# MAPPING OF FIRE SEVERITY AND COMPARISON OF SEVERITY INDICES ACROSS VEGETATION TYPES IN GIBRALTAR RANGE NATIONAL PARK, AUSTRALIA

Lalit Kumar *, Peter Clarke, Carlos Muñoz and Kirsten Knox

University of New England, School of Environmental and Rural Sciences. Armidale, NSW 2351, Australia-
(lkumar, pclarke1)@une.edu.au

**KEY WORDS:** Fire severity, Burn severity, Spectral Indices, NDVI, NBR

**ABSTRACT:**

The effect of fire on natural resources is termed "fire severity" and is related to the energy output of the fire. Recently the term "burn severity" has been introduced to identify the impacts of fire on soil and plants when the fire has been extinguished. This study addresses the assessment of a large wildfire in Gibraltar Range National Park, Australia, through remote sensing of fire severity and explores the spatial relationships between fire severity and biophysical factors. Burn severity indices were developed from Landsat TM satellite images using pre-fire and post-fire images. Reflectance values computed from Landsat Enhanced Thematic Mapper (ETM) images acquired before and after the fire were used to estimate the Normalised Burn Ratio (NBR), which incorporates the near and mid infrared bands. Spatial distribution of ΔNBR data were calibrated with field observations and threshold values of burn severity were used to classify fire severity into 5 severity classes per vegetation type. ΔNBR values were extracted from different representative fire severities and spatial relationships were developed between ΔNBR and vegetation type, fuel type, fire danger index, time since fire, fire frequency, slope and rockiness in order to account for variables influencing fire severity patterns. General linear models and tests of significance were used to ascertain whether the effects of individual factors were statistically significant. The various models tested showed that no single factor (weather, fuel or landscape) accounted for the burn severity pattern. Fire weather and vegetation type were found to be the key factors in the models.

## 1. INTRODUCTION

Fire severity is predicted to increase over the next 50 years with a 15-70% increase in the number of days of cert high to extreme Forest Fire Danger Index (FFDI) (Hennessy *et al.*, 2005). FIRESCAPE modelling for the ACT has also simulated a 12-70% increase in fire return and a 7-12% increase in fire-line intensity (Cary, 2002).

Fire intensity is a component of fire regime that affects both the ecological and geophysical condition of fire prone landscapes on the New England Tablelands of Australia. Inappropriate fire regimes are listed as a key threatening process to biodiversity in the state of New South Wales hence understanding fire regimes and their biological impacts are critical to the development of fire management plans. One aspect of fire regime which we know little about is the spatial variation in fire intensity/severity and its short and long-term biological effect when combined with other components of fire regime.

### 1.1 Assessment of burn severity

The term 'fire severity' refers to the effect of fire on natural resources such as plants and soil and is related to the energy output of fire known as fire intensity measured as Kw m$^{-2}$ (Lentile *et al.*, 2006). The term 'fire severity' is more usually applied to the immediate effect of the fire and therefore its behaviour across the fire ground.

More recently the term 'burn severity' has been introduced to identify the impacts of fire on soil and plants when the fire is extinguished (Lentile *et al.*, 2006). The term burn severity expresses the physical, chemical and biological changes on a site as a result of fire disturbance (White *et al.*, 1996). Burn severity has routinely been assessed by on ground measurements in forest ecosystems in the northern hemisphere but has only been recently used to assessed burn severity in Australian vegetation (Hammill and Bradstock, 2006). A range of on ground measures have typically been used to quantify burn severity including: tree mortality, decrease in plant cover, soil transformation, and burn tip measures (de Santis and Chuvieco, 2007). One of the most widely used measures is the 'Composite Burn Index' (CBI) developed by the US Forest Service (Key and Benson, 2006). The CBI was specifically designed to examine the biological effects of fire at a scale (30m) that then could be used to provide an index for extrapolation using moderate resolution remote sensing. The scores are numeric and range from 0 to 3 across a gradient from unburned to extremely burned.

