

Spatial Distribution of Fuel Models Based on the Conditional-Fuel-Loading Concept

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Abstract

Fuel model mapping has followed in general two trends: 1) indirect inferences, where some factors, presumably associated with fuel production, are related to a given fuel model; and 2) experts consulting, which has been used to classify and to validate other people classifications. However, reliance on expert judgment implies a subjective approach. Thus, I propose the integration of geostatistic techniques and the Conditional-Fuels-Loading concept (CFL) to define a more objective perspective in the fuel-model mapping. The information used in this study was collected in a forest of Chihuahua, Mexico, where fuels were inventoried in 554 (1000 m²) sample plots. These sample plots were classified using the CFL; and ordinary kriging (Gaussian, spherical and exponential) was used to interpolate the fuel-model values. Using the Akaike's Information Criterion the spherical model performed best. The methodology allowed a finer definition of spatial distribution of fuel models. Some advantages of the CFL are: 1) it is based on actual fuel loads, and not only on vegetation structure and composition; 2) it is objective and avoids the bias of different classifiers (experts); and 3) it avoids the need of the advice of experts.

Keywords

Validation, Fuel Mapping, Geostatistics, Ordinary Kriging

1. Introduction

Many strategies for fire management are based on prior knowledge of the potential fire behavior of a given forest [1] [2]. Based on this knowledge many fire behavior simulation systems have been developed. Among them, FARSITE [3] is one of the most complete and used systems. All these simulation systems require information of the spatial distribution of forest fuels, which in most cases is

represented through fuel-models (a generalized description of fuel physical characteristics [4]). Fuel-model mapping in general has followed two trends: 1) indirect inferences, where some factors like vegetation, species, and density, presumably associated with fuel production, are related to a given fuel-model [5] [6]; and 2) experts consulting, which implies a subjective approach. Regardless the complexity of a new technology, many fuel-model classifications are validated through the experts' judgment [7].

Although an expert can classify a forest into a given number of fuel-models, the spatial limits between one fuel-model and another are difficult to establish [8] [9]. Moreover, there is no guarantee that the same area will be classified the same way by two or more experts [10]. To avoid these two limitations, the use of the Conditional Fuels Loading concept (CFL) [11] is suggested in this study. CFL is based on certain proportion of fuels loading that correspond to each fuel-model. Because fuel is the basic element in a fire behavior prediction, its direct estimation avoids the use of inference methodologies, which have shown highly variable accuracy (ranging from 30% to 70% [4]). Direct fuels surveys are both costly and time consuming [12], so in this paper I propose the use of geostatistical techniques to define more accurate estimations. Geostatistics provides a method to describe the spatial continuity of many natural phenomena [13] [14]. Moreover, geostatistical techniques perform well with sparse data, thus it is possible to work with less data [15], reducing both the cost and time required in a fuel survey. The use of geographic information systems (GIS) techniques allowed the integration of both geostatistics capabilities and fuel inventory information to define the spatial distribution of fuel-models [16] [17].

2. Material and Methods

2.1. Study Area

The study area is located within a region that covers approximately 250,000 hectares of primarily coniferous-oak forest, which is an important component of Mexico's Sierra Madre Occidental [18]. This study was carried out using information from a commercial forest of the ejido (rural community) "El Largo y Anexos". This ejido is located within the region called Mesa del Huracán, northwest of the state of Chihuahua, México (Figure 1). The predominant tree species are *Pinus durangensis*, *P. arizonica*, *P. engelmannii* and *Quercus sideroxylla*. Most of the topography is mountainous, with some valleys. The annual mean temperature ranges from 8.5°C to 12°C. The extreme minimum temperature registered is -26°C. The extreme maximum temperature is 38°C. The range of precipitation is between 690 and 1130 mm/year (most of the rainy season occurs from July to September). Elevation ranges from 1400 up to 2400 m. Fire season is in summer, during the dry season (from May to June) [18].

