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# Analysis of Vegetation Fires in India Using Spatial Point Pattern Statistics

## Introduction

Understanding the impact of fires requires detailed knowledge about where fires occur, how they are influenced by landscape biophysical factors and precise calculations of fire regime parameters (Vazquez and Moreno, 2001). For the same, satellite remote sensing technology with its synoptic and repetitive coverage, provides valuable information on characterizing fires. For example, satellite images acquired by low spatial resolution sensors, such as the Advanced Very High Resolution Radiometer (AVHRR) and the Along-Track Scanning Radiometer (ATSR), provide information at a scale from regional to global and with a high temporal resolution, on fire timing, frequency and extent (Stroppiana et al., 2003). In addition to remote sensing technology, geographic information system (GIS) is used increasingly for fire management studies. Because most of the fires quantified from satellite remote sensing datasets quantify fires in the form of event data, spatial point pattern statistics can be effectively used to quantify some of the fire characteristics. To quantify spatial patterns in fire occurrences, statistical methods can be integrated with GIS to answer several important questions such as: (1) How are the fire events distributed across different vegetation types, topographic gradients and geographical regions? (2) Are the fire distributions random? If not, how are they different from random pattern? (3) What is the spatial scale at which fire events cluster? As each fire event is the result of the certain spatial process at a given time and in a given space, the above questions have important implications for fire management. We addressed the above questions in the Indian region using ATSR satellite datasets for the year 2006.

## Data

### *Fire count data*

We used fire count datasets derived from Along Track Scanning Radiometer (ATSR) satellite for the year 2006 to characterize spatial patterns in fires over the Indian region. The ATSR channels are at wavelengths of 1.6µm (visible) and three thermal bands at 3.7µm, 11µm, and 12µm. These data sets were derived from night time passes with a single, rule-based threshold applied to band 5 (3.55–3.93µm), where an active fire is detected if the land surface within a pixel was greater than or equal to 308 K. ATSR band 5 spatial resolution is 1 km, and it is probable that a small fire within a pixel (less than 1/10 of a pixel's area) is sufficient to produce a positive fire detection (Fuller and Murphy, 2006). This dataset provided active fire occurrences and basic information about the location of the fire events over the Indian region. We specifically aggregated the fire data from February to June, as this season represents the dry season in several states of the Indian region.

### *Vegetation*

To infer the number of fire pixels in each vegetation type, SPOT satellite derived global land cover (GLC) 1km vegetation cover data over the Indian region at a scale of one kilometer has been used. GLC 2000 makes use of the VEGA 2000 dataset: a dataset of 14 months of pre-processed daily global data acquired by the VEGETATION instrument on board the SPOT 4 satellite. We specifically used the south central Asian regional product that covered the Indian region. Further, while assessing fires over different vegetation categories, we eliminated some of the non-vegetation categories such as water bodies, barren areas, etc.

### *Topography*

We used GTOPO30 digital elevation model (DEM) with a horizontal grid spacing of 30 arc seconds (~1km) to extract slope and elevation values, corresponding to fire events.

## Spatial statistical methods

Fire ignitions detected from ATSR satellite data with the event location information (*x* and *y* co-ordinates) were assessed using spatial statistical tools. The simplest theoretical model for a spatial point pattern is that of complete spatial randomness (CSR) (Gatrell et al., 1996; Diggle, 2003). Statistical tests of the CSR hypothesis can be based on the counts of events in regions (quadrats), or distance-based measures using the event locations. The first-order properties describe the way in which the expected value (mean or average) of the process varies across space, while second-order properties describe the covariance (or correlation) between values of the process at different regions in space (Gatrell et al., 1996).

### *Quadrat analysis*

This method evaluates a point distribution by examining its density changes over space. The density measured by Quadrat analysis is then compared with the density of a theoretically constructed random pattern to see if the point distribution in question is more clustered or dispersed than the random pattern. As a process, a regular grid (hexagon in our case) is overlaid on the point pattern fire data, the numbers of fire pixels are counted and a frequency distribution is constructed based on those points falling in each grid. Then the frequency distribution is compared with that of a known pattern, generally a theoretically constructed random pattern to assess clustered or dispersed patterns.

### *Nearest neighbor analysis*

Nearest neighbor analysis (Clark and Evans, 1954), is specifically designed for measuring pattern in terms of the arrangement of a set of points in two or indeed three dimensions. The nearest neighbor index is simply the observed mean nearest-neighbor distance divided by the expected mean nearest neighbor distance for a random arrangement. Different orders in the neighbor analysis refer to the different ways points are considered as neighbors with respect to the reference point.

