still carrying their dead leaves in April 2011, and did not start shedding them until May/June 2011 (G. Matusick, personal observation). Consequently, if later-date unclouded images for June/July 2011 had been available, the performance of i35 relative to NDVI would probably have improved as a predictor of affected forest areas, and therefore should routinely be considered in this type of study.

Long-term average rainfall and temperature were found to be significant predictors of areas where tree dieback damage was predicted across the FE. The inclusion of more detailed climatic and soil related predictor variables, however, did not significantly
contribute to explaining the observed damage across the landscape. In Brouwers et al. (2013), the reliability of the modelled dataset used to compute these predictor variables was discussed. Our current analysis revealed that the difference between temperature averages for affected and unaffected sites (0.1°C) lay well within the uncertainty range of the parent dataset used (0.7 – 1.0 °C) (Jones et al., 2009), again urging caution in using this variable as an individual landscape indicator for the observed damage. The logistic regression analysis also revealed the lesser importance and strength of this variable compared to the other landscape indicators. For rainfall, however, a higher confidence was obtained in comparison with results from Brouwers et al. (2013). We found that the difference between averages for affected and unaffected sites was 113.0 mm, which falls well outside the uncertainty range of the parent dataset (19.6 – 21.2 mm) (Jones et al., 2009). Backed by our logistic regression analysis, this indicates that 30-year average rainfall can confidently be used as one of the primary landscape indicators for where drought/heat damage might occur in the FE and the wider NJF region in the future.

Managers are increasingly in need of tools to assist in climate change mitigation and adaptation strategies for forest ecosystems (Millar et al., 2007; Lindner et al., 2010). In this study, two management tools were developed. One robust data processing and modeling tool to map where tree dieback damage occurred after the climatic events of 2010/11 in the FE (Figure 3), and one predictive tool to identify areas where changes are likely to occur across the NJF region in the future (Figure 4b). The operational mapping tool that was developed uses satellite remote sensing techniques to rapidly produce maps that indicate where drought/heat related tree damage has occurred in the forest estate
within the NJF region. The accuracy of the maps was tested using an on-ground collected validation set. In this analysis, NDVI was found to be a better index for predicting damage. The accuracy assessment based on the on-ground delineated validation sites found that the optimum NDVI change threshold was 0.10. For the NJF region this threshold seems appropriate, however, this threshold should be determined for each forested region and each cause of canopy dieback separately. The approach we presented here can assist with this, as it is transferable and repeatable at other geographical locations.

The observed agreement between the satellite-derived dataset and the validation sites was 83\% (Kappa = 0.66). The level of accuracy may be improved by more precisely matching the timing of the on-ground delineations of the affected areas with the capture dates of the satellite imagery. In our study, there was a significant gap between the April 2011 image used for the change detection and the dates of the on-ground delineations (Jun – Nov 2011). It is therefore plausible that some of the affected areas that were delineated on the ground were not present or were smaller in the satellite imagery, as the emergence of affected areas continued until the beginning of May 2011 (Matusick et al., 2013). The estimate of the area affected in the FE based on the change map we produced in this study (Figure 3) is therefore likely to be an underestimation. Additionally, we found a clear pattern of a higher damage incidence in the western and central part of the FE, and less to no tree damage in the east (Figure 3). Extrapolation of the damage estimate based on findings for the FE area across the entire NJF region is therefore likely to be an overestimation. This issue has likely also resulted in an overestimation of the affected
area reported by Matusick et al. (2013). Altogether, the total forest area that suffered significant tree dieback and mortality in the NJF region is therefore predicted to be at the lower end of the range between our estimate of 4,711 ha and the 16,515 ha estimated by Matusick et al. (2013).

To date, forest and vegetation cover changes have been monitored over time using Landsat imagery at global (Hansen et al., 2013) and local scales (e.g., Wallace et al., 2006). The causes of the observed changes indicated by these types of study are, however, likely to be diverse because of the long timeframe used (>10 years) and consequently the occurrence of multiple disturbance events during this period. Our approach was different where it started with the disturbance event (i.e., one-year heat/drought) and used the observed effects to make predictions of sensitivity and vulnerability of the forest in the future based on the specific underlying landscape characteristics. Determining relationships between damage patterns from extreme climatic events with specific landscape characteristics are useful in itself (e.g., Stueve et al., 2007), but even more so if they can be used to construct predictive tools that can assist forest management.

The SWWA has experienced a continuous decline in rainfall and increases in temperature since the mid-1970s (Bates et al., 2008). The decreasing health of several tree species and changes within associated fauna and soil communities have been linked with these changing climatic conditions (Cai et al., 2010; Brouwers et al., 2012; Moore et al., 2013) and might represent early indications of a decrease in the resilience of the forest.
ecosystem (Reyer et al., 2015). The climatic changes in SWWA are projected to continue (CSIRO and BOM, 2007) as well as for Mediterranean climate regions around the world (Klausmeyer and Shaw, 2009; IPCC, 2013). It is therefore imperative for forest managers to have suitable tools that can assist in timely climate change adaptation strategies. The techniques and tools developed, and applied, in this study are readily transferable and can assist in the sustainable management of forests in this time of rapid environmental change.