2.2. Data Collection

The information used in this study was collected based on a traditional forest

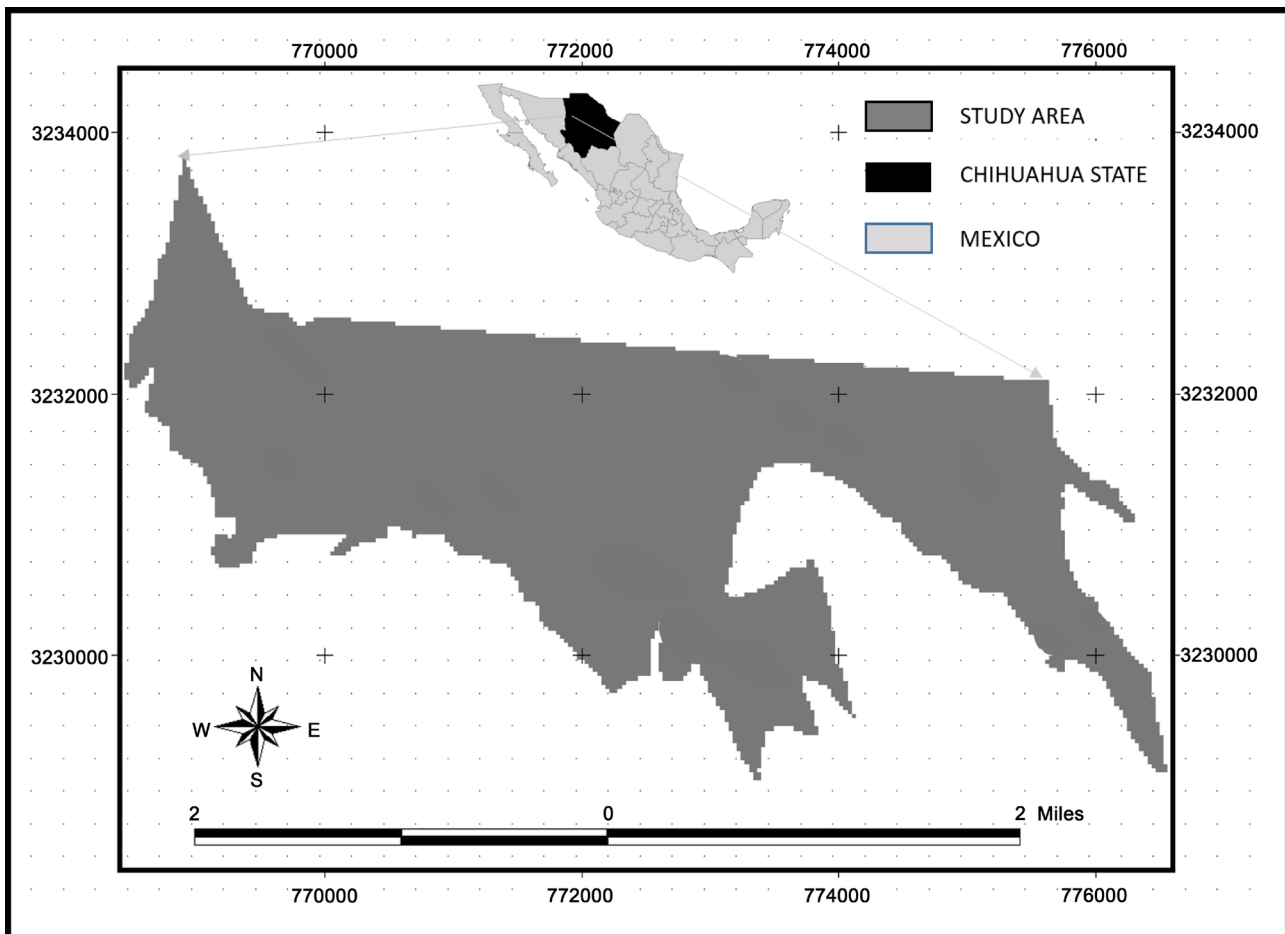


Figure 1. Location of the study area within “Mesa del Huracán”, at 270 km of Chihuahua City, Mexico (UTM Zone 12).

inventory of Mexico. A total of 554 (1000 m²) sample plots were measured distributed randomly into 142 sub-stands (defined by species, density, and aspect). An inventory was conducted within an area of about 1200 ha. In the inventory I evaluated the 1 hr, 10 hr, 100 hr, and live woody forest fuels. Forest fuels evaluation was based on the techniques and methodologies described by Brown *et al.* [19]. Plots center location was determined using a global positioning system (GPS) receiver.

