Spatial distribution of forest fuels based on classification and regression trees

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Abstract - Fire management planning require of a precise information of quantity and quality of many factors, such as forest fuels. Moreover, it is important to know fuels location and the spatial variation of fuel loads. Many direct and indirect techniques have been tested, some of the work with ancillary information, such as satellite imagery. In fact satellite imagery has become a practical alternative to classify land covers, with a acceptable level of accuracy, which is strongly related to forest fuels. We also count with spatial information of topography, climate, altitude, soil, etc, which can used to define spatial distribution of forest fuels. This paper illustrate the use a classification and regression trees (CART), to spatially model forest fuel distribution. The study area is located at the central part of Jalisco state. The results showed a good accuracy in the spatial estimation of fuels loading.

Keywords: forest fire, fuels management, fuels mapping

1. INTRODUCTION

Forest fire management require to count with precise information of quality and quantity on many factor, such as forest fuels. Moreover, it is required to know the spatial location of such forest fuels and their spatial variation of fuels loads (Flores, 2001). This problem could be more complicate if we consider that there are many types of forest fuels, which define different fire behaviours (Flores and Omi, 2003). Potential fire effects can be predicted through the simulation of fire behavior. Currently there are many systems to simulate not only the rate of spread and intensity of a forest fire, but also other behavioral factors (i.e., flame length, flame depth, and reaction intensity). Since all such systems require reliable spatially referenced data, their use poses a more complicated problem. For instance, FARSITE (Finney, 1998) requires five spatial data layers (elevation, aspect, slope, surface fuels, and canopy cover) for prediction of fire growth for surface fires. Though most of these layers are relatively easy to get, the surface fuels layer requires much more effort and analysis to develop. Moreover, fuels characterization and their spatial distribution are critical factors to simulate fire behavior. In an attempt to simplify the fuels characterization, the "fuel model" concept was created (Anderson, 1982). This concept allows the categorization of areas into classes of potential fire behavior. However, the assignation of the fuel model that best represents the fuel conditions of a given area has represented one of the more complicated challenges facing forest fire scientists. Furthermore, if one considers the spatial variations in the distribution of surface fuels that could exist within a given fuel-model area, new approaches should be evaluated. For this reason, it is necessary to develop thematic maps that represent the spatial distribution of fuels, as precise as possible. For this purpose many sources of information has been used, such as vegetation maps, digital elevation models, satellite imagery, etc. In fact the use of satellite imagery has become a very practical and reliable alternative in order to classify land-covers. However, because forest fuels are located under the forest canopy it is very difficult to define directly such layer. This happen because fuels reflectance is not detected by satellite imagery. As an alternative approach is the use of satellite imagery to define vegetation, and then associate a given fuel model with certain vegetation type. This has some advantage if we consider to work in a large scale. However, if we are planning to worn in small areas (50 ha or less) such approach is not practical, because could be considerable spatial variations of fuel loads inside a certain vegetation type. This means that new approaches should be tested.

The increment of computer capabilities has allowed to develop and test different statistical approaches under a geographical context, such as artificial neural networks (ANN) and classification and regression trees (CART). Although such techniques have been tested in many fields, including forest arena, they have not been tested in order to develop forest fuel maps. Therefore, this paper shows a process to generate thematic maps of different forest fuels, which is based on CART. This study 3was carry out in a forest located in Jalisco state, Mexico. Classification and regression trees (CART) utilizes non-parametric statistics methods to create a classifier for land use/cover. In the traditional approach to classification, a common set of features is used jointly in a single decision step. An alternative approach is to use a multistage or sequential hierarchical decision scheme, which allows rejection of class labels at intermediate stages. In this way, CART offer an effective implementation of such hierarchical classifiers (Pal and Mather, 2001).

