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Fire Ignition Trends in Durango, México

Marín Pompa-García and Eusebio Montiel-Antuna
Universidad Juárez del Estado de Durango, Col. Valle del Sur, Durango
Faculty of Forest Sciences, UJED
México

1. Introduction

The spatial analysis of wildfire occurrence is a key factor in understanding forest fire incidences in forest ecosystems. Most of the applications are used in Wildfire Threat Rating Systems, and many of them have been completed or are in progress around the world (Lin, 2000; San-Miguel-Ayanz *et al.*, 2003). A major issue today is how to undertake the analysis more accurately and efficiently for the purposes of planning and to design suitable strategies and actions for forest fire management (Gollberg *et al.*, 2001).

In Mexico, most hazard systems use remote sensing techniques that measure weather and climate assessments, topography and fire interaction. (Flasse and Ceccato, 1996; Giglio *et al.*, 2003; Sepulveda *et al.*, 2001). In Durango State for instance, Drury and Veblen (2008) applied the spatial pattern of forest fire occurrence and showed that the rate of forest fires is correlated to years when extreme variations in weather occur. Renteria (2004) developed models for forest fire risk, which are now applied as support tools for decision-making in fuel management. Furthermore, Avila *et al.* (2010a) analysed the spatial patterns of forest fire occurrence, showing that the ignition locations did not exhibit a random distribution. In a subsequent spatial analysis using geographical weighted regression, Avila *et al.* (2010b) explicitly identified that human activities are the main factors determining the occurrence of forest fires, followed by vegetation and lack of precipitation.

All of these studies were concerned with the analysis of spatial patterns of forest fires, but the majority did not examine fire ignition history. Although electronic data is not available, a Geographic Information System (GIS) layer can be generated from local fire reports or associated records, including attribute data such as the number, date, size, cause, and other relevant information relating to the fires. Creating density points of fire locations helps to identify high fire frequency areas and to find any noticeable trends. It is known from experience that forest fires in Durango have tended to occur in patches, but no study has taken quantitative measurements. This information should give managers and researchers an adequate perspective as to where efforts should be focused.

Recently interest in several statistical techniques that focus on local measurements of spatial dependence have been growing. These techniques make it possible to have a discussion about tests for the detection of clusters without any preconceptions about their locations or spatial trends**.** The Getis-Ord G-statistic is used for the detection of clusters and is especially useful in cases where global traditional statistics, such as kernel estimation, k-function

analysis, Moran's I index and the semi-variogram, did not display any global spatial pattern. However, in these cases there may still be significant points of clustering (Ord and Getis, 1995). Therefore, wildfire clustering metrics would be useful for providing knowledge to build more sophisticated modelling methods, including fire risk systems, optimizing fuel treatments, and prevention planning.

In this study, the objective was to assess wildfire ignition history in order to develop clustering maps that would be easy for managers to understand in setting up a strategy for fighting forest fires. It was hypothesized that the locations of ignition would have a clustered distribution. However, this study did not attempt to model ignition probability or historical fire regimes.

2. Methods

2.1 Study area

The state of Durango is located in the northwest of Mexico (22°16'–26°53'N, 102°29'–107°16'W) and covers a surface of 123,181 km² with a high diversity of ecosystems (Rodríguez *et al.*, 2010). It is divided into four ecozones, which are large ecological units containing landscapes of similar climate, topography, and vegetation (Figure 1). The coniferous and oak forest ecozone, situated on the plateau of the Sierra Madre Occidental, contains several species of pine and oak for commercial activities. The deciduous tropical forest is located in one of the numerous large canyons that cut through the irregular terrain and is mainly composed of tropical and subtropical species. The xeric shrub-lands have species with the ability to grow in dry and saline flat areas. Additionally, the grasslands are big areas with several species of grass, sometimes mixed with scrublands, in rolling terrains, which are mainly used for cattle grazing. Most of the ecosystems are owned communally, but a sprinkling of private owners exists.

2.2 Data sources

In order to measure the clustering of forest fires, the study area was further subdivided into 1,343 physiographical units (also known as terrestrial systems), digitized on a 1:250,000 scale (SEMARNAT and PGC, 2001). These spatial units provide information regarding the location, slope, land use and main vegetation (Pompa *et al.*, 2011).

A forest fire database, that tracked the dating information with the location of ignition within the area of study, was obtained from a daily report collected in the field by the National Commission for Forestry, for the period 2001 to 2010. This database layer was overlaid with the terrestrial systems data to provide a complete dataset for each system, including the physical properties of the system and the frequency of forest fires.

