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USING NDVI IMAGE TEXTURE ANALYSIS FOR BUSHFIRE-PRONE LANDSCAPE ASSESSMENT

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ABSTRACT: Bushfire, as a major external ecological factor, diversifies bushland environments. Monitoring bushfire-prone landscape patterns and vegetation recovery after fires is critical for the long-term bushland management. Landscape ecology studies using remotely sensed imagery have been effective to identify the relationship between landscape patterns and ecological processes. This paper uses the Normalised Difference Vegetation Index (NDVI) as a surrogate for vegetation biomass and applies two texture statistics to quantitatively examine biomass variability in bushfire-prone landscapes. Specifically, the texture number is used to describe landscape heterogeneity and post-fire vegetation recovery, and the fractal dimension is applied to evaluate landscape pattern changes with post-fire vegetation successional stages. Results show that bushland spatial patterns are heavily affected by bushfires and human disturbances, and the fractal dimension of post-fire vegetation decreases with successional stages. It is suggested that the use of NDVI image texture analysis is a potential technique to examine pre- and post-fire landscape changes, and these methods can be applied using remotely sensed imagery in a cost-effective way.

1. INTRODUCTION

Bushfires affect the distribution and evolution of vegetation communities and other ecosystem processes, and have far-reaching implications for bushfire-prone landscapes. In Australia, most vegetation types are fire adapted (Gill, 1981), and bushfire is a major factor for vegetation regeneration within the eucalypt forests (Florence, 1996). For example, during a post-fire recovery of tree crowns, the eucalypt may regrow more vigorously than it did before the fire. Trees may be defoliated and shrubs burnt back to the ground level, yet within only a few years, the tree crowns and understorey shrubs may have recovered their pre-fire state (Florence, 1996). Monitoring of landscape changes and vegetation successional stages is important for bushland management. Quantitative assessment of spatial heterogeneity is a useful means of increasing our understanding of bushfire-prone landscapes. Landscape ecology studies examining the relationship of landscape patterns and their changes on ecological processes, with remotely sensed imagery have been effective and successful at regional or local scales (e.g. Haines-Young et al., 1993; Frohn, 1998).

Previous research on the use of remotely sensed imagery in identifying vegetation changes between pre-fire and post-fire shows that biomass-based vegetation indices can be very useful (Marchetti et al., 1995). A commonly used vegetation index is the Normalised Difference Vegetation Index (NDVI). Heavily vegetated areas usually display high positive values, whereas high density residential areas have low NDVI values. Landscape ecology studies with NDVI images have been recently reported. For example, monitoring the changes of post-fire Mediterranean vegetation structure is feasible using a fractal analysis of an NDVI image derived from a Landsat Thematic Mapper (TM) image (Ricotta et al., 1998). Chuvieco (1999) describes and compares several texture statistics (e.g. spatial auto-correlation, diversity) to measure landscape pattern changes, using pre- and post-fire NDVI data derived from both TM and Advanced Very High Resolution Radiometer (AVHRR) images.

The purpose of this paper is to apply two image texture statistics, texture number and fractal dimension, to evaluate the bushfire-prone landscape heterogeneity and spatial pattern changes as post-fire vegetation undergoes recovery. Different areas of a bushfire-prone region are tested.

2. STUDY AREA AND DATA SOURCES

The Shire of Hornsby (Figure 1), located approximately 20 km north of the Sydney central business district, is a local government area of the state of New South Wales, Australia. The area is characterised by its diverse natural environment with extensive coverage of bushland. Bushlands provide habitats for flora and fauna, reduce soil erosion and protect water quality, but they are associated with significant bushfire hazard and risk (e.g. Conroy, 1996; Hornsby Shire Council, 1996).

Two primary data sources were used in this study: (1) a Landsat TM image captured on 9 November 1991, and (2) local fire history maps of 1989 and 1990 from Hornsby Bushfire Service. The TM image was resampled by the nearest-neighbour algorithm to an Australian Map Grid (AMG) coordinate system with a spatial resolution of 30 metres. An NDVI image was created from bands 3 and 4 of the Landsat TM: (TM4-TM3)/(TM4+TM3).