2. METHODOLOGY

This project was divided into two phases: I) Sampling field data; and II) Generating thematic fuel maps. For the former, the following fuel types were sampled to support thematic maps generation: (a) 1-HR fuels; (b) 10-HR fuels; (c) Depth of litter; and (d) Litter weight. The information used in this study was collected based on a special forest inventory. Since we knew well the study area, we used a stratified sample design, with sample plots located randomly into each stratum. Such stratum were defined based in the reflectance of satellite imagery, in an area of around 270,000 ha. Both stand data (trees and environment) and fuel loading were measured. A total of 79 sample plots were measured, during. Forest fuels evaluation was based on the techniques and methodologies described by Brown and Bevins. (1986). Plot center locations were determined using a global positioning system (GPS) receiver. To evaluate fuels we divide them into two groups: a) fine fuels (mainly litter); and b) thick fuels (branches). These fuels were measured based in a global sample plot, which was designed to support a more complex forest inventory (Figure 1). The structure of the sample plot is based on a 30 x 30 m square, which at the same time is divided into 9 sub-plots. In such sub-plots several forest variables are evaluated, such as tree density, tree diameter, tree height, etc. Specifically for forest fuels evaluation is carry out in sub-plots 3, 5 and 7, where are located a 30 x 30 cm square, to measure fine fuels, and a 14 transect to measure thick fuels.

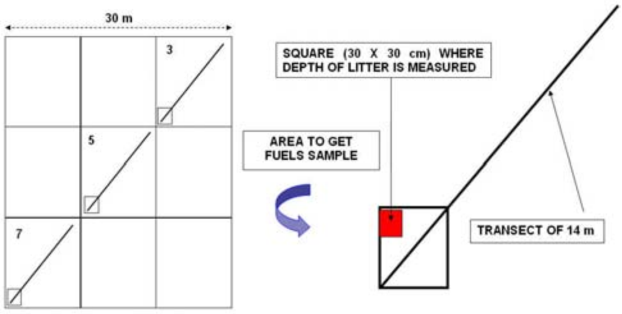

Figure 1. Sample plot design used to measure forest fuels characteristics: a) A 30 x 30 cm square for sampling fine fuels (litter and humus); b) *C* ; A 14 m transect to evaluate downed woody of 0 - 7.5 cm of diameter.

To generate the thematic maps we use the technique CART, which was based on the use of each band of the Landsat TM imagery of 2003. Recently, CART, also known as recursive partitioning regression, has received more attention from land use/cover classifiers. CARTs subdivide the space spanned by the predictor variables into regions, for which the values of the variable response are approximately equal, and then estimate the variable response by a constant in each of these regions (Moisen and Frescino, 2001). The tree is called a classification tree if the variable response is qualitative and regression tree if the variable response is quantitative. Very few studies have assessed the use of decision trees as classifiers. However, this technique has substantial advantages for remote sensing classification problems due to their non-parametric nature, simplicity, robustness with respect to non-linear and noisy relations among input features and class labels, and their computational efficiency (Pal and Mather, 2001). As it was mentioned, CART process was also based on ancillary information to support the classification of satellite imagery of the study area. As ancillary variables we work with those that can be generated based on a digital elevation model, such as elevation, slope, aspect, etc. We generated CART´s for the following variables of forest fuels: litter depth, organic matter depth, 1-hour fuels, 10-hours fuels, and 100-hours fuels.

3. RESULTADOS Y ANALISIS

According to the CART´s generated, the variables defined using the digital elevation model have a higher influence to modeling the spatial distribution of fuels (Figure 2). The resulting maps shows that higher fuel loads (tn/ha) occurs in the central region of the study forest land (Figure 3). The larger depth measures of both litter and organic matter were located were pine species occur: Due to the low amount of sample plots, there are some limitations regarding models precision. Nevertheless the methodology showed allows to consider a larger number of control plots and improve the resulting models.

Figure 3a shows the spatial distribution of litter, where the higher fuel loads are located in the forested areas. The black spot located in the center of the map corresponds to Guadalajara, city (Jalisco state, Mexico). The areas with lower values correspond mainly to agricultural lands or grass lands. On the other hand, Figure 3b it is possible to see the spatial distribution of fuel loads corresponding to 1-hour fuels (0-0.6 cm of diameter). In this case, the higher values are located in a strip at the north center region of the study area. This area is defined by the riparian vegetation along the Lerma river, which mostly is low tropical forest. In general we found a low amount of 1-hour fuels in the study area.