2.3 Statistical analysis

Considering that the study area was subdivided into 1,343 polygons whose Cartesian coordinates are known and where each feature has a respective number of fire ignitions, the G-statistic introduced by Getis and Ord (1992) can detect whether features with high values or features with low values are more likely to cluster.
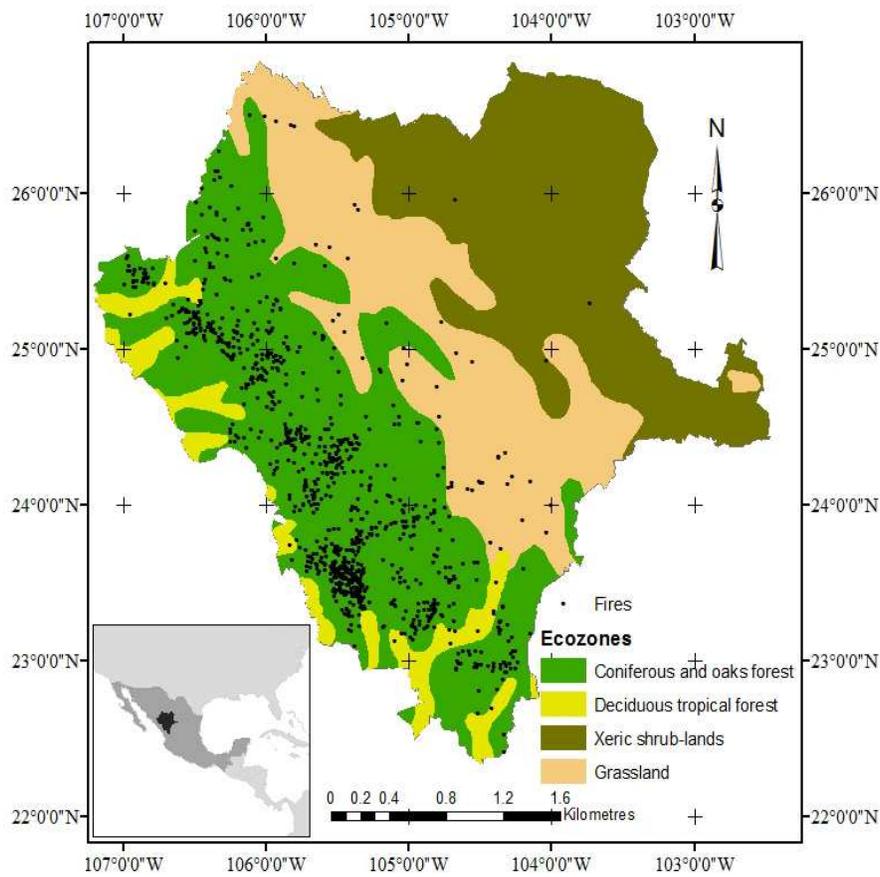
Fig. 1. Location of the Durango State in Mexico, indicating ecozones and fire ignitions from 2001 to 2010.

The G-statistic is defined as:

$$G = \frac{\sum\limits_{i=1}^{N}\sum\limits_{j=1}^{N} w_{ij}(d)x_i x_j}{\sum\limits_{i=1}^{N}\sum\limits_{j=1}^{N} x_i x_j} \, i \neq j \tag{1}$$

Where $x_i x_j$ is the measured attribute for features i and j, respectively; and $w_{ij}(d)$ is a symmetric one/zero spatial weight matrix for detecting the vicinity between i and j at the distance given by d.

In order to indicate how the observed G-statistic is significantly different from the expected value (and hence significantly different from a random distribution), the following formula was applied:

$$Z - score = \frac{G(d) - G_E(d)}{Std\,Dev} \tag{2}$$

The test procedure assumes no global autocorrelation, but when global autocorrelation exists it has a significant impact on the expected value of G. This makes any proposed inferences on the presence of local clusters misleading (Haining, 2003). To remedy this problem, the study area was divided into small polygons.

The G-statistic was computed by physiographical units, using the hot spot analysis available in ESRI ArcMap™ version 9.3. G is calculated by looking at each feature within the context of neighbouring features. If a feature's value is high, and the values for all of its neighbouring features are also high, it is part of a hot spot. The local sum of a feature and its neighbours are compared proportionally to the sum of all features. When the local sum is much different than the expected local sum, and that difference is too large to be the result of random chance, a statistically significant Z score is the result (ESRI, 2008).

Due to the fixed spatial scale of the dataset and its reflection of good spatial autocorrelation, the level of clustering among fires was assessed using the fixed distance band option and calculated using the Euclidian distance method. Therefore, the Z-scores were reliable.

3. Results

In order to test whether or not the observations are spatially dependent, Figure 2 shows the clustering found for forest fires in terms of probabilities. The red grid cells indicate a cluster with high attribute values or clustering (hot spots) and are where fires are most likely to occur; while green tones imply low clustering (cold spots) and represent locations where the fires are less likely to occur. Finally, yellow tones denote areas where there is no concentration of either high or low values surrounding the target feature. This occurs when the surrounding values are all near the mean or when the target feature is surrounded by a mix of high and low values.

As a statistical test on the validity of the clustering, *p*-values test was carried out. Figure 3 shows the accuracy of the G-statistics. The best results are represented in red, and the worst are in green. A more conservative significance level was used (α=0.0001) in order to compensate for the effect of the large sample size (N=1,343), which may detect local pockets. Figure 2 reflects the clustering degree of occurrence in the ignition plots and is evidently varied among ecozones, which appeared to be supported by the spatial patterns.