To quantitatively assess the bushfire-affected landscape, four different areas were used (Figure 1). Bushland A was burnt in the summer of 1989, two years before the TM image was captured, and Bushland B was burnt in the summer of 1990. Bushland C, without recent fires, represents an undisturbed vegetation structure, whereas the Residential area D represents the area where human impacts take place. Through visual inspection of the raw TM image, Bushland B can be discriminated from surrounding non-burnt areas. However, Bushland A cannot be easily identified from the image. Data sets to be analysed for Bushland A were carefully selected for two reasons. First, fire history maps are usually very generalised, so data generated by random sampling schemes may include many spots which were not burnt in a fire. Second, a bushfire generally does not burn all vegetation in a region. Bushfire behaviour depends on environmental factors, such as aspect, slope and elevation. Slopes which are generally in shade have cooler temperatures and vegetation there contains higher moisture. Some vegetation in valleys will not burn while trees on drier slopes are readily burnt. Therefore, samples for Bushland A were selected from bushland ridges.

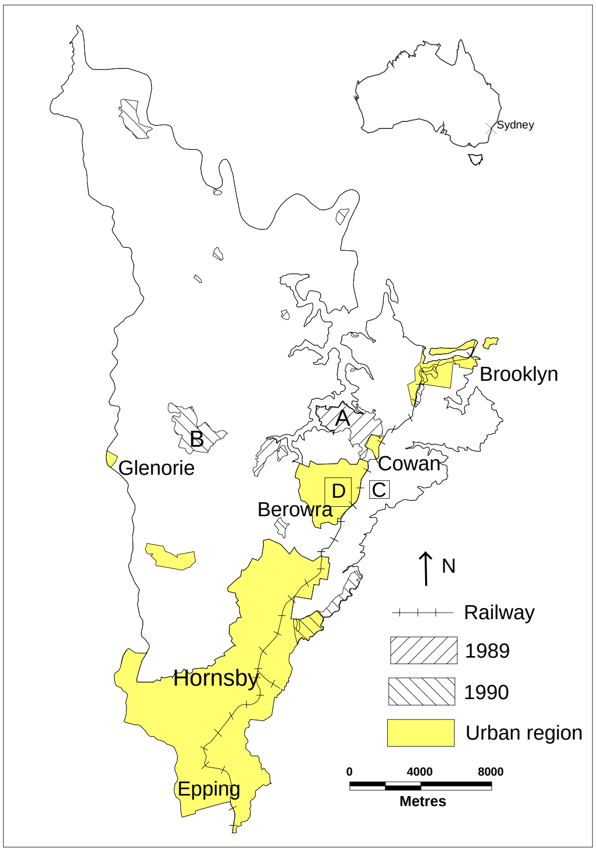
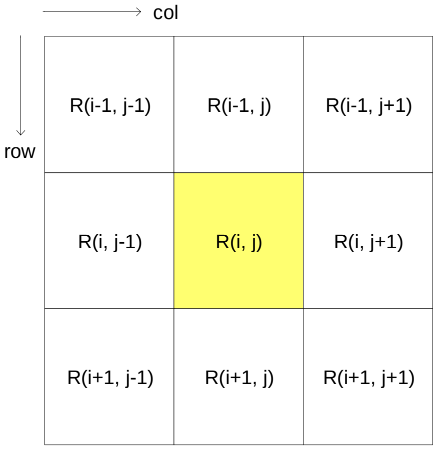


Figure 1. Shire of Hornsby and Bushfire Burnt Areas in 1989 and 1990.

3. METHODS

3.1 Texture Number (TN)

Many texture statistics have been applied to process digital imagery (e.g. Haralick et al., 1973). For example, in a landscape ecology study with an NDVI image, texture statistics have been used to create spatial information on vegetation biomass variability (Chuvieco, 1999). Due to its computational efficiency (Ricotta et al., 1996), the absolute difference statistic described by Rubin (1990) was chosen for use in this study. Using a 3×3 pixel window as a basic spatial unit, the statistic sums the absolute values of the differences between all horizontally and vertically adjacent pixels within a moving window and replaces the central pixel number with the calculated value. The TN of R(i, j) can be calculated as illustrated in Figure 2.



$$TN = \sum_{row=i-1}^{i+1} \sum_{col=j}^{j+1} |R(row,\ col-1) - R(row,\ col)| + \sum_{row=i}^{i+1} \sum_{col=j-1}^{j+1} |R(row-1,\ col) - R(row,\ col)| \quad (1)$$

Figure 2. Texture Number Calculation with a 3 × 3 Pixel Window.

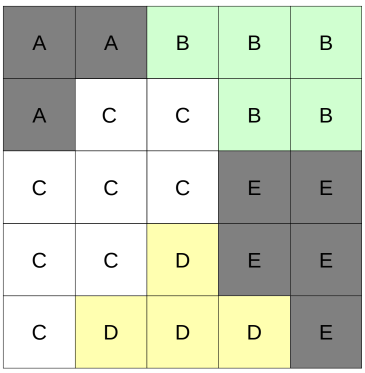
3.2 Fractal Dimension (D)

Research (e.g. De Cola, 1989; Turner, 1990) has shown that fractals can inform a great variety of landscape ecology problems because they can conveniently depict many of the irregular, fragmented patterns found in nature (Mandelbrot, 1983). Since ecosystems are open and dynamic systems, it could be expected that changes in the dynamics are reflected in corresponding spatial patterns. Fractal geometry can be used to objectively measure important aspects of complex vegetation patterns and to describe the underlying dynamics which give rise to these patterns (Hastings and Sugihara, 1993).

Fractal dimension is usually derived by computing the slope of a regression line between the natural logarithm of perimeter and area pairs calculated from the feature(s) of interest. This technique accounts only for patch shape and is generally only applied to large landscapes (Olsen et al., 1993). A non-regression method to calculate the fractal dimension for a small landscape, such as a classified image in a grid-based GIS, was discussed by Ricotta et al. (1998). The method takes patch geometry and patch juxtaposition into account. The equation for calculating the fractal dimension for individual patches in a gridded GIS layer is as follows:

$$D = 2 \times \ln(P/4) \ / \ \ln(A) \quad (2)$$

Where: A = total patch area, P = total patch perimeter, and D = fractal dimension. A more detailed explanation is given in Olsen et al. (1993) and Ricotta et al. (1998). The method calculates the fractal dimension of a sub-landscape. The calculation of *D* with a 5 × 5 pixel window sub-landscape is shown in Figure 3.



Patch	*Area*	*Perimeter*
A	3	8
B	5	10
C	8	14
D	4	10
E	5	10
Total	25	52

Landscape Fractal Dimension
D = 1.5937

Figure 3. Example of How the Fractal Dimension is Calculated Using a 5 × 5 Pixel Window.

Using the above equation, when a sub-landscape has only a single value, D is 1.0. On the other hand, for a highly heterogeneous sub-landscape composed of entirely different single cell patches (e.g. 25 different patches for a 5 × 5 window), D would be equal to 2. This sub-landscape represents the highest diversity possible and therefore has the highest fractal dimension possible (Ricotta et al., 1998).

4. ANALYSIS AND RESULTS

The possible range of NDVI is from -1.0 to 1.0. Before calculating the texture number and the fractal dimension, the initial NDVI image was scaled to an 8-bit image (0-255), with a value of 127 equal to a computed NDVI of zero. Two programs were written to calculate the texture statistics from the scaled NDVI image, and statistical analysis was conducted using MATLAB. The landscape heterogeneity of the four areas described above was quantified by calculating TN. Prior to calculation of the fractal dimension, a smoothing filter (i.e. 5×5 pixel window) was applied to the scaled NDVI image, to overcome the wide variability of the image. Three areas (i.e. Bushland A, Bushland B, and Bushland C) were used for the calculation of fractal dimension.

4.1 Using TN to Assess Landscape Heterogeneity under Bushfires and Human Perturbations

To compare the TN distribution for the four areas, histograms with 20 classes between maximum and minimum values are shown in Figure 4. Figure 5 shows the stratifications of the TN for the each area. Bushland C without fires in recent history exhibits the lowest TN values and variations of the value are low. On the other hand, the TN distribution for the residential cover type displays very large TN values with considerable variations. In the study area, bushland without recent fires tends to have a high degree of homogeneity, and residential area under intensive human activities results in spatial heterogeneity. These findings are in agreement with the results of Ricotta et al. (1996).

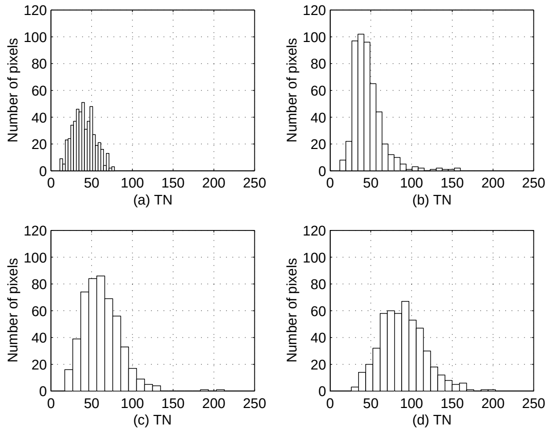


Figure 4. Histograms of the NDVI Image Texture Number for Four Areas. (a) Bushland C without fires, (b) Bushland A burnt in 1989, (c) Bushland B burnt in 1990, and (d) residential area.

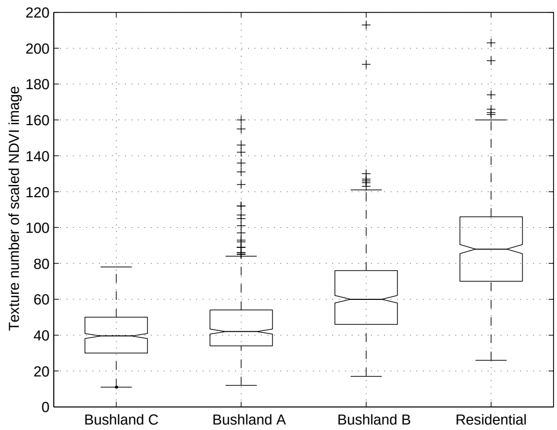


Figure 5. Notched Boxpots Show the Stratifications of the NDVI Image Texture Number for Four Areas. The box has lines at the lower quartile, median (notched line), and upper quartile values. Outliers are data with values beyond the ends of the whiskers and plotted as '+' symbols.

By comparing the TN values of Bushland A and Bushland B, the NDVI variability of Bushland B is much greater than that of Bushland A, indicating a great degree of spatial heterogeneity. The similar TN distributions of

Bushland C without fires and Bushland A suggest that Bushland A is close to homogeneous vegetation patterns after a two-year period of regeneration. Irregular patches of the land cover have exceedingly large TN values. The outliers of Bushland A imply that some fire scars in the sample areas still exist or may be due to other factors such as sandstone benching. Bushland B was burnt in the summer of 1990, about a year before the date of image acquisition, whereas Bushland A was burnt in 1989, about two years before the acquisition date of the image. Bushland A has had approximately double the time for bush regeneration than Bushland B, and therefore Bushland B retains more profound fire impacts. This analysis indicates that texture number could serve as a good indicator of vegetation regrowth to discriminate the phases of vegetation succession after fires.

4.2 Using Fractal Dimension to Assess Post-fire Vegetation Recovery

The distribution of fractal dimension for three different bushlands is shown in Figure 6. From sub-figure 6 (b), the median D for Bushland B burnt in 1990 is larger than that of Bushland C (without recent fires) and Bushland A (burnt in 1989), while Bushland C and Bushland A have very similar values and ranges. These results indicate that Bushland A, with a similar landscape arrangement to Bushland C, has recovered its spatial vegetation patterns two years after the fire. In contrast, one year after the fire Bushland B retains heterogeneous landscape patches and thus results in a very large D. These results imply that the D value associated with a bushland cover decreases with vegetation successional stages. Late successional patterns are less patchy than early successional patterns. Thus, D could be seen as an indicator to examine the dynamics of bushland vegetation recovery after fires.

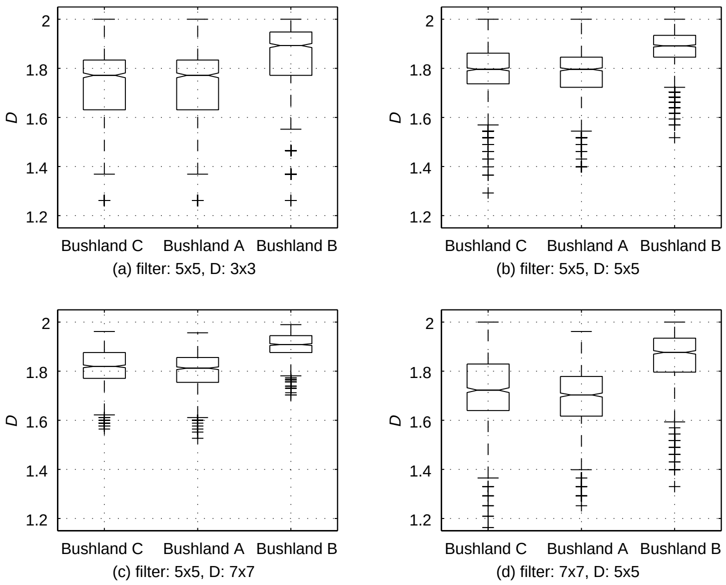


Figure 6. Fractal Dimension of the Scaled and Filtered NDVI Image Based on Different Window Sizes at Two Stages. First, a 5×5 window was used to decrease high variability of the input NDVI image, and 3×3 (a), 5×5 (b) and 7×7 (c) windows were tested to generate D. Second, 5×5 (b) and 7×7 (d) windows were used to decrease high variability of the input NDVI image while a 5×5 window was used to generate D.

The calculated fractal dimension values depend on the analysis (e.g. filtering) involved. The use of different window sizes in image texture analysis may generate different results. Therefore, a series of window sizes at both the filtering stage of the scaled NDVI image and for the calculation of D were tested. Two comparisons were tested. First, using a constant window size (5×5) to filter the scaled NDVI image, different window sizes (3×3, 5×5, and 7×7) were used to calculate D for the three bushland areas. Comparison of Figure 6 (a, b, c) shows the calculated median D for Bushland C and Bushland A (approximately 1.8) differed only slightly, and was consistently smaller than the calculated median D for Bushland B. In other words, D was relatively insensitive to different window sizes in the fractal calculation. Second, using two window sizes (5×5 and 7×7) to smooth a scaled NDVI image and the same window size (5×5) to generate D (Figure 6 (b, d)), a large filter window (i.e. 7×7) resulted in lower D values (approximately 1.7) for Bushland C and Bushland A, and a larger difference between these two areas and Bushland B. This also suggests that the spatial patterns of Bushland C and Bushland A tend to be more homogeneous than those of Bushland B.

5. CONCLUDING REMARKS

As a result of past bushfires, urban encroachment and bushland management practices, bushfire-prone landscapes have complex spatial patterns. Applications of a texture number and a fractal dimension to the three vegetation areas in this paper indicates that after bushfires landscape patterns tend to become more homogeneous as vegetation regenerates. This result agrees with previous observations in the forest of the Mediterranean region (Chuvieco, 1999). The use of texture statistics with an NDVI image to assess bushfire-prone landscapes has potential to quantitatively monitor landscape pattern changes and post-fire vegetation recovery. As these methods are relatively easy and based on remotely sensed images, they can be applied to large areas in a cost-effective way. An understanding of bushfire-prone landscapes is useful for bushland management.

The methods may be further improved by taking into account the changes in NDVI values with phenological cycles and seasonal variations, and the intensity of different bushfires. If a time-series of images over the same area are available, the post-fire spatial pattern changes could be monitored temporally.

REFERENCES

[1] Chuvieco, E., 1999. Measuring changes in landscape pattern from satellite images: short-term effects of fire on spatial diversity. International Journal of Remote Sensing, 20, pp. 2331-2346.
[2] Conroy, R.J., 1996. To burn or not to burn? A description of the history, nature and management of bushfires within Ku-Ring-Gai Chase National Park. Proceedings of the Linnaean Society of NSW, 116, pp. 79-95.
[3] De Cola, L., 1989. Fractal analysis of a classified Landsat scene. Photogrammetric Engineering and Remote Sensing, 55, pp. 601-610.
[4] Florence, R.G., 1996. Ecology and Silviculture of Eucalypt Forests. CSIRO Publishing, Canberra.
[5] Frohn, R.C., 1998. Remote Sensing for Landscape Ecology: New Metric Indicators for Monitoring, Modelling, and Assessment of Ecosystems. Lewis Publishers, Boca Raton.
[6] Gill, A.M., 1981. Adaptive response of Australian vascular plants species to fires. In: Fires and the Australian biota, edited by Gill, A.M., Groves, R.H., and Noble, I.R., Australian Academy of Science, Canberra, pp. 243-271.
[7] Haines-Young, R., Green, D.R., and Cousins, S. (eds.), 1993. Landscape Ecology and Geographical Information Systems. Taylor & Francis, London.
[8] Haralick, R.M., Shanmugam, K., and Dinstein, I., 1973. Texture features for image classification. I.E.E.E. Transactions on Systems, Man, and Cybernetics, 3, pp. 610-621.
[9] Hastings, H.M., and Sugihara, G., 1993. Fractals: A User's Guide for the Natural Sciences. Oxford University Press, Oxford.
[10] Hornsby Shire Council, 1996. Sensitive Urban Lands Study. Hornsby Shire Council, Sydney.
[11] Mandelbrot, B.B., 1983. The Fractal Geometry of Nature. Freeman Press, New York.
[12] Marchetti, M., Ricotta, and C., Volpe, F., 1995. A qualitative approach to the mapping of post-fire regrowth in Mediterranean vegetation with Landsat TM data. International Journal of Remote Sensing, 16, pp. 2487-2494.
[13] Olsen, E.R., Ramsey, R.D., and Winn, D.S., 1993. A modified fractal dimension as a measure of landscape diversity. Photogrammetric Engineering and Remote Sensing, 59, pp. 1517-1520.
[14] Ricotta, C., Avena, G.C., and Ferri, F., 1996. Analysis of human impact on a forested landscape of central Italy with a simplified NDVI texture descriptor. International Journal of Remote Sensing, 17, pp. 2869-2874.
[15] Ricotta, C., Avena, G.C., Olsen, E.R., Ramsey, R.D., and Winn, D.S., 1998. Monitoring the landscape stability of Mediterranean vegetation in relation to fire with a fractal algorithm. International Journal of Remote Sensing, 19, pp. 871-881.
[16] Rubin, T., 1990. Analysis of radar texture with variograms and other simplified descriptors. ASPRS'89, Sparks, NV, pp. 185-195.
[17] Turner, M.G., 1990. Spatial and temporal analysis of landscape patterns. Landscape Ecology, 4, pp. 21-30.