ORIGINAL RESEARCH ARTICLE

Digital cartography of soil classes with fuzzy logic in mountain areas

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ABSTRACT

In order to strengthen the study of soil-landscape relationships in mountain areas, a digital soil mapping approach based on fuzzy set theory was applied. Initially, soil properties were