The G-statistic estimates of spatial clustering allowed us to generate maps of annual clustering for forest fires from 2001 to 2010 (Figs. 4 - 13). For comparative purposes, the estimated values in all of these figures were subjected to the same scaling.

The fires exhibited most clustering in the ecozones of the coniferous and oak forests, as a result of fire progressively aggregating in this zone over the considered time period. This suggests that the increased incidences are following a rather stable pattern over time. These areas neighbour the deciduous tropical forest, which have rugged topography and are difficult to access. The ecozone that had less fire activity was the xeric shrub-lands, characterized by sandy areas and an arid climate. Although this study did not attempt to assess intra-ecozone variability and causes of such interaction, the results in Figure 2 lead us to believe that some features (physical, anthropogenic factors, etc) vary considerably among

ecozones, and even within each, individual ecozone. This type of analysis requires more detailed data pertaining to the factors responsible for the ignition and spread of fires (Flannigan *et al.*, 2005).
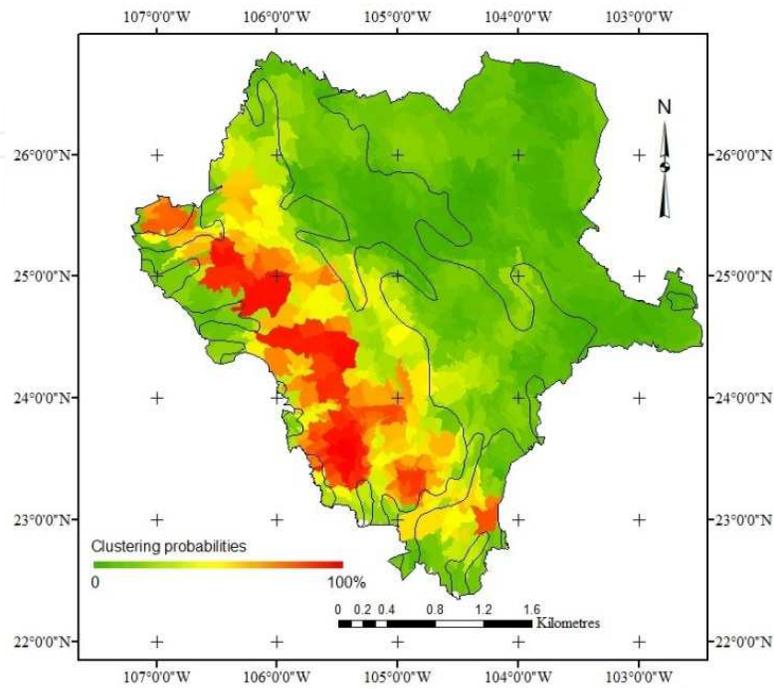

Fig. 2. Estimated spatial intensity of the occurrence of forest fires in Durango for the whole period 2001-2010.
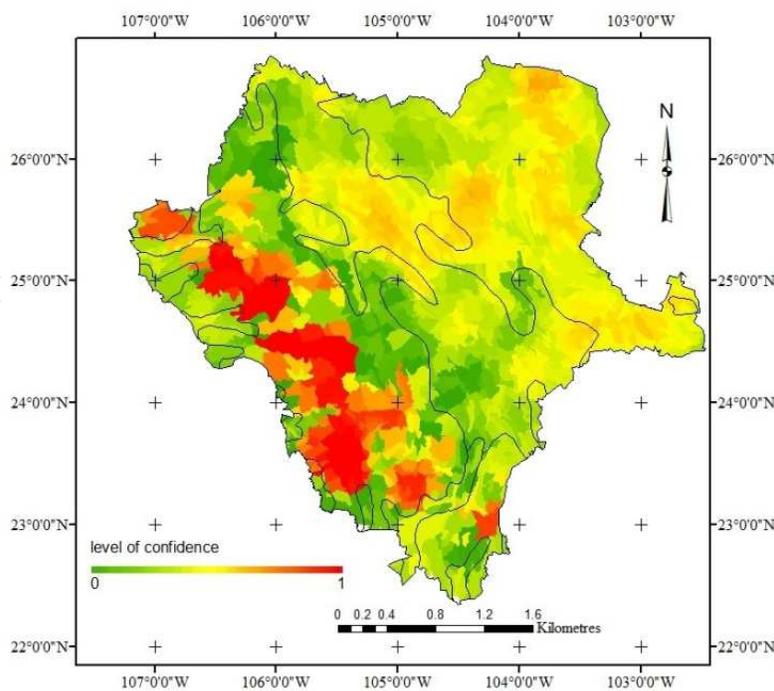