Acknowledgements

We like to thank the Forest Management Branch of the Western Australia Department of Parks and Wildlife (DPaW) for supporting this work. For providing spatial datasets we like to thank Graeme Behn, Geoffrey Banks, Michael Raykos, Greg Strelein, John Dunn, and Martin Rayner from (DPaW); Damian Shepherd and Jeffrey Watson from the Department of Agriculture and Food; Bradley Evans (Murdoch University); and Peter Biggs and Michael Raupach from CSIRO Marine and Atmospheric Research for access to the Australian Water Availability Project (AWAP) datasets. We further like to thank Graeme Behn and Graham Loewenthal (DPaW) for helping with data processing, and Margaret Andrew (Murdoch University) for useful suggestions on data analysis. This research was undertaken as part of the State Centre of Excellence for Climate Change, Woodland and Forest Health.
Table 1 Logistic regression best-fit model including landscape related factors associated with the tree dieback observed in the forest estate and Northern Jarrah Forest region. The model was compiled using the variables that were found to be the most important in Brouwers et al. (2013).

<table>
<thead>
<tr>
<th>Model y(x_i)</th>
<th>β_i</th>
<th>S.E. β_i</th>
<th>z</th>
<th>P</th>
<th>Odds</th>
<th>C.I.</th>
<th>AIC_c</th>
<th>R^2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elevation (m)</td>
<td>0.0043</td>
<td>0.0011</td>
<td>3.862</td>
<td>&lt;0.001</td>
<td>1.0044</td>
<td>1.0021</td>
<td>1.0066</td>
<td>1760.8</td>
</tr>
<tr>
<td>Slope (°)</td>
<td>0.1784</td>
<td>0.0138</td>
<td>12.914</td>
<td>&lt;0.001</td>
<td>1.1953</td>
<td>1.1634</td>
<td>1.2281</td>
<td></td>
</tr>
<tr>
<td>Distance to rock (m)</td>
<td>-0.0004</td>
<td>0.0001</td>
<td>-8.773</td>
<td>&lt;0.001</td>
<td>0.9996</td>
<td>0.9995</td>
<td>0.9997</td>
<td></td>
</tr>
<tr>
<td>Av rainfall (1981-2010) (mm)</td>
<td>0.0115</td>
<td>0.0007</td>
<td>16.516</td>
<td>&lt;0.001</td>
<td>1.0116</td>
<td>1.0102</td>
<td>1.0130</td>
<td></td>
</tr>
<tr>
<td>Av temperature (1981-2010) (°C)</td>
<td>0.8222</td>
<td>0.1435</td>
<td>5.732</td>
<td>&lt;0.001</td>
<td>2.2755</td>
<td>1.7178</td>
<td>3.0143</td>
<td></td>
</tr>
<tr>
<td>Intercept (β_0)</td>
<td>-26.2800</td>
<td>2.8370</td>
<td>-9.263</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Model y(x_i): shows the variables and intercept included in the logistic regression model. β_i: indicates the slope and direction of the relationship for the individual variables with the observed tree dieback damage. S.E. β_i: Standard Error for β_i. Odds: indicates the odds ratio for tree dieback to take place for every unit increase of the variable. C.I.: 95% confidence interval for the Odds ratio. AIC_c: corrected Akaike Information Criterion. R^2: quantifies the explained variation by the model (range 0-1). Model presented passed all goodness-of-fit tests and assumptions following Logan (2010). Av: averages are based on annual data from 1981-2010. n = 1932 (affected: 944, unaffected: 988).
Table 2 Bias values for the forest sample area used in this study (FE) and in the Brouwers et al. (2013) study (FLP) in comparison to the whole NJF region (see also Figure 1). Bias values <0.05 (+ or -) indicate a good representation of the landscape variables within the samples (FE and FLP) compared to the entire NJF region.

<table>
<thead>
<tr>
<th>Sample</th>
<th>NJF</th>
<th>FE</th>
<th>FLP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Min</td>
<td>Max</td>
<td>Median</td>
</tr>
<tr>
<td>Distance to rock (m)</td>
<td>0</td>
<td>38,299</td>
<td>1,556</td>
</tr>
<tr>
<td>Av rainfall (1981-2010) (mm)</td>
<td>416</td>
<td>1,070</td>
<td>797</td>
</tr>
<tr>
<td>Elevation (m)</td>
<td>6</td>
<td>585</td>
<td>291</td>
</tr>
<tr>
<td>Slope (°)</td>
<td>0</td>
<td>54</td>
<td>3</td>
</tr>
<tr>
<td>Av temperature (1981-2010) (°C)</td>
<td>15</td>
<td>18</td>
<td>16.17</td>
</tr>
</tbody>
</table>

NJF: Northern Jarrah Forest IBRA region forest extent (~1,127,600 ha), FE: Forest Estate forest sample (~537,161 ha), FLP: Flight path forest sample (~83,313 ha). For Av temperature, Median = Mean.
Figure captions

