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Using remotely-sensed fuel connectivity patterns as a tool for fire danger monitoring

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Abstract

Spatial connectivity of areas of dry fuels is considered a significant influence on the incidence of large fires. Precipitation patterns can dynamically affect fuel connectivity through controls on the distribution of dry fuels. Spatio-temporal monitoring of precipitation-driven variations in dry fuel connectivity patterns could therefore offer the potential to monitor fire danger. In this paper we present an innovative graph theoretic-based approach to monitor fire danger using remotely sensed patterns of dry fuel connectivity. We analysed the temporal evolution of dry fuel connectivity in south-eastern Australia during recent fire seasons. The analysis showed that rapid changes in the connectivity of dry fuels determine the pre-conditions for major fires. We found that large fires affected highly connected dry portions of the landscape, confirming the potential of this approach to monitor the temporal evolution of fire danger.

Keywords

monitoring, fuel, danger, sensed, remotely, fire, tool, patterns, connectivity

Disciplines

Life Sciences | Physical Sciences and Mathematics | Social and Behavioral Sciences

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Using remotely-sensed fuel connectivity patterns as a tool for fire danger monitoring

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[1] Spatial connectivity of areas of dry fuels is considered a significant influence on the incidence of large fires. Precipitation patterns can dynamically affect fuel connectivity through controls on the distribution of dry fuels. Spatio-temporal monitoring of precipitation-driven variations in dry fuel connectivity patterns could therefore offer the potential to monitor fire danger. In this paper we present an innovative graph theoretic-based approach to monitor fire danger using remotely sensed patterns of dry fuel connectivity. We analysed the temporal evolution of dry fuel connectivity in south-eastern Australia during recent fire seasons. The analysis showed that rapid changes in the connectivity of dry fuels determine the pre-conditions for major fires. We found that large fires affected highly connected dry portions of the landscape, confirming the potential of this approach to monitor the temporal evolution of fire danger.
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1. Introduction

[2] Fire is a complex phenomenon affecting different regions across the world [*Pyne et al.*, 1996]. Large fires can result in significant loss of lives, properties and environmental resources [*Williams and Bradstock*, 2008]. Spatially-explicit monitoring of the potential of a fire to burn a specific area (i.e., fire danger) can help fire managers to mitigate impacts of large fires [*Schneider et al.*, 2008].

[3] Fuel connectivity is a multi-scale property (e.g., connectivity between-fuel particles, between-fuel patches) with significant influence on fire activity [e.g., *Peters et al.*, 2004]. At larger spatial scales (e.g., continuity of large fuel patches), high connectivity of fuels can facilitate fire spread across the landscape and increase the potential for large fires [*Peters et al.*, 2004; *Allen*, 2007; *Falk et al.*, 2007]. Variations in fuel moisture, as determined by precipitation patterns [e.g., *Dennison et al.*, 2008], can critically affect the large-scale connectivity of fuels because moisture constrains flammability and areas of moist fuels provide natural barriers to fire spread [*Dimitrakopoulos and Papaioannou*, 2001; *Allen*, 2007]. Spatio-temporal monitoring of precipitation-driven variations in dry fuel connectivity could therefore offer a basis for large-scale predictions of fire danger.

[4] This study presents an innovative technique to monitor fire danger using multi-temporal maps of fuel connectivity derived from the integration of Moderate Resolution Imaging Spectrometer (MODIS) data and graph theory. Our objectives were to: (i) monitor spatio-temporal patterns of fire danger across large landscapes based on monthly variations in large-scale connectivity (i.e., 500 meters resolution) of dry live fuels, and; (ii) explore the temporal evolution of large-scale connectivity of dry live fuels under changing precipitation patterns. The study analysed the 2001/02 and 2002/03 fire seasons in south-eastern Australia because they represent the two most severe fire seasons in that region since the launch of MODIS [*Bryant*, 2008]. Thus, they provided an opportunity to monitor the rate and spatial extent of drying needed to create the anticipated pre-conditions for large fires (i.e., spatially extensive array of dry fuel). The analysis also included the 2004/05 and 2008/09 seasons to contrast patterns of connectivity in years where less total area burned.