Fig. 3. Level of confidence of the clustering of forest fires in Durango for the whole period 2001-2010.
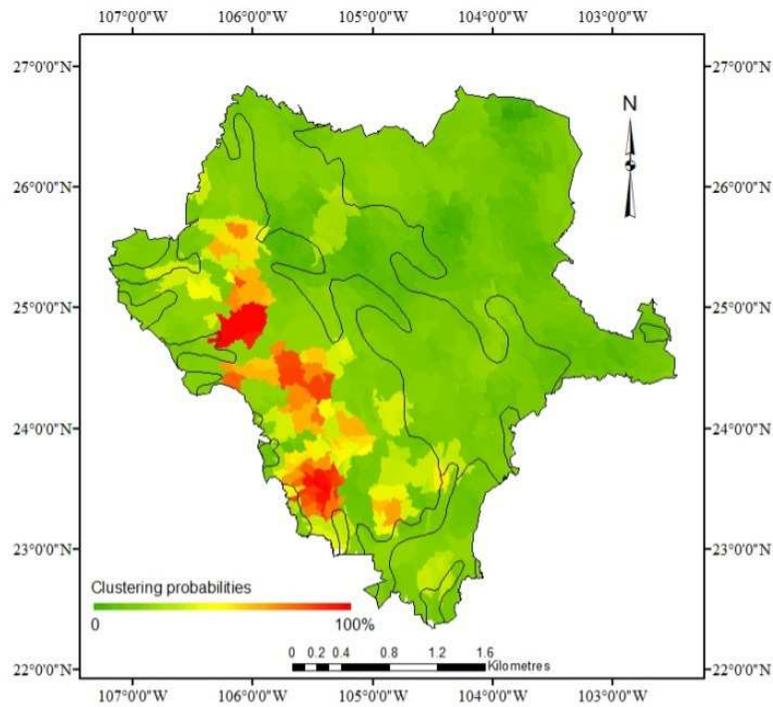
Fig. 4. Estimated spatial intensity of the occurrence of forest fires in Durango for the 2001 year.
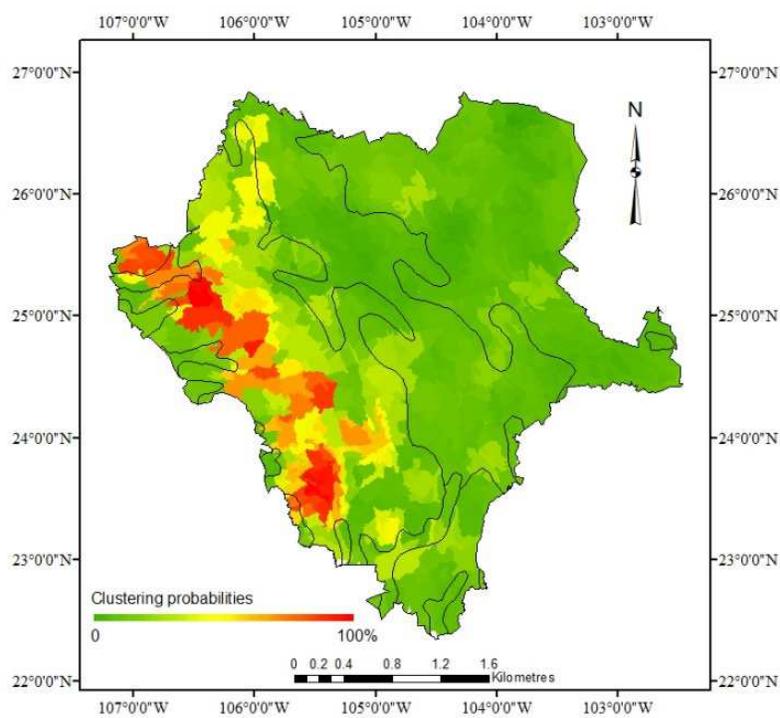
Fig. 5. Estimated spatial intensity of the occurrence of forest fires in Durango for the 2002 year.
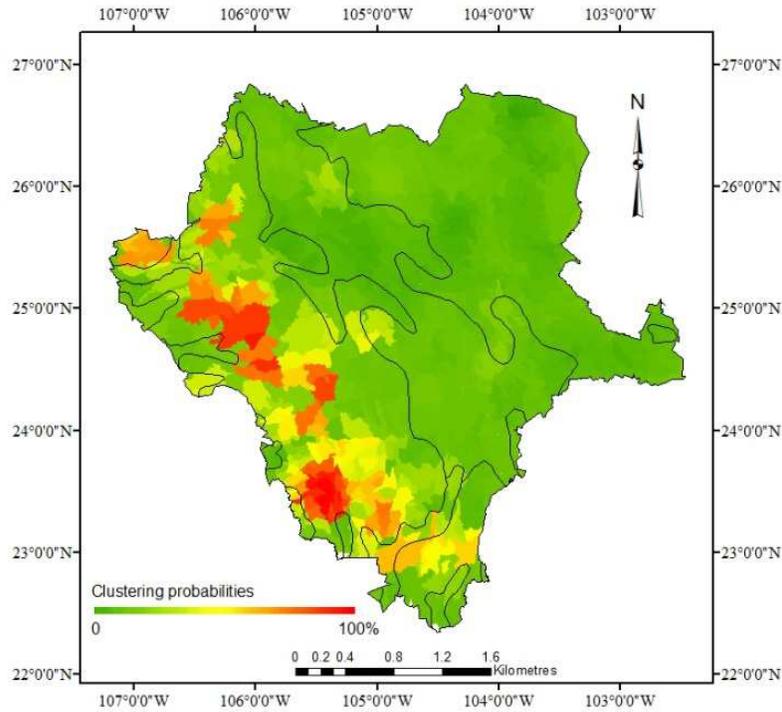