2.3. Conditional Fuels Loading Concept

To classify the sample plots into their corresponding fuel-model class, the CFL concept was used [11], which considers that each fuel-model contain a characteristic amount and proportion of 1-hour, 10-hour, and 100-hour fuel classes. In general the study area was considered within the “Timber litter” fuel complex (fuel-models 8, 9, and 10) [20]. Based on the characteristic fuels loading that corresponds to fuel-models 8, 9, 10 (Table 1), the following “conditional proportions” were evaluated for each sample plot:

1) The sum of the characteristic 10-HR and 100-HR fuels loading for FM-8 is 7.84 ton/ha. For practical purposes this value was considered as integer (=8). Thus:

Table 1. Fuel loads (ton/ha) corresponding to the “timber litter” fuel complex, of the NFFL* classification [21].

Fuel model	Typical fuel complex	1-hr	10-hrs	100-hrs
		ton/ha		
FM-8	Closed timber litter	3.36	2.24	5.60
FM-9	Hardwood litter	6.55	0.92	0.34
FM-10	Timber (litter and understory)	6.75	4.88	11.23

*Northern Forest Fire Laboratory [22].

$$\text{if } (10\text{-HR} + 100\text{-HR}) < 8 \Rightarrow \text{FM-9.} \tag{1}$$

2) Based on a manual qualification of several sample plots, a factor of 18.8 (approx. 19) (that corresponds to the multiplication of 1-HR fuel loading times the 100-HR fuel loading) has been defined to separate sample plots between FM-8 and FM-10. Thus:

$$\text{if } (1\text{-HR} \times 100\text{-HR}) > 19 \Rightarrow \text{FM-10.} \tag{2}$$

3) The remaining unclassified sites corresponded to FM-8.

4) Oak species are typical in FM-9 [20]. Therefore, once the sites are classified, a final filter is used. Thus, all the sites where *Quercus spp* occurred are reclassified as FM-9.

2.4. Fuel Model Mapping

After a fuel-model value was defined for each 1-hr, 10-hrs, and 100-hrs fuel class, ordinary kriging (OK) technique was used to interpolate the fuel-model values of the 554 sample plots. OK is applied when the mean of the data values is stationary, but unknown. OK is considered as the “best linear unbiased estimator” [23] [24]: 1) Linear, because its estimates are weighted linear combinations of the available data; 2) Unbiased, because it tends to generate a mean square error equal to zero ($E[\text{Estimated}(x_0) - \text{True}(x_0)] = 0$, and $\sum \lambda_i = 0$); and 3) Best, because it aims at minimizing the variance of the errors ($E[\text{Estimated}(x_0) - \text{True}(x_0)]^2 = \text{minimum}$). Isaaks and Srivastava [24] describe in detail the mathematical derivation of these constraints, and of the systems of equations to determine interpolation weights (λ_i). The following formulas are used to calculate the OK estimates and variance respectively [23] [24]:

$$\hat{Z}_{OK}(x_0) = \sum_{i=1}^n \lambda_i \cdot Z(x_i) \tag{3}$$

$$\sigma_{OK}^2(x_0) = C(x_0, x_0) - \sum_{i=1}^n \lambda_i \cdot C(x_i, x_0) + \mu \tag{4}$$

where:

$\hat{Z}_{OK}(x_0)$ = ordinary kriging estimate at location x_0 ;

λ_i = the weight for sample point i at location x_i ;

$Z(x_i)$ = the value of the observed variable Z at location x_i ;

$\sigma_{OK}^2(x_0)$ = ordinary kriging variance at location x_0 ;
 $C(x_0, x_0)$ = the covariance of the point to estimate at location x_0 with itself;
 $C(x_i, x_0)$ = the covariance of the sample point at location x_i and the point to estimate at location x_0 ; and
 μ = Lagrange parameter.