### 1.2 Remote sensing of burn severity

From an ecological point of view, it is vital to establish whether high severity wildfires have distinctive ecological effects that cannot be easily predicted from the knowledge of more frequent, low-severity events (Wimberly and Reilly, 2007). However, a large amount of data is required to characterise the spatial patterns of wildfires and assess their ecological effects. Since patterns of burn severity can be quantified as changes in spectral signatures following the fire, satellite data constitutes an important tool for monitoring fire effects (Cocke *et al.*, 2005; Key and Benson, 2002). One of the primary effects of fire on vegetation is its reduction of leaf water content, which should be able to be inferred from canopy spectral reflectance properties in the near infrared bands (Tucker, 1980). In addition to the changes in reflectance due to the decrease on leaf water

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* Corresponding author. This is useful to know for communication with the appropriate person in cases with more than one author.

content, a number of spectral changes occur due to the fire consuming the vegetation, destroying chlorophyll, leaving the soil bare, charring the roots and altering soil moisture (Escuin *et al.*, 2008). Reduction of chlorophyll absorption causes an increased reflectance in the visible electromagnetic region, along with leaf tissue damage originating a decrease in reflectance in the near infrared (NIR) region (Jensen, 2000). Furthermore, burned areas are partially or totally devoid of green vegetation and characterised by dry soil surfaces, originating decreased absorption in the visible and SWIR wavelengths. Thus, these wavelengths are sensitive to plant cell structure and have been used effectively to monitor forest mortality due to fire (Rogan and Yool, 2001). In addition, with a decline in crown shadow and a decrease in canopy moisture as a result of fire effects, mid-infrared (MIR) reflectance normally increases (van Wagtendonk *et al.*, 2004).

Remote sensing has been used extensively to map burn severity because changes in cover are known to be related to changes in reflectance (Lentile *et al.*, 2006). An important factor in evaluating burn severity is the fact that the spectral signature of stressed vegetation after a fire may well indicate not only the level of stress but also the type of stress (Iverson *et al.*, 1989).

Approaches to remotely assess burn severity using multi-spectral data have included the use of single date, post-burn and bi-temporal, pre- and post-burn indices. Even though bi-temporal indices can introduce errors caused by differences in sensor calibration and atmospheric effects, they can be minimised by means of radiometric and atmospheric corrections and mapping results can be improved on spectrally similar areas by providing a pre-burn image (Epting *et al.*, 2005).

The ability of spectral indices combining the red and infrared regions to identify burnt areas has been successfully tested. Studies using the Normalised Difference Vegetation Index (NDVI) include the work done by Díaz-Delgado *et al.* (2003), Escuin *et al.* (2008), Hammill and Bradstock (2006), and Lozano *et al.* (2007). However, the potential of the MIR to discriminate burnt areas has given place to the Normalised Burn Ratio (NBR) which has been specifically developed for mapping of burnt areas and burn severity (De Santis and Chuvieco, 2007; Escuin *et al.*, 2008; Key and Benson, 2002; Lozano *et al.*, 2007; van Wagtendonk *et al.*, 2004; Wimberly and Reilly, 2007).

This study addresses the assessment of a large wildfire in Gibraltar Range National Park, Australia, through remote sensing of fire severity using the NDVI and NBR developed from Landsat TM satellite images using pre-fire and post-fire images. Also, it explores the spatial relationships between fire severity and biophysical factors.

## 2. METHODOLOGY

### 2.1 Study area

The study area is located within the New England Tablelands (NET) Bioregion of eastern Australia (Figure 1). The area is within the Cfb (dry cool temperate) climate region which has an altitudinal range of 750-1500 m with rainfall varying from 1800 mm in the eastern sites to 750mm per year in the western site. Rainfall maxima are in summer (January). Five major sclerophyllous habitats occur in the Bioregion; grassy eucalypt open forests and woodlands, shrubby eucalypt open forests, dry heathlands and heathy eucalypt scrub, heathlands and

sedgelands and mesic tall eucalypt open forests. In addition, non sclerophyllous, warm and cool temperate rainforest are also widespread and are listed as World Heritage Rainforests.

These broad groups form distinct floristic associations that are related to climate gradients, lithology and local physiography. As a generalization, nutrient poor siliceous soils provide habitats for scleromorphic shrub-dominated woodlands and forests whilst the more clayey soils derived from metasediments and basalts support grassy woodlands and forests. Shrubs occur throughout the landscape but are less abundant and less species rich in the grassy woodlands which are excluded from the study.
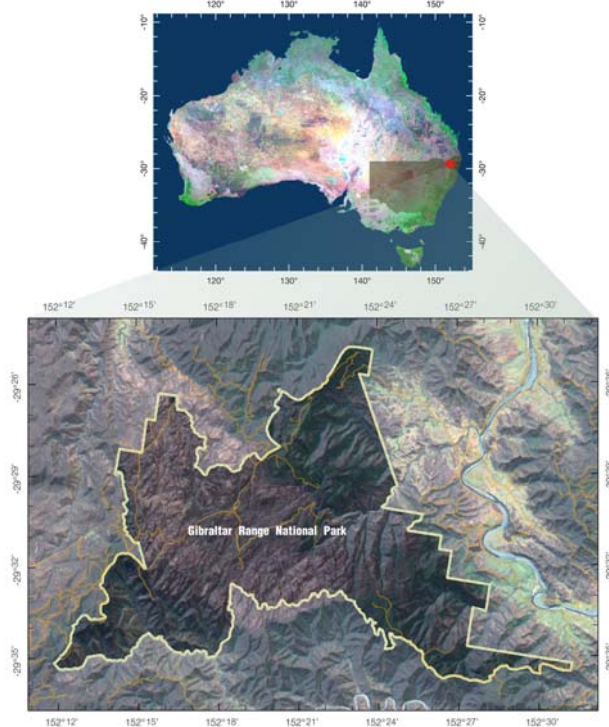