Fig. 6. Estimated spatial intensity of the occurrence of forest fires in Durango for the 2003 year.
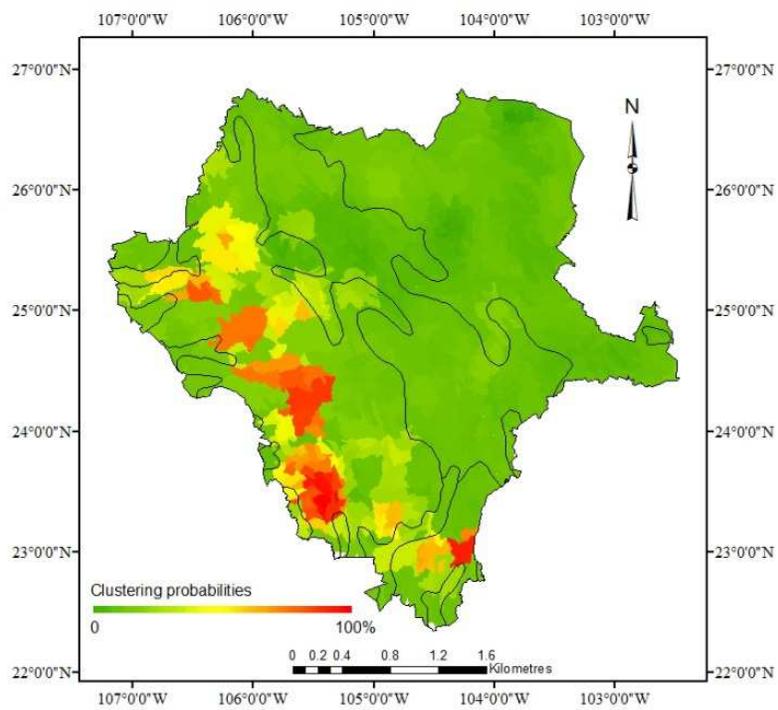
Fig. 7. Estimated spatial intensity of the occurrence of forest fires in Durango for the 2004 year.
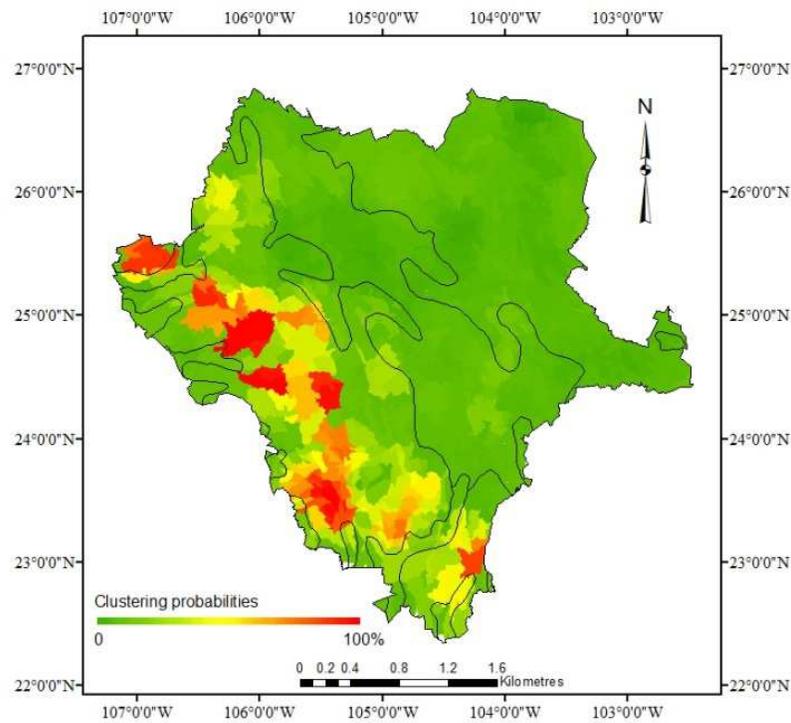
Fig. 8. Estimated spatial intensity of the occurrence of forest fires in Durango for the 2005 year.
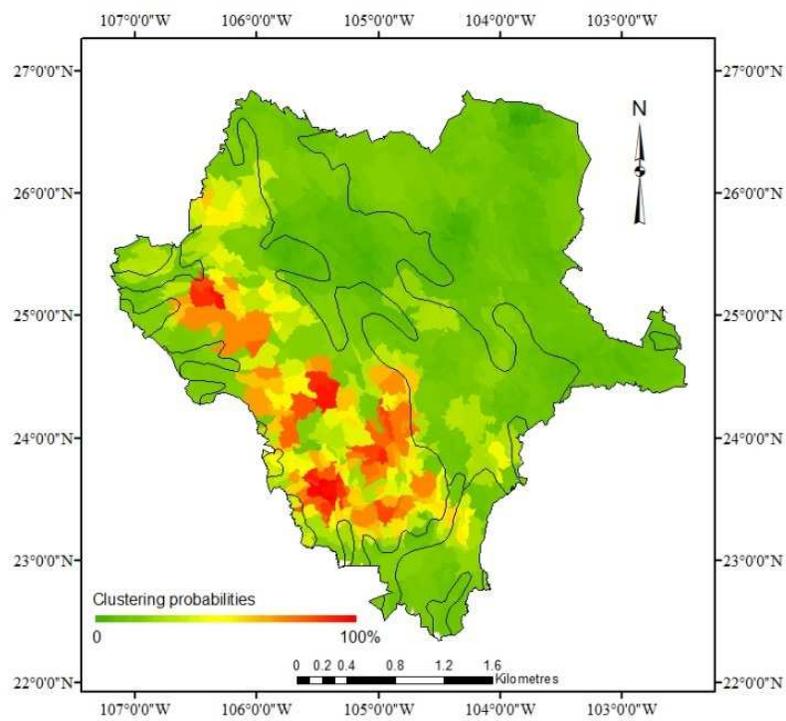