### *Ripley's K statistic*

The quadrat analysis and nearest neighbor analysis are the first order properties and attempt to offer overall descriptions (global pattern) of the point patterns being analyzed. However, the underlying spatial process may not be homogenous over the study region. For example, neighboring units may not cluster at the same magnitude across different parts of the region. For the same, Ripley's K function is quite useful (Ripley, 1976). The Neighborhood analysis of point patterns using 'K' statistic is based on distances between all pairs of points; it counts the number of points within a certain distance 't', of each point, with 't' taking a range of values. Commonly, K (t) is presented as the linearised L-function (Besag 1977). L (t) = 0; if points are regularly dispersed, L (t)<0. The higher values (positive) in this function indicate clustering at the corresponding spatial lag distance 't', and low values (negative) values indicate dispersion of points at that distance.

### *Hierarchical clustering*

To detect active fires or areas where fire incidents are most prevalent, we used nearest neighbor hierarchical (Nnh) clustering technique (Levine and Kim, 1999). For detecting the clusters, Nnh uses a threshold distance and compares the threshold to the distances for all pairs of points. Only points that are closer to one or more other points than the threshold distance are selected for clustering. In addition, minimum number of ignition points to be included in a cluster can be specified using this technique. Only fire ignitions that fit both criteria, i.e., closer than the threshold distance and belonging to a group having the minimum number of fire ignition points, are clustered at the first level (first-order clusters).

## Results

Results from ATSR fire count data suggested total fire counts of 1279 during the dry season (February to June) for the year 2006 (Tab.1). Of these, nearly 1140 ignitions have been found in the vegetation categories (Table 2). The other fire signals were from gas flares from petroleum refineries and occurred close to Arabian Sea near Gujarat state. These fire counts were eliminated in the analysis. Of the different states, maximum number of fires was recorded in Madhya Pradesh

(14.77%) followed by Gujarat (10.86%), Maharastra (9.92%), Mizoram (7.66%), Jharkhand (6.41%), etc. (Tab.1 and Fig.1). With respect to the vegetation categories, highest number of fires were recorded in agricultural regions (40.26%) followed by tropical moist deciduous vegetation (12.72), dry deciduous vegetation (11.40%), abandoned slash and burn secondary forests (9.04%), tropical montane forests (8.07%) followed by others. Analysis of fire counts based on elevation and slope range suggested that maximum number of fires occurred in very low and low elevation types and also in areas having very low to low-slope (Tab.2).

**Table 1.** Fire counts in different states of India derived from ATSR satellite data during the dry season (February – June 2006)

| State | Fire counts | % Fire counts |
|---|---|---|
| Andhra Pradesh | 42 | 3.283 |
| Arunachal Pradesh | 7 | 0.547 |
| Assam | 30 | 2.346 |
| Gujarat | 139 | 10.868 |
| Haryana | 2 | 0.156 |
| Himachal Pradesh | 4 | 0.313 |
| Jammu And Kashmir | 44 | 3.440 |
| Karnataka | 58 | 4.535 |
| Kerala | 1 | 0.078 |
| Maharashtra | 127 | 9.929 |
| Manipur | 39 | 3.049 |
| Meghalaya | 14 | 1.095 |
| Mizoram | 98 | 7.662 |
| Nagaland | 36 | 2.814 |
| Orissa | 33 | 2.580 |
| Punjab | 44 | 3.440 |
| Rajasthan | 8 | 0.625 |
| Sikkim | 2 | 0.156 |
| Tamil Nadu | 27 | 2.111 |
| Tripura | 49 | 3.8311 |
| Madhya Pradesh | 189 | 14.777 |
| Jharkhand | 82 | 6.411 |
| Bihar | 1 | 0.078 |
| West Bengal | 8 | 0.625 |
| Chattisgarh | 42 | 3.283 |
| Uttaranchal | 16 | 1.250 |
| Uttar Pradesh | 41 | 3.205 |
| Other Ignitions | 96 | 7.505 |
| **Total** | **1279** | **100** |

The results obtained on fire characteristics at state level and vegetation categories in our study should help resource managers and environmental scientists to identify potential critical areas where fire management efforts can be focused. Although, no attempt has been made to infer the causative factors of fires in this study, our previous studies suggest that, several of the agricultural fires were related to crop residue burning including slash and burning agriculture in different states (Kiran Chand et al., 2006). Also, dry deciduous forests are one of the most dominant vegetation types in India and fires in these forests are attributed to high level of anthropogenic activities, mainly due to dependence for fuel, food and fodder. Similar to dry deciduous forests, fires in the thorn forests are also attributed to anthropogenic disturbances including accidental fires. Information on fire events categorized based on topographic characteristics can be used in predictive modeling to assess potential fire 'hotspots'.