Figure 1. Location of Gibraltar Range National Park, New South Wales, Australia

### 2.2 Image processing

Landsat ETM images with a spatial resolution of 30 m were used for the purpose of this analysis. Two scenes, acquired in 10 July 2002 and 10 May 2003 (Path 089, Row 081) were used as pre-fire and post-fire images respectively. Both scenes were registered to each other and rectified to a Universal Transverse Mercator (UTM) grid, zone 56. The computation of spectral indices was carried out in ERDAS Imagine© 9.0 and spatial analysis was performed in ArcINFO© 9.0 and ArcGIS© 9.1.

In order to reduce the variability between scenes and be able to perform a multi-temporal analysis, we converted digital number values into surface reflectance values. Therefore, digital numbers were converted into at-satellite reflectance values according to the NASA (2007) and Chander and Markham (2003). This conversion involved the normalisation of the differences in sun-sensor geometry, sensor calibration, and atmospheric conditions. Next to the estimation of reflectance values, NDVI and NBR indices were computed for both pre-fire and post fire scenes:

$$NDVI = \frac{\rho 4 - \rho 3}{\rho 4 + \rho 3} \qquad (1)$$

Where $\rho 4$ and $\rho 3$ are the surface spectral reflectance measured in bands 4 (NIR) and 3 (RED) of the ETM sensor

and,

$$NBR = \frac{\rho 4 - \rho 7}{\rho 4 + \rho 7} * 1000 \qquad (2)$$

Where $\rho 4$ and $\rho 7$ are the surface spectral reflectance measured in bands 4 (NIR) and 7 (MIR) of the ETM sensor

The bi-temporal, differenced images ($\Delta$NDVI and $\Delta$NBR) where then estimated by substracting the post-fire spectral values from the pre-fire scene:

$$\Delta NDVI = NDVI_{prefire} - NDVI_{postfire} \qquad (3)$$

and,

$$\Delta NBR = NBR_{prefire} - NBR_{postfire} \qquad (4)$$

### 2.3 Field calibration

The link between field burn severity class, as identified by low level aerial photography and remote sensing burn severity indices was made by sampling polygons that had been classified into fire severity classes in each vegetation type. In independent training areas, a set of pixels was selected and the index values assigned to the ground burn severity classes. The mean values were then compared among the severity classes using a single factor ANOVA after normality and variance homogeneity assumptions were checked. The remote sensing index values were then used to define thresholds for classifying images based on the mean values for each field class. We used the mid point between each mean as the cut-point to bound each class following the method of Hammill and Bradstock (2006). Maps of the burn severity classes were taken into the field in July 2007 to verify the relationship between burn severity class and the amount of canopy damage still present five years after the fire. The proportions of each burn severity class, within each vegetation class, were calculated using a GIS.

### 2.4 Factors influencing burn severity

To assess the relationship between fire severity indices derived from remote sensing and environmental factors that may influence these patterns, GIS data on fire weather, standing fuel, physiography, and antecedent fire were assembled. Also, training areas were defined in known rocky areas and spectral statistics were estimated and used as input of a supervised classification to discriminate the rocky areas. An antecedent fire layer was derived from fire history layers prior to the landscape fire.

In the analyses, firstly, individual factors to assess if the effects were statistically significant using general linear models and

tests of significance were examined. Secondly, we used a modelling approach and fitted models with combinations of variables to examine which ones had the greatest information gain using an information theoretic approach (Burnham and Anderson, 2002). In these model selection approaches we used Akaike's Information Criterion (AIC) (Burnham and Anderson 2002) and compared a number of candidate models.

### 2.5 Validation

Validation points were distributed using a stratified random sampling. At least 10 points per severity class within 3 vegetation types were located. Due to the lack of validation points in the Rainforest, Hethlands and Grassy Woodlands, no accuracy assessment was carried out for these communities. Error matrices were calculated in order to estimate the overall accuracy and the kappa coefficient.