Fig. 9. Estimated spatial intensity of the occurrence of forest fires in Durango for the 2006 year.
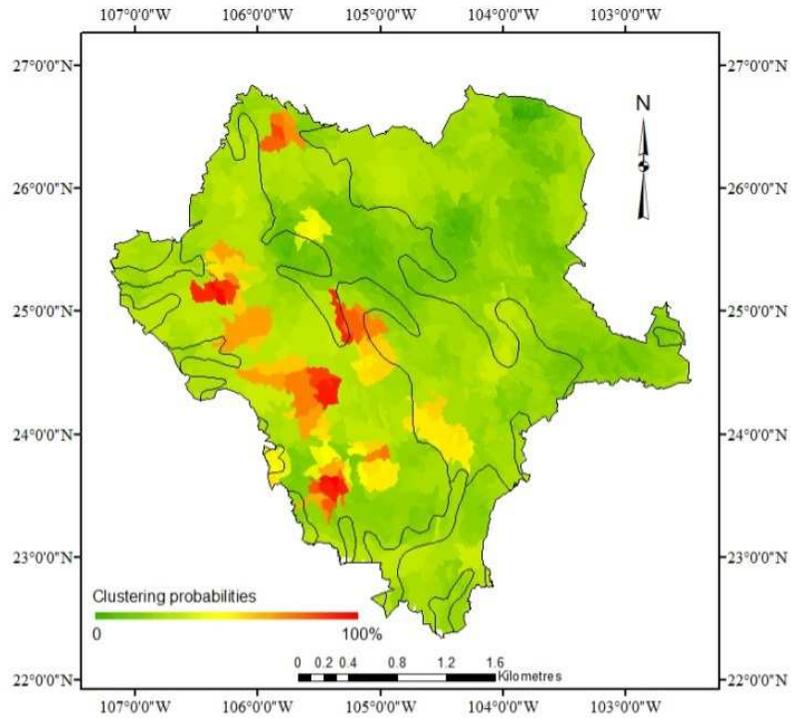
Fig. 10. Estimated spatial intensity of the occurrence of forest fires in Durango for the 2007 year.
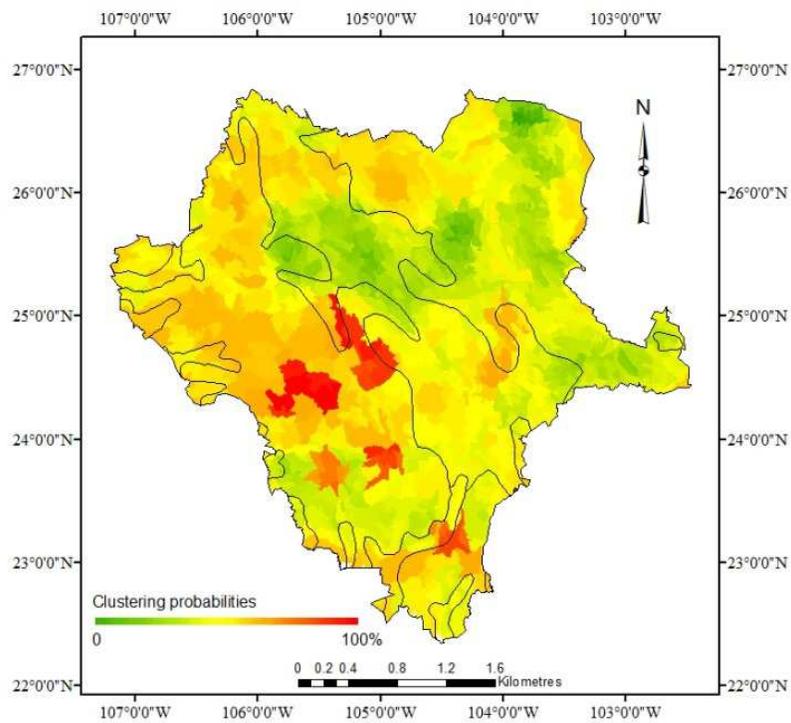