The general process for ordinary kriging is illustrated in **Figure 2**, which starts with the sample data that are used to calculate an experimental variogram. Then, a variogram model is fitted to the experimental variogram. After that, the sample data and the variogram model are used as inputs of the ordinary kriging procedure. Finally both, the ordinary kriging estimates and the ordinary kriging variances are generated [23].

3. Results

3.1. Variogram Analysis

The results of a general proximity matrix are shown in **Table 2**. Although the maximum distance between points was more than 8.5 km, 75% of the sample plots have a distance lower than 3.8 km. The knowledge of the minimum distance between points (in this case 40 m) was useful to define the lag distance used to define the experimental variogram.

An omnidirectional variogram for Fuel-Models (FMs) was developed under an isotropic approach (**Figure 3**). The lag distance of 20 m, and two neighbors,

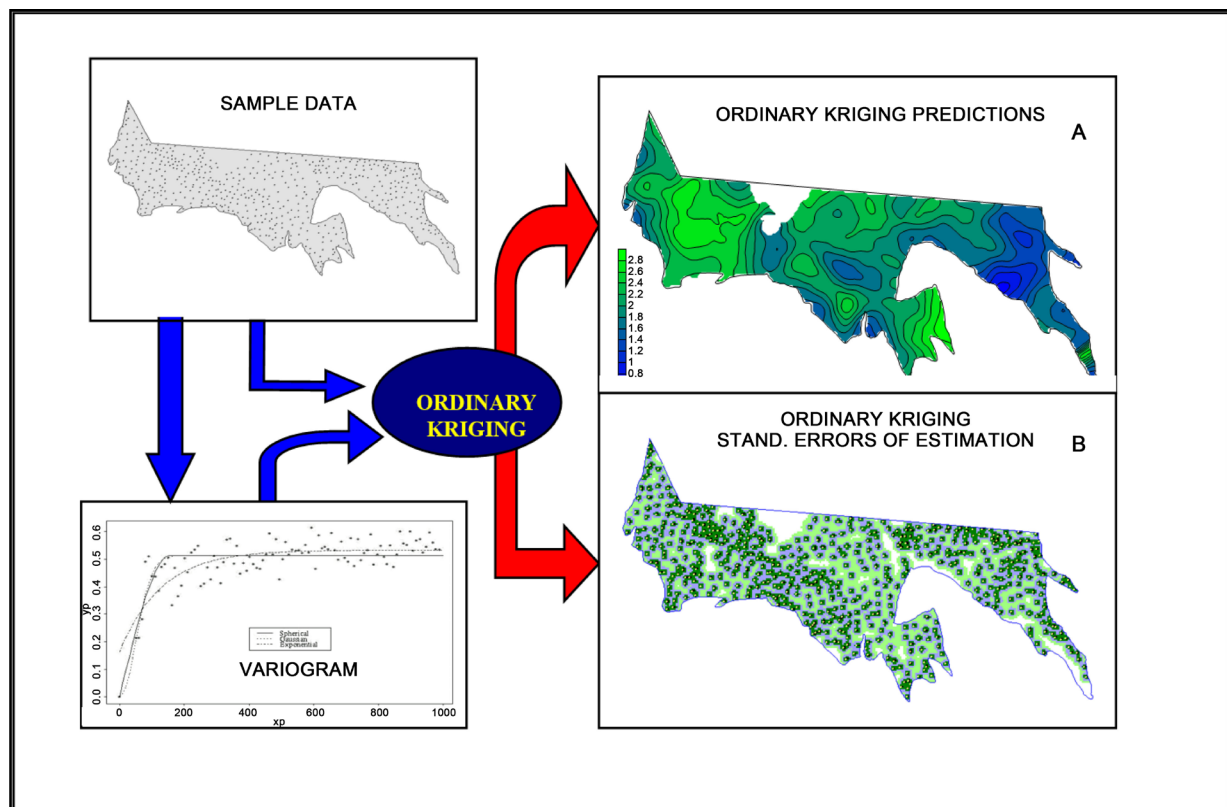


Figure 2. Diagram of the ordinary kriging process. Variogram graph illustrates three different models for spatial continuity.