2. Background: Graph Theory

[5] Graph theory is a branch of mathematics widely used in connectivity analysis [*Urban et al.*, 2009].Graphs are models (Figure 1) which use nodes to represent units (e.g., fuels) and edges to depict functional connections (e.g., fuel continuity) among units [*Urban et al.*, 2009]. Nodes can have attributes (e.g., coordinates), and edges can be weighted to reflect differences in functional connections (e.g., dryness level) [*Urban et al.*, 2009]. The strength of a node is a connectivity measure representing the total weight of its edges [*Barrat et al.*, 2004]. In Figure 1, the weights of ‘ac’ and ‘cd’ are one and two, respectively, thus the strength of ‘c’ is three. For this study, we created graphs where nodes represented units of live fuels at 500 meter resolution (i.e., MODIS pixel) and edges were weighed based on moisture-related live fuel condition. Strength was used to measure the large-scale connectivity of nodes (i.e., live fuels) as a function of the number and weight (i.e., moisture condition) of their edges.

3. Study Area

[6] This study focused on the fire-prone Sydney Basin Bioregion, Australia (Figure 2a). The landscape presents an array of highly flammable vegetation types dominated by sclerophyll *Eucalyptus* formations [*Keith*, 2004]. This region is characterized by a temperate climate and exhibits a significant inter-annual variability in rainfall patterns [*Caccamo*

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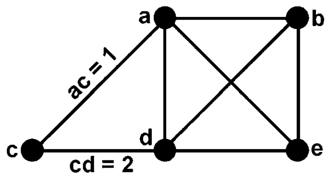

Figure 1. Schematic of a graph G defined by the sets of V = nodes {*a*, *b*, *c*, *d*, *e*}, and E = edges {*ab*, *ae*, *ad*, *ac*, *be*, *bd*, *cd*, *de*}. The weight of the edges *ac* and *cd* are 1 and 2, respectively.

et al., 2011] during fire season (i.e., October to March). This study focused on the large fire events of the summers 2001/02 and 2002/03, and two less severe fire seasons in 2004/05 and 2008/09. In 2001, fires were ignited by lightning on 24th December, burning over 580,000 ha [*NSW Parliament*, 2002], while several fires ignited between October and mid January in 2002/03, burning over 425,000 ha. In contrast, the total area burned was significantly lower in 2004/05 and 2008/09 (i.e., ~11,000 and ~20,000 ha respectively) (New South Wales Office of Environment and Heritage, unpublished data, 2010).

4. Data and Methods

4.1. Satellite Data

[7] We used a time-series (2000–2009) of MODIS data (8-day composite surface reflectance, MOD09A1) to normalize (i.e., z-score) fuel conditions in 2001, 2002, 2004 and 2008 against a ten year historical range. For each year, we used two MODIS data granules in August (i.e., 233 and 241), September (i.e., 265 and 273), October (i.e., 289 and 297), November (i.e., 321 and 329) and December (353 and 361) to depict fuel conditions at the end of each month. Only the granule '353' was used for December 2001 because the majority (~80%) of that image was acquired on the 23rd of December and therefore provided a suitable representation of pre-fire fuel condition. Data anomalies (e.g., cloud) were masked using quality assurance (QA) metadata. Based on previous research [*Caccamo et al.*, 2012], the Normalized Difference Infrared Index – band 6 (NDIIb6) [*Hunt and Rock*, 1989] was selected as an indicator of moisture-