Fig. 11. Estimated spatial intensity of the occurrence of forest fires in Durango for the 2008 year.
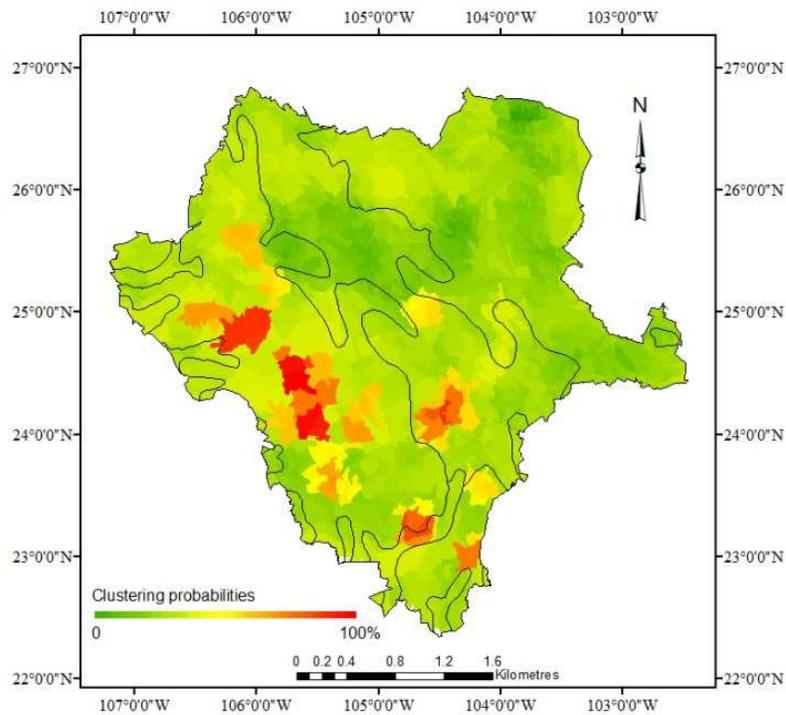
Fig. 12. Estimated spatial intensity of the occurrence of forest fires in Durango for the 2009 year.
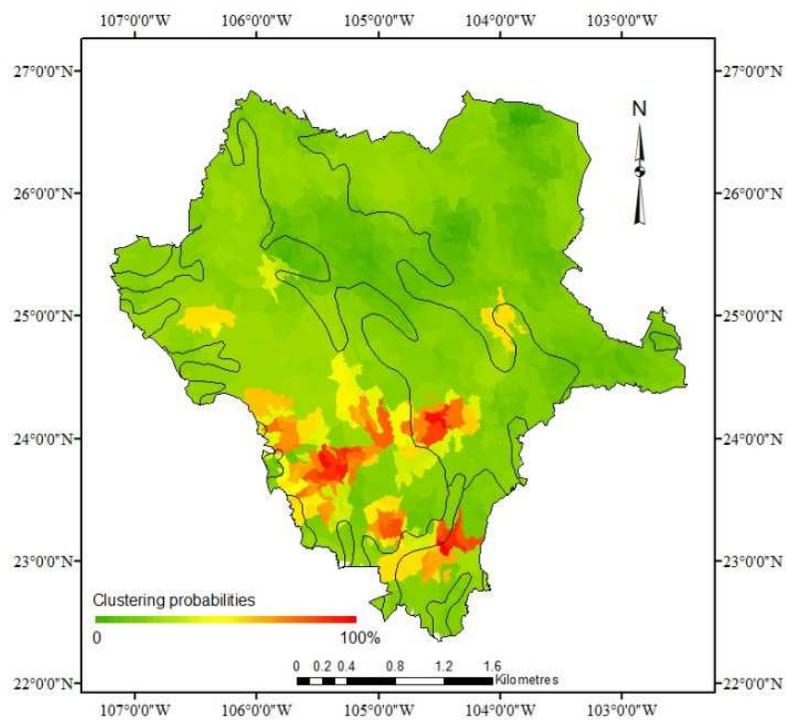
Fig. 13. Estimated spatial intensity of the occurrence of forest fires in Durango for the 2010 year.