Table 2. Characteristics of the distance matrix corresponding to the 1-hour fuels within the study area.

Statistics	Value
Number of sample plots	535
Average distance between points	2791.10 m
Distance range	8599.28 m
Minimum distance between points	40 m
Quartiles	
First	1435.86 m
Median	2522.76 m
Third	3896.03 m
Maximum distance between points	8639.28 m

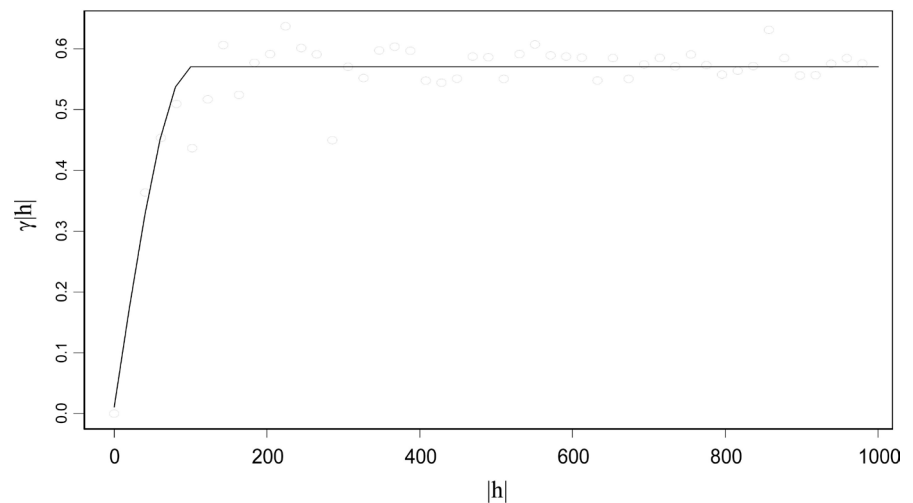


Figure 3. Experimental variogram and the corresponding model for fuel-models (spherical). The variogram values ($\gamma|h|$) are half the average squared difference between the paired data values.

showed best results in the definition of this experimental variogram. The lag tolerance applied was one half of the lag distance. Three positive definite models (Gaussian, spherical and exponential) were tested to select the best fit to the experimental variogram. The Akaike’s Information Criterion (AIC) [9] was used as criterion to select the best model. The AIC is a way of selecting a model from a set of models. The chosen model is the one that minimizes the Kullback-Leibler distance between the model and the truth [25]:

$$AIC = -2(\ln(\text{likelihood})) + 2K \tag{5}$$

where:

likelihood = the probability of the data given a model.

K = the number of free parameters in the model.

From **Table 3**, we see that the spherical model resulted in the lower AIC. The variogram that define this model reached the maximum variance (sill) at a dis-

tance of 100 m (range). After this distance the FM variable is no longer spatially autocorrelated. The spherical model resulted in a very low nugget effect, which help to define a better fitting.

3.2. Kriging Results

FM estimates were produced for unsampled sites considering two neighbors (sampled points). OK estimations were made under a 40×40 m grid, which correspond to the minimum distance between sample plots (Table 2). The resulting estimations were not discrete, therefore the following criteria were used to group each cell: FM-8 cell values from 8 to 8.66; FM-9 from 8.66 to 9.33; and FM-10 from 9.33 to 10. Figure 4 shows the spatial pattern of the three fuel models, which resulted from the ordinary kriging process. Most of the study area falls in the fuel models 8 and 9 (38.1% and 34.8% respectively). FM 10 has coverage of 15.1%.

The standard errors associated with the estimates were also calculated. Figure 5 shows a contour map and a surface map of the standard errors resulting from the estimation of FMs. This error was spatially distributed quite homogeneously.

Table 3. Characteristics of the models that correspond to the experimental variogram of the spatial continuity of fuel-models.

Model	Nugget	Sill	Range	AIC
Spherical	0.0109	0.5704	100.8600	-110.68
Gaussian	0.0148	0.5703	79.7320	-109.97
Exponential	0.000	0.5768	57.6739	-45.6167

AIC = Akaike's Information Criterion. The best model is that that minimize the AIC [9].

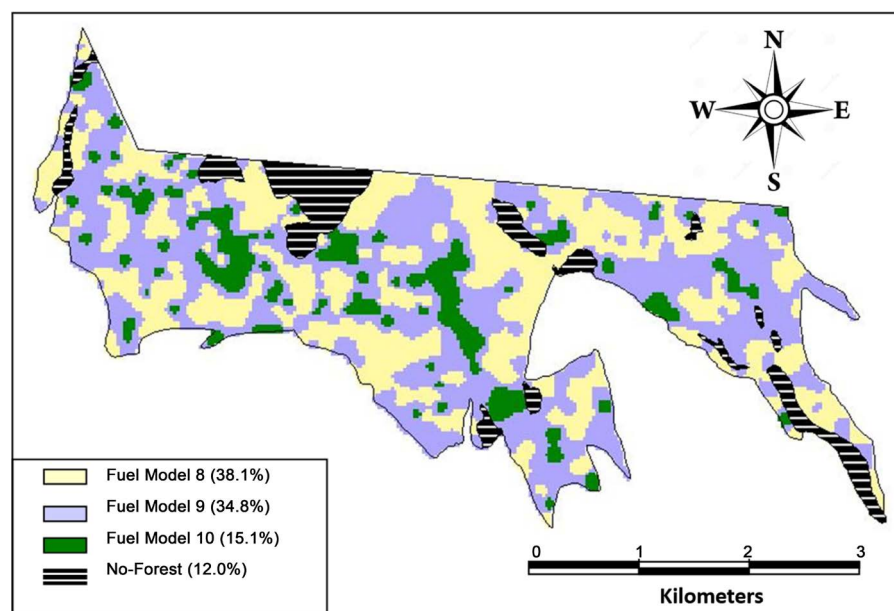


Figure 4. Spatial pattern of fuel models in the study area, of the “timber litter” complex, resulting from ordinary kriging analysis.

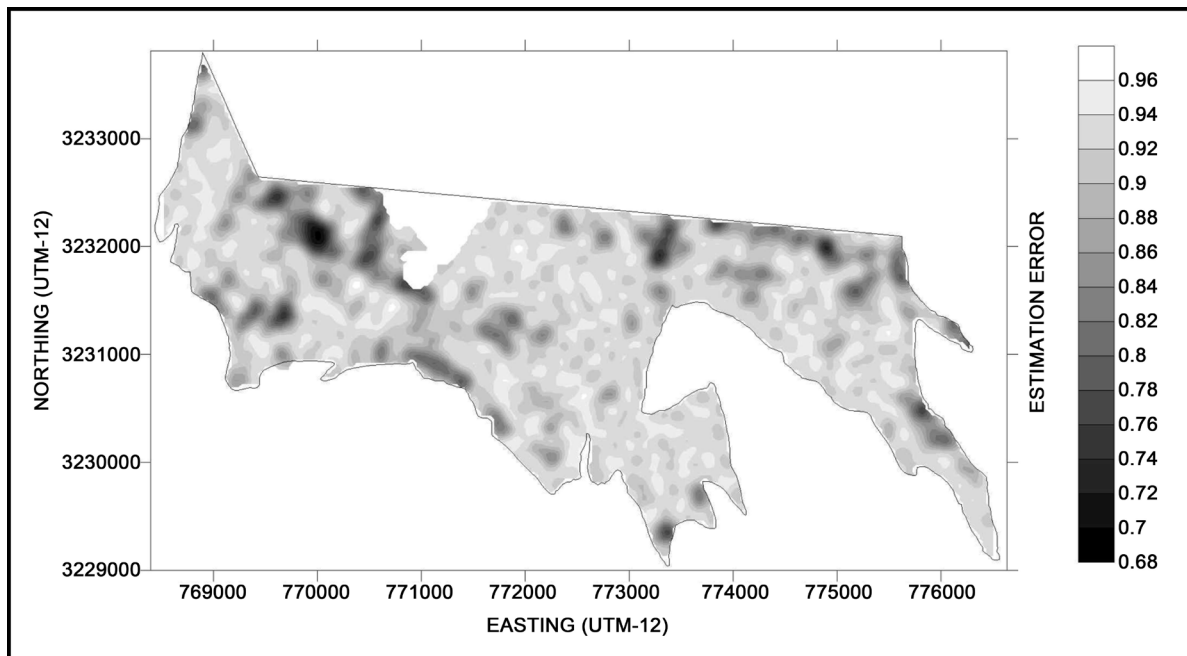


Figure 5. Spatial distribution of the standard error resulted from the estimation of fuel-models.

This could be explained by the high concentration of sample plots. The minimum and the maximum values were 0.68 and 0.96 respectively. Most of the standard error values were higher than 0.86.

4. Discussion

The spatial implementation of the fuel-model concept has caused many technical problems, such as the difficulty to mapping fuel-models in a given area. Furthermore, fuel-models do not reflect the actual spatial variability of fuel characteristics. This is so because fuel-model maps tend to qualify big areas, that are considered homogeneous, into the same fuel model, assuming a homogeneous fire behavior (for a given projection period). Therefore the fuel-model approach would be useful in areas where vegetation and fuels are spatially homogeneous. However, in practice this condition is very rare. Although current fuel-model mapping approaches have been useful in many cases [3] [4], its use is limited to support fire management strategies at large scale. Eventually, the next step would be to define fire behavior at a smaller scale, basically to locate risky areas.

A FM classification of a given area has to combine two requirements: 1) a correct determination of a FM (classification component); and 2) an accurate definition of the spatial distribution of FMs (spatial component). The use of experts' judgement could help to overcome the first requirement. However, with the "experts judgement" approach the definition of the FM spatial distribution (size, limits and location) has presented serious problems. Although, the use of GIS and remote sensing technology has solved the second requirement, the resultant accuracy has been rather low [4]. The methodology illustrated in this paper overcomes these two requirements. Moreover, until now there was not

any objective way to validate not only the FMs classification based on inference procedures, but also to validate the experts' judgements. Therefore, the present methodology could be used for both validation and calibration purposes. On the other hand, the advantages of large scale classifications (based on inference alternatives (e.g. remote sensing)) and lower scale classifications (based on the present methodology) could be combined, through the implementation of double sampling methodologies [26] [27].

The use of ordinary kriging, as a spatial interpolation technique, was very practical. However, the classification of the resulting continuous estimations could present certain level of subjectivity. Therefore, specific thresholds between one FM and another should be defined. Nevertheless, the consistency of the estimations from using the proposed methodology makes much simpler to define such limits than to classify the same area based on an expert judgement.

Because of cost and time constraints the methodology presented in this paper could result impractical in operative evaluations. However, the advantage of interpolation techniques such as kriging is that it is possible to work with sparse and less data [15]. This condition allows to experiment with lower amounts of sample plots, which positively affect both the time and cost required. Moreover, the spatial definition of the estimation error resulting from the kriging analysis can be used to define better sampling strategies (sampling intensity and design). On the other hand, ancillary data could be used, through co-kriging techniques, to enhance the precision of the estimations of FMs. However, very few have been done in the use of geostatistical alternatives to support the classification of fuel-models. Thus, an indirect objective of this paper was to show the potential of using kriging techniques.

5. Conclusions

The methodology showed in this paper allows a finer definition of spatial distribution of fuel models. This could support a more accurate prediction of the spatial fire behavior. The application of the CFL Concept does not require previous experience in fuel-model classification. Moreover, working within the same area the implementation of the CFL concept results in the same classification of the sample plots. Other advantages of this classification methodology are: 1) it is based on actual fuel loads, and not only on vegetation structure and composition; 2) it is objective and avoids the bias of different classifiers (experts); and 3) it avoids the need of the advice of experts.

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