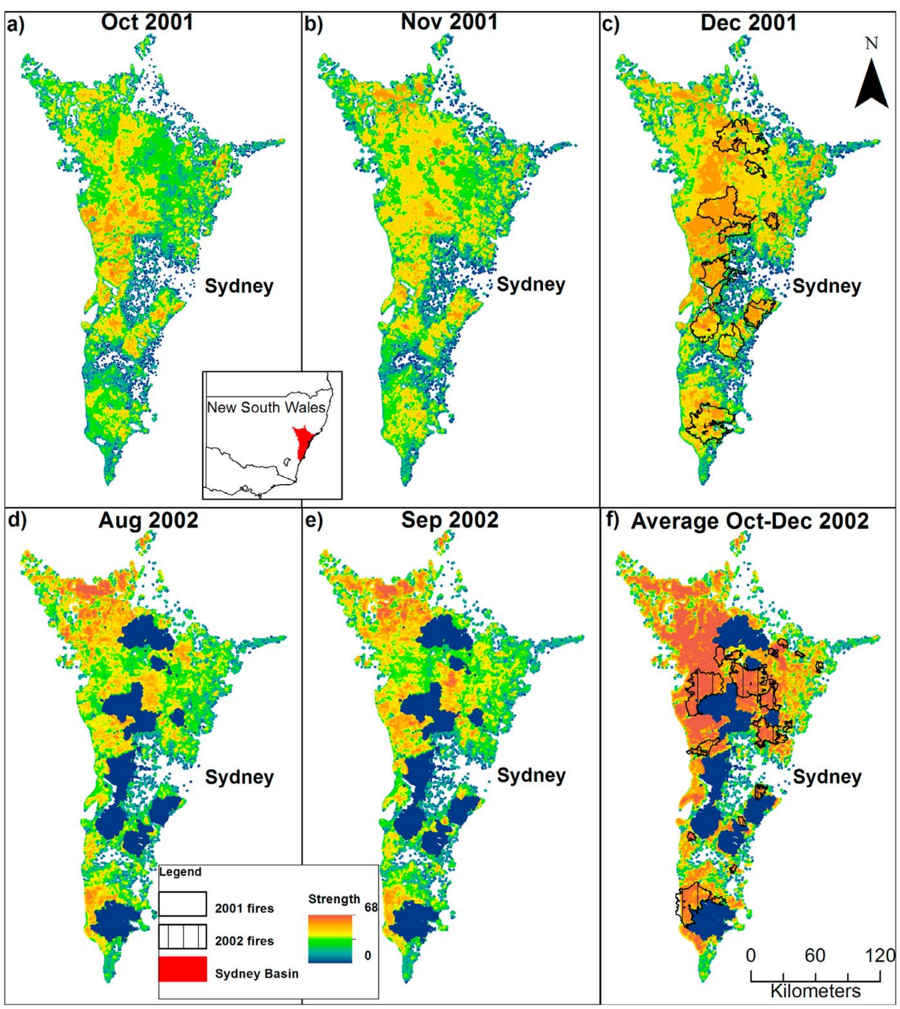

Figure 2. Maps of strength for (a) October (Oct) 2001, (b) November (Nov) 2001, (c) December (Dec) 2001, (d) August (Aug) 2002, (e) September (Sep) 2002, and (f) averaged October, November and December (Average Oct–Dec) 2002 in the Sydney Basin.

Table 1. Dryness Classes and Fuel Weights Based on NDIIb6 z-Score Ranges

Dryness Class	NDIIb6 z-Score	Description	Fuel Weight
1	N/A	Time since last fire <5	0
2	>=1.5	Severely wet	1
3	<1.5 and >=0.5	Wet	2
4	<0.5 and >−0.5	Normal	3
5	<=−0.5 and >−1.5	Dry	4
6	<=−1.5	Severely dry	5

related condition of live fuels, and calculated using the formula:

$$\mathrm{NDIIb6} = (\mathrm{Band2} - \mathrm{Band6})/(\mathrm{Band2} + \mathrm{Band6}), \quad (1)$$

where, Band2 is MODIS band 2 (841–876 nm) and Band6 is MODIS band 6 (1628–1652 nm).

[8] Fuel-free (e.g., water bodies) and non-flammable vegetation types (e.g., wetland) were masked using the National Vegetation Information System [*National Vegetation Information System*, 2005] and the National Geoscience Dataset for Australia [*Kilgour*, 2001] maps. For each month (i.e., August, September, October, November, and December) in each year (2000–2009), we averaged the two NDIIb6 images. Recently burned areas (i.e., time since last fire <5 years) in each NDIIb6 average image were identified (Table 1) using an official fire history dataset (New South Wales Office of Environment and Heritage, unpublished data, 2010). These areas were not used for the normalization process (i.e., z-score) because preliminary analysis indicated that live fuels require about 5 years to recover and display spectral patterns similar to pre-fire conditions (unpublished data). NDIIb6 values of fuels within that time range are therefore not indicative of their moisture conditions because the values are biased by the lower quantity of biomass present.

[9] NDIIb6 anomalies (i.e., z-score) were calculated as the departure from the mean (2000–2009), normalized by the standard deviation:

$$Z_{kxy} = (\mathrm{SI}_{kxy} - \alpha_{kx})/\sigma_{kx}, \quad (2)$$

where, Z_{kxy} is z-score of pixel k for month x in year y. SI_{kxy} is NDIIb6 value of pixel k for month x in year y. α_{kx} is the mean value of pixel k for month x over n years (2000–2009) and σ_{kx} is the standard deviation of pixel k for month x over n years. NDIIb6 z-score values were classified into six dryness classes and weighted (Table 1). We assigned higher fuel weights to negative anomalies because they reflect drier fuels in the study area [*Caccamo et al.*, 2011, 2012]. Fuels with time since last fire <5 years (Table 1) were assigned with the lowest weight (i.e., 0) because of the effect of reduced fuel quantity, soon after previous fire (i.e., <5 years), in impeding both the propagation and severity of wildfires in the study area [e.g., *Conroy*, 1996; *Price and Bradstock*, 2010; *Bradstock et al.*, 2010].