4. Discussion

Many studies of forest fires have been conducted in Mexico over the past few years, but no effort has been made to quantitatively compare the spatial characteristics of clustering. This spatial analysis allows us to answer the hypothesis that had been posed earlier. Several clusters of fires had been formed in Durango between 2001 and 2010, as was confirmed by our results. The G-statistic was satisfactory as a quantitative tool for such estimations.

In spite of the difficulties in interpreting their causes, the clustering metrics that were used show the relative differences in clustering among terrestrial units. This approach is consistent with the results of Parisien *et al*. (2006) which showed that several clusters of large fires were formed in Canada from 1980 to 1999. They hold that the clustering of fires is a function of cumulative year intervals, which supports an analysis made a few years before by Vasquez and Moreno (2001). They showed that fires aggregate spatially and over time, producing larger interconnected burned patches. Wang and Anderson (2010) have demonstrated that the interaction is dynamic; it changes from year to year.

However, clustering depends on a dataset that has been complied over a long period of time, and therefore, it is likely that it would have shown different patterns in clustering. Many studies have reported from simulations that the clustering varies with vegetation cover (Keane *et al*., 2002; Miller, *et al.,* 2008). According to Cumming (2001), and Duncan and Schmalzer (2004), the extent and configuration of flammable vegetation and non-flammable landscape features clearly influence patterns of fire ignition. They also speculate that these patterns are likely to respond differently to changes in spatial scale. Indeed, Parisien *et al*. (2006) show that splitting the clusters, and therefore reducing study units, will avoid some bias in the estimates and surely dilute the effect of clustering. In this approach, the choice of terrestrial systems as study units was not entirely arbitrary, as it was based on units for which fire activity is known to vary throughout Durango.

Flannigan *et al*. (2005) showed that smaller study units nested in ecozones performed more poorly than the terrestrial units used here. To this end, these units provided a useful and objective means to spatially stratify the ecozones in order to study fire. Wang and Anderson (2010) highlighted the importance and challenges of analysing different spatial data sets, assessing and identifying the spatial scales that are the most relevant for the study of spatial fire patterns. Podur *et al*. (2003) explicitly identified the spatial scales at which fires exhibit clustered, random, or inhibited distribution.

In addition, our results reaffirm the importance of recording historical ignitions. They are thus consistent with those documented by Van Wagner (1988), Rollins *et al*. (2002) and Podur *et al*. (2003) who noted that historical fire records have been useful in understanding the spatial distribution of fires and in helping managers to conceptualize where ignitions could occur, due the assessment of fire clustering can provide useful new information in predicting potential fire dangers across the ecosystems. They will also enable managers to understand the level of the fire threat. However, creating an ignition density from fire locations only indicates where fires have started, not where or under which conditions the fires will spread or the impact which will occur. Thus, fire occurrence data alone are of limited value to risk assessment (Stratton, 2006).

Historical recording was attractive in terms of expediency, simplicity, low costs, and transparency. Although it is not possible to ensure that this database contains all fire

ignitions, it does represent the vast majority of them. Therefore, the lack of more available temporal explicit data has made it difficult to undertake a detailed study of spatial fire patterns over a considerable period of time (e.g. decades).

As noted earlier, Avila *et al.* (2010a) have noted the clustering of forest fires; however, they used the Moran I index. The G-statistic focuses on the clustering around each terrestrial system, since it does not take into account the rate of forest fires in the area of study itself. This approach helps to monitor local behaviour due to G being more sensitive to high clusters than low ones. On the other hand, Moran's index is mainly affected by the scale of the clusters (Zhang, 2007). The question of the interaction between local and global coefficients is an important one and much more remains to be done in this context (Ord and Getis, 1995).

5. Conclusion

In this study, the history of fire ignitions over an ecologically heterogeneous landscape during the period of a decade was compared. The fires of all ecozones from 2001 to 2010 exhibited a clustered spatial distribution remarkable in oak forest ecosystems. However, it was beyond the scope of the present study to thoroughly analyse the underlying mechanisms responsible for the spatially clustered fires. Regardless of the factors that may have contributed to any increase in wildfire frequency, the assessment of fire clustering can provide useful new information to researchers in predicting potential fire dangers and behaviours across the landscape. Also, it is important to take into consideration the importance of the updated geographic data from preceding data fields. Results such as these will hopefully encourage more detailed analyses that investigate the relative roles of weather, fuels, landscape features, and others factors on the progression of fire ignition. The same methods could be applied to smaller and ecologically homogeneous landscape units, such as stand management units, over a finer timescale (e.g. months or even days). Finally, it should also be possible to use these methods to study clustering fires at other levels where ignition data are available.

6. Acknowledgement

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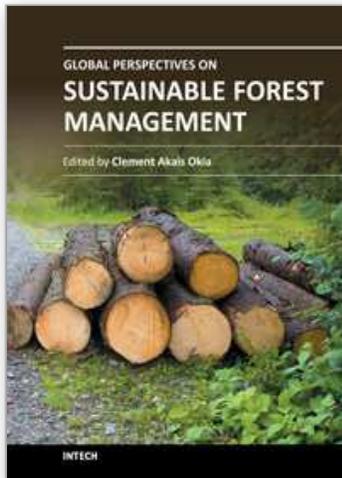
This book is dedicated to global perspectives on sustainable forest management. It focuses on a need to move away from purely protective management of forests to innovative approaches for multiple use and management of forest resources. The book is divided into two sections; the first section, with thirteen chapters deals with the forest management aspects while the second section, with five chapters is dedicated to forest utilization. This book will fill the existing gaps in the knowledge about emerging perspectives on sustainable forest management. It will be an interesting and helpful resource to managers, specialists and students in the field of forestry and natural resources management.

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