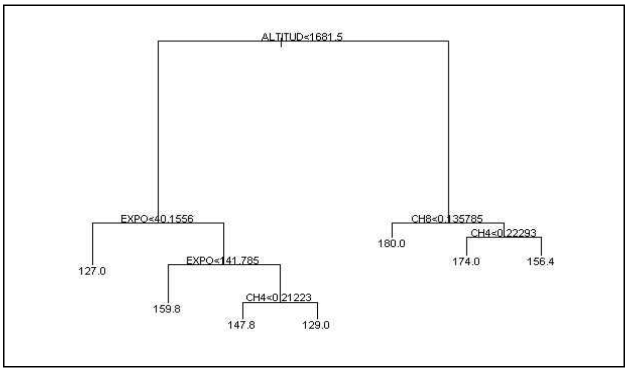

Figure 2 . Regression tree defined to estimate the spatial distribution of 1-hour fuels.

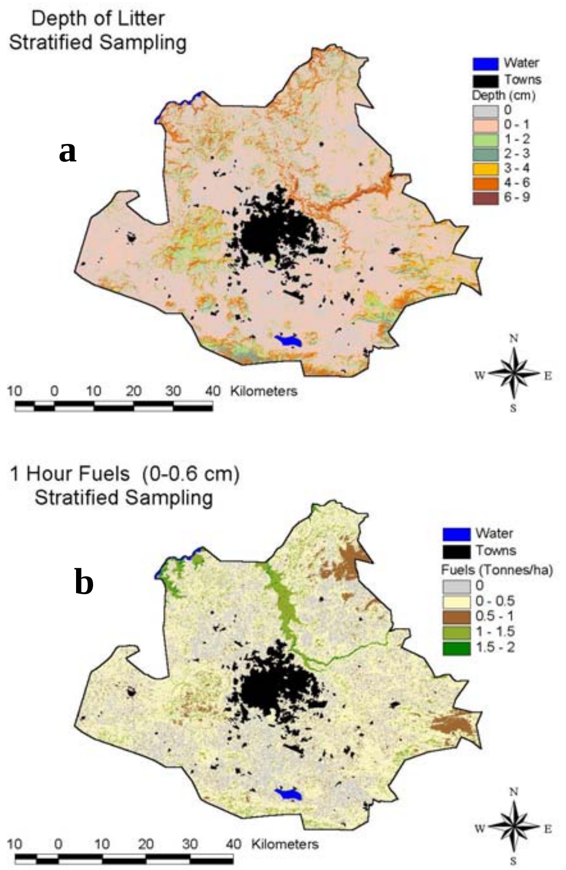

Figure 3. a) Litter depth; and b) 1-hour fuels (branches less than 0.6 cm in diameter).

4. CONCLUSIONS

Since the study area is affected frequently by wildfire, it make sense that any attempt of a sustainable management considers both fire occurrence and fire effects. This information has its higher usefulness when it is considered under a spatial approach. It is not enough to know that we have different fuel loadings along our managed areas, but it is essential to define their spatial variability. The definition of continuous surfaces is a great alternative to understand better the gradual changes of forest fuels. Based on this it will be possible to prioritize which areas have more risk of fire (related mainly in 1-HR distribution), and which areas could produce higher negative effect of the forest ecosystem elements (tree, grasses, soil, water, etc.). The latter is focused mainly on the potential of fire intensity fire, which are related to large dimensions fuels (Albini, 1976). Nevertheless, in Mexico this kind of spatial information is not considered, and most of the forest management plans mention the implementation some practical activities as the solution to the fire problem. However, there is not a clear support not only on the implementation of such practices, but also in their location and dimension. The thematic maps resulted under the illustrated methodology illustrated in this paper, could be used to: i) prioritize areas; ii) give dimension to the problem (calculating a given area; and iii) calculate time and cost requirements. Finally, decision makers should consider other ancillary data, such as climate, roads, altitude, wind, vegetation, and human activities. Thinking on fire as a factor that can alter considerably any sustainable management plan, it is important to spend some time and resources to develop the type of maps showed in this paper.

Regardless that we can consider that the amount of sample plots is limited, the results are good enough. However, we want to point out the methodological process of CART is adequate to model the spatial distribution of forest fuel features. Although CART has certain level of complexity its use is very practical. Mainly because it so flexible that allows to test different layer of information. In further studies we recommend to compare the results when using other techniques, such as kriging, cokriging, non-supervised and supervised classifications, etc.

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