With respect to the spatial patterns, the three basic types of point pattern, namely random, clumped and uniform are well recognized in spatial statistical literature depending on the relative position of one point observation to another. There are driven processes that are responsible for the generation of those patterns (Upton and Fingleton, 1985). For instance, random patterns presuppose environmental homogeneity and non-selective processes while non-random patterns, either clumped or uniform indicate environmental heterogeneity and the existence of favorable and selective mechanisms as well as constraints that govern those processes (Ludwig and Reynolds, 1988). In our case, spatial analysis clearly suggested that fire events had a clustered / clumped pattern at 125 miles scale. This pattern implies some sort of environmental heterogeneity, which in turn can be effectively used to understand fire characteristics at landscape scale. Hierarchical nearest neighboring technique identified significant clusters of active fires in states pertaining to northeast and central India. These results imply that fire management in these states should be given priority. We infer that use of spatial statistics is the first step in exploring patterns of point distributions. Since the basic fire patterns in the Indian region are detected, this information can be now effectively used to build models and hypothesis to explain the underlying causative factors of fire events. Such an attempt is underway through integrating biophysical as well as socioeconomic information covering highly diverse ecoregions of India.

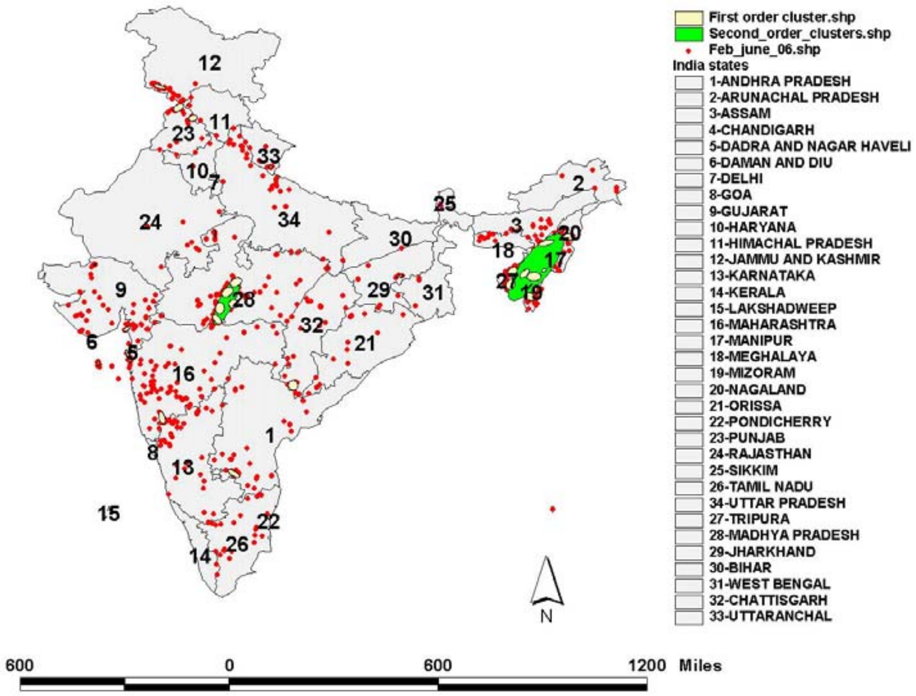

**Figure 1.** Clustering of fire events in northeast and central India obtained from nearest neighbor hierarchical technique.

**Table 2.** Fire counts in different vegetation types of India derived from ATSR satellite data (February – June 2006)

| Class | Vegetation Type | Fire Counts | % Fires |
|---|---|---|---|
| 1 | Tropical evergreen | 24 | 2.11 |
| 2 | Subtropical evergreen | 2 | 0.18 |
| 3 | Temperate broadleaved | 4 | 0.35 |
| 4 | Tropical montane | 92 | 8.07 |
| 5 | Tropical semi-evergreen | 3 | 0.26 |
| 6 | Subtropical conifer | 5 | 0.44 |
| 7 | Tropical moist deciduous | 145 | 12.72 |
| 8 | Tropical dry deciduous | 130 | 11.40 |
| 9 | Junipers | 50 | 4.39 |
| 10 | Degraded forest | 50 | 4.39 |
| 11 | Dry woodland | 1 | 0.09 |
| 12 | Thorn forest | 65 | 5.70 |
| 13 | Abandoned *Jhum* | 103 | 9.04 |
| 14 | Savannahs, grasslands, meadows | 7 | 0.61 |
| 15 | Agriculture | 459 | 40.26 |
|  | **Total** | **1140** | **100** |

**Table 3.** Fire counts in the Indian region aggregated according to elevation range (February to June 2006)

| **Elevation range (m) and categories** | **Fire counts** | **% Fires** |
|---|---|---|
| 0-218 (very low) | 537 | 49.17 |
| 219-395 (low) | 280 | 24.24 |
| 396-597 (medium) | 205 | 16.97 |
| 598-938 (high) | 95 | 6.30 |
| 938-1664 (very high) | 66 | 3.29 |
| **Total fires excluding other ignitions** | **1183** | **100** |

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