## 3. RESULTS AND DISCUSSION

### 3.1 Mapping of burn severity

The burn severity $\Delta$NBR and $\Delta$NVDI indices produced very similar results across vegetation types. However, since the NBR involves the use of infrared bands, showed a better performance on a small area covered by clouds; hence $\Delta$NBR results will be reported. There were pronounced differences (P<0.001) in the burn severity index across vegetation types with Dry Sclerophyll Forest and Rocky Outcrops having high mean indices whilst grassy forest had low indices reflecting the 'greening up' post fire.

Remote sensing $\Delta$NBR values for each major vegetation unit were found to overlap for each of the burn severity classes that were determined from aerial photography. However, the mean values for each of the classes differed significantly so that threshold ranges could be determined by midpoints between means (Table 1). The number of sites used for validation was limited by the post-fire aerial photography. Therefore, only classification accuracies for Dry Sclerophyll Forest, Wet Sclerophyll Forest and Rocky outcrop were evaluated. In the case of Rocky outcrop and Wet Sclerophyll forest, a few low severity areas were identified in the aerial photographs, therefore low and moderate severity classes were amalgamated.

| Vegetation type | Sites | ΔNBR Severity classes | | | |
|---|---|---|---|---|---|
| | | *U* | *L* | *M* | *H* |
| *HL* | 8 | <-178 | na | -52--178 | >-52 |
| *RO* | 7 | <110 | na | 110-188 | >188 |
| *DSF* | 14 | <76 | 76-159 | 159-284 | >284 |
| *WSF* | 13 | <41 | na | 41-74 | >74 |
| *RF* | 13 | <46 | 46-60 | 60-101 | >101 |
| *GW* | 4 | na | <221 | na | >221 |

Vegetation types: *HL* = Heathlands; *RO* = Rocky outcrop; *DSF* = Dry Sclerophyll Forest; *WSF* = Wet Sclerophyll Forest; *RF* = Rainforest; *GW* = Grassy Woodland. Burn severity classes: *U* = Unburnt; *L* = Low; *M* = Moderate; *H* = High

Table 1. ΔNBR threshold values used to classify satellite data and derive fire severity maps. Thresholds are midpoints between mean values for replicated training sites.

Spatial distribution of burn severity across vegetation types is shown in Figure 2 and the extent of area burned per burn severity level and vegetation community can be observed in Table 2. Dry Sclerophyll Forest and Wet Sclerophyll Forest were the most affected vegetation types in terms of burned area and burn severity level. However, the spatial pattern of burn severity was affected by fuel continuity and the presence or absence of exposed rocks.

| Vegetation Type | Burn severity class | | | | |
|---|---|---|---|---|---|
| | U | L | L-M | M | H |
| HL | 0 | 141 | 0 | 246 | 184 |
| RO | 62 | 0 | 42 | 0 | 2 |
| DSF | 1,778 | 2,166 | 0 | 3,868 | 3,415 |
| WSF | 1,341 | 0 | 463 | 0 | 1,784 |
| RF | 519 | 80 | 0 | 180 | 188 |
| GW | 623 | 0 | 0 | 0 | 149 |

Vegetation types: *HL* = Heathlands; *RO* = Rocky outcrop; *DSF* = Dry Sclerophyll Forest; *WSF* = Wet Sclerophyll Forest; *RF* = Rainforest; *GW* = Grassy Woodland. Burn severity classes: *U* = Unburnt; *L* = Low; *L-M* = Low to moderate; *M* = Moderate; *H* = High

Table 2. Extent of burned areas (ha) per vegetation type and severity class.

The influence of fuel continuity on the burn severity index was pronounced across most community types. In both Dry Sclerophyll Forest and Rocky Outcrops high levels of exposed rock decreased the fire severity index whereas in the Grassy Forests, Heaths and Wet Sclerophyll Forest it increased fire severity.
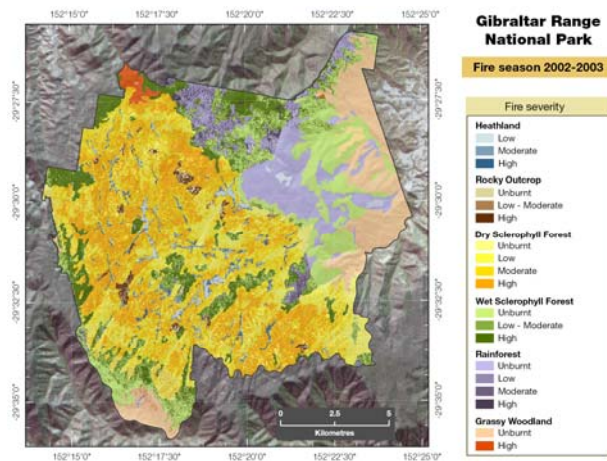