4.2. Fuel Graph

[10] Fuel graphs were derived from NDIIb6 z-score images. Each pixel was converted into a node and connected to its eight neighbouring nodes (when present) using edges. Each edge was weighted by summing the fuel weights (Table 1) of the two nodes it connected. Thus, weights ranged from 0 to 10, with higher values indicating connections among drier fuels (Table 1). We applied a correction factor of √2 for diagonal connections accounting for the longer distance [*Gonzalez et al.*, 2008]. The weight of edges 'to' and 'among' pixels where time since last fire was <5 years (Table 1) were set to '0' because similar fuels tend to impede fire spread [e.g., *Price and Bradstock*, 2010]. The graphs therefore represented functional connections among fuels based on their spatial configuration and dynamic moisture conditions.

4.3. Graph Analysis

[11] For each fuel graph, the strength of all nodes was calculated using the igraph [*Csárdi and Nepusz*, 2006] package in R environment [*R Development Core Team*, 2010]. The strength value for a given node increases when it is connected to a larger number of dry nodes. As a consequence, areas of higher strength represent more strongly connected (lower fragmentation and moisture content) portions of a graph where, in case of ignition, fires can successfully propagate supported by higher fuel continuity [*Peters et al.*, 2004]. Average monthly precipitation anomalies were calculated using gridded maps (5 km resolution) of total monthly rainfall from 1970 to 2010 acquired from the Australian Bureau of Meteorology [*Jones et al.*, 2009]. We explored how the large-scale connectivity of dry fuels and spatio-temporal patterns of fire danger evolved, under changing precipitation patterns, in the months leading to widespread ignitions in 2001/02 (i.e., October through December) and 2002/03 (i.e., August through December), and in non-severe fire seasons (i.e., 2004/05 and 2008/09).

5. Results and Discussion

[12] The pattern of fuel connectivity in the Sydney Basin changed markedly from October to December 2001 and from August to December 2002 (Figures 2a–2f and 3a), with connectivity of dry fuels increasing throughout the region prior to widespread ignitions on 24th of December 2001 and October–December 2002. In particular, strength increased

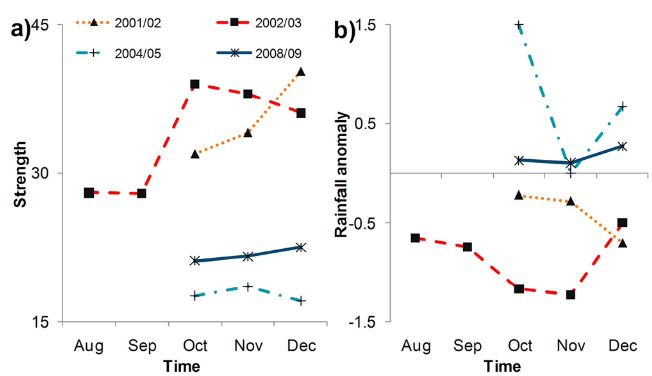

Figure 3. (a) Averaged strength and (b) precipitation anomaly for August (Aug), September (Sep), October (Oct), November (Nov) and December (Dec) in 2001/02, 2002/03, 2004/05 and 2008/09 seasons. The legend in Figure 3a applies to Figure 3b.

rapidly after November in 2001 and after September in 2002 (Figures 2a–2f and 3a). This expansion affected the majority of the study area in 2002, and resulted in a more localized highly connected 'backbone' of dry fuels extending from north to south and around the metropolitan area of Sydney in 2001 (Figures 2c and 2f).

[13] The spatio-temporal variations in fuel connectivity (Figures 2a–2f) mirrored the temporal trend of precipitation anomaly (Figures 3a and 3b) in 2001 and 2002, confirming the suitability of integrated remote sensing-graph theoretic approaches to monitor weather-driven influences on the connectivity of dry fuels. A mild precipitation deficit was evident at the start of fire season in October and November 2001 (Figure 3b). The precipitation anomaly decreased strongly after November, markedly worsening the moisture deficit by late December (Figure 3b) and resulting in high connectivity of dry fuels across the landscape (Figures 2a–2c). Similarly, a rapid decrease in the precipitation anomaly after September 2002 resulted in a significant increase in the spatial distribution of highly connected dry fuels across the basin (Figures 2d–2f, 3a, and 3b). During wetter fire seasons (i.e., 2004/05 and 2008/09) dry fuels remained persistently less connected from October through December (Figures 3a and 3b).