**Figure 1** The study region situated in the southwest of Western Australia (SWWA). The black regions in the inset indicate Mediterranean climate conditions (Csa and Csb, following Peel *et al.*, 2007) in Australia. All shades of grey together indicate the remaining native vegetation in SWWA, which predominantly includes forest and shrubland. Light grey indicates all native vegetation outside the Northern Jarrah Forest (NJF) region, dark + darkest grey indicates the forested area within the NJF region (~1,127,600 ha), darkest grey indicates forest in the satellite-derived sample area (i.e., forest estate (FE) (~537,161 ha)). The thick black line indicates forest within the boundaries of the airborne-derived sample area used in Brouwers *et al.* (2013) (i.e., flight path (FLP) (~83,313 ha)). White areas primarily represent agricultural land and urban development.

**Figure 2** The percentage observed agreement between 35 on-ground delineations of drought affected and unaffected forest areas and the predictive maps representing different levels of change in NDVI or i35. NDVI map numbers represent a negative change in NDVI values between January and April ranging from >0.07 (= map no. 7) to >0.15 (= map no. 15) negative change. i35 map numbers represent a negative change in i35 values for the same period ranging from >3 (= map no. 7) to >11 (= map no. 15) negative change.
**Figure 3** Predicted areas based on the satellite data that suffered tree dieback (black) after the 2010/11 extreme drought and heat conditions within the forest estate (FE) forest sample area (dark grey). Black areas are based on the map indicating a >0.10 negative change in NDVI (map no. 10, NDVI, see Figure 2). All shades of grey together indicate the remaining native vegetation in SWWA. White areas primarily represent agricultural land and urban development.

**Figure 4** Probability maps indicating where forest change is likely to occur in the NJF region in the future. The maps were computed using Equation 1 and the variable estimates of the best-fit models using the flight path sample (derived through the airborne method) (a; see top model ($R^2 = 0.15$), Table 4 in Brouwers et al. (2013)) and the Forest Estate sample (derived through the satellite method) (b: Table 1). These two models include exactly the same variables, but, because of the different sample areas used, they differ in the values of the variable estimates. The light grey underlying layer indicates the remaining native vegetation in SWWA. White areas primarily represent agricultural land and urban development.

**Figure 5** The frequency distribution for the landscape variables elevation (a), slope (b), and 30-year average annual rainfall (c) as represented by the different forest sample areas. NJF: Northern Jarrah Forest IBRA region forest extent (~1,127,600 ha), FE: Forest
Estate forest sample (~537,161 ha), FLP: Flight path forest sample (~83,313 ha). The x-axes were truncated for clarity. For (c), the x-axis values represent groups with an interval of 25 mm (e.g., 850 represents areas receiving an average of 825-849 mm on an annual basis).
Figure 2
Figure 4a, b
Figure 5a, b, c
Appendix 1 Comparison between the different remote sensing approaches that were adopted to monitor drought and heat effects across the Northern Jarrah Forest in this and the Brouwers et al. (2013) study. Landsat 5 image availability is discontinued and Landsat 7 imagery is affected by data gaps at the edges, which is affecting the area that can be monitored. After pre-processing, all Landsat images from the different satellites are comparable and interchangeable.

<table>
<thead>
<tr>
<th></th>
<th>Satellite</th>
<th>Airborne</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(Landsat 5, 7, 8)</td>
<td>(Cessna plane)</td>
</tr>
<tr>
<td>Delineation method</td>
<td>Automatic</td>
<td>Manual</td>
</tr>
<tr>
<td></td>
<td>(Inferred from Landsat spectral data, processed with ERDAS ER Mapper 2011; see further Methods)</td>
<td>(Visual examination and georeferenced photography from a plane, processed through manual delineation in OziExplorer GIS, version 3.95.5; see further Matusick et al. (2013))</td>
</tr>
<tr>
<td>Precision of delineation</td>
<td>30x30m square pixel</td>
<td>Actual</td>
</tr>
<tr>
<td>Initial data capture, processing, and validation time</td>
<td>160 h (including 60 h ground-truthing and validation)</td>
<td>105 h (including 60 h ground-truthing and validation)</td>
</tr>
<tr>
<td>Repeat data capture and processing time</td>
<td>10 h</td>
<td>35 h</td>
</tr>
<tr>
<td>Cost</td>
<td>Free download</td>
<td>$1,100 AUD per flight</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>---------------</td>
<td>-----------------------</td>
</tr>
<tr>
<td>Data capture flexibility</td>
<td>One image every 8 days (based on Landsat 7 and 8 combined, else 16 days) with potential for cloud cover issues.</td>
<td>Flexible and cloud cover issues can be avoided</td>
</tr>
<tr>
<td>Area coverage</td>
<td>Unlimited</td>
<td>Limited: flight path field of view only</td>
</tr>
<tr>
<td>Ground-truth accuracy</td>
<td>83%</td>
<td>86%</td>
</tr>
</tbody>
</table>
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