Figure 2. Burn severity classes for each vegetation class at Gibraltar Range national Park based on calibrated ΔNBR indices

### 3.2 Accuracy assessment

Higher overall accuracies were obtained for the Dry Sclerophyll Forest and Wet Sclerophyll Forest 73% and 70% respectively. The lowest accuracy was observed for the Rocky outcrop (52%). Error matrices and overall kappa coefficients are shown in Table 3, Table 4 and Table 5 for each assessed vegetation type.

| | HIGH | MODERATE | LOW | TOTAL |
|---|---|---|---|---|
| HIGH | 16 | 2 | 1 | 19 |
| MODERATE | 4 | 14 | 1 | 19 |
| LOW | 4 | 2 | 7 | 13 |
| TOTAL | 24 | 18 | 9 | |
| ACCURACY | 73% | | | |
| KAPPA | 0.58 | | | |

Table 3. Error matrix between ΔNBR and field observations for Dry Sclerophyll Forest, overall accuracy and overall kappa

| | HIGH | LOW-MODERATE | TOTAL |
|---|---|---|---|
| HIGH | 8 | 5 | 13 |
| LOW-MODERATE | 2 | 8 | 10 |
| TOTAL | 10 | 13 | |
| ACCURACY | 70% | | |
| KAPPA | 0.40 | | |

Table 4. Error matrix between ΔNBR and field observations for Wet Sclerophyll Forest, overall accuracy and overall kappa

| | HIGH | MODERATE | TOTAL |
|---|---|---|---|
| HIGH | 6 | 5 | 11 |
| MODERATE | 5 | 5 | 10 |
| TOTAL | 11 | 10 | |
| ACCURACY | 52% | | |
| KAPPA | 0.05 | | |

Table 5. Error matrix between ΔNBR and field observations for Rocky outcrop, overall accuracy and overall kappa

The obtained accuracies are slightly low if compared to previous works (Escuin *et al.*, 2008; Cocke *et al.*, 2005). However, those studies do not report on burn severity within different vegetation types, which may conduct to a better classification due to a similar burn severity response as result of homogeneous vegetation.

### 3.3 Modelling the cause of fire severity

Our modelling showed that no single factor (weather, fuel or landscape) accounted for the burn severity pattern. Both fire weather and type of vegetation were important factors in the model. More importantly our analyses showed interactive effects which means that each vegetation type responds differently in combinations with other variables. For example, increasing rockiness decreased severity in Dry Sclerophyll Forests, but increased severity in the Wet Sclerophyll Forest. Time since the previous fire did not appear to affect severity strongly in the more fire prone landscape but we had no data for < 8 years since the last fire. Areas with higher fire frequency tended to have higher burn severity. This suggests that frequent fire in the more mesic parts of the landscapes increases the severity of succeeding fires.

| MODEL | MODEL No. | AIC | Δ AIC |
|---|---|---|---|
| *FW + SF + P + AF* | 1 | 122702 | 0 |
| *FW + SF + P* | 2 | 122759 | 58 |
| *FW + SF* | 3 | 122876 | 175 |
| *FW* | 4 | 126197 | 3495 |

*FW* = Fire weather; *SF* = Standing fuels; *P* = Physiography; *AF* = Antecedent fire

Table 6. Models that best explain fire severity indices. Lowest AIC values are the best models. A change in AIC (ΔAIC) of < 10 is regarded as an appropriate alternate model

The high degree of fit for model No. 1 suggests that it could be feasible to infer past fire severity if there is knowledge about the FFDI over the duration of the burn and some information on antecedent fire history.

## 4. CONCLUSIONS

This study has shown it is possible to use remote sensing imagery to classify and map burn severity in different vegetation types on the New England Tablelands. We are aware of only one other study in Australia that has progressed fire severity mapping to this stage (see Hammill and Bradstock, 2006). Our results are comparable with their study in terms of the limitations and scope of mapping, but our study covers a wide range of community types.

Classification accuracy of burn severity could be improved by a) increasing the spatial resolution of imagery; however, this can result in loss of spectral resolution (e.g. SPOT5); b) collecting burn severity ground data for developing a specific field-based burn severity index. Future research in Gibraltar National Park should take into account these factors.

Results from this study can be incorporated into management strategies in terms of designing fire management zones and strategic burns.

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