[14] When dry fuel is highly connected, the landscape imposes fewer natural barriers to fire propagation creating the potential, if ignition occurs, for the development of large fires [*Peters et al.*, 2004; *Allen*, 2007; *Bradstock et al.*, 2009]. Such pre-conditions for large fires were therefore potentially met by the end of December 2001 and from October 2002 (Figures 2e, 2f, and 3a). When ignitions occurred, increased connectivity of dry fuels (Figures 2c and 2f), combined with severe fire-weather conditions (high temperature, wind speed and low humidity *Bradstock et al.*, 2010]) resulted in extensive fires ($\sim$1, 000,000 ha in total, Figures 2c and 2f). In contrast, fire seasons with persistent limited connectivity of dry fuels (2004/05 and 2008/09, Figure 3a) were characterized by significantly less area burned (i.e., $\sim$31,000 ha in total). The large fires affected highly connected dry portions of the landscape (i.e., the dry 'backbone' in 2001 and the extensively connected dry fuels in 2002, Figures 2c and 2f) which had an average strength value of 52.07 (i.e., maximum possible strength value == $\sim$68). This therefore suggests that fuel connectivity patterns can provide suitable information for monitoring fire danger because extensive tracts of highly connected dry fuel are an important pre-condition for development of large fires.

[15] Our results indicate that dynamic variations in precipitation patterns during the fire season can be a major determinant of fire activity in temperate forested systems (Figures 3a and 3b). A, short-term, pronounced increase in moisture deficit (e.g., November to December 2001 and September to October 2002, Figures 3a and 3b) can rapidly increase the connectivity of dry fuels across the landscape and create the potential for large fires (Figures 2a–2f). This may explain why large fires are possible in this region in years without prolonged antecedent drought [*Bradstock et al.*, 2009]. Remote monitoring of short-term variations in dry fuel connectivity is therefore important to track the temporal evolution of fire danger in forested systems.

[16] As expected, fires did not affect all of the areas with elevated pre-fire dry fuel connectivity (Figures 2c and 2f) because fuel connectivity is not the sole influence on fire propagation [e.g., *Pyne et al.*, 1996]. The location of ignitions, wind patterns [*Moritz et al.*, 2010] and fire suppression operations are likely influences on the pattern of burning within the landscape-scale template of dry fuels that developed in late 2001. Nonetheless, MODIS-based maps of fuel connectivity provide a demonstrable template to define the spatial and temporal domain of potential fire (Figures 2c and 2f). The proposed method can be used with readily available imagery by fire managers with minimal expertise in fire modelling and, given that it is based on the widely applicable relationship between connectivity of dry fuels and occurrence of large fires, is clearly robust [e.g., *Peters et al.*, 2004].

6. Conclusion

[17] Spatio-temporal variations in large-scale fuel connectivity can be used for monitoring patterns of fire danger combining remote sensing and graph theory. Short-term variations in moisture deficit can have a significant impact on the connectivity of dry fuels in forested systems, and the proposed MODIS-based approach is suitable to monitor these dynamics. Dry fuel connectivity increased rapidly in the months preceding widespread ignitions and remained low during less severe fire seasons. The proposed method could therefore be implemented into operational tools for monitoring the temporal evolution of fire danger in near real-time. These tools could be potentially suitable for application in other forested systems across the world (e.g., Russian Far East) where moisture patterning is expected to be a significant driver of fire activity [e.g., *Maki et al.*, 2004]. Multi-temporal maps of fuel connectivity could be used to identify those regions where the connectivity of dry fuels and scope for significant fires is developing. Such information could be used to prioritize the allocation of resources and to take informed decision about fire management (e.g., fire warnings, prescribed burning). The proposed method could be improved through integration with models accounting for the moisture status of dead fuels [e.g., *Sharples et al.*, 2009] because moisture patterns of live and dead fuels could be potentially different. A similar approach would provide a two-layer representation of fuel connectivity and improve understanding of the relative influence of both components (i.e., live and dead fuels) on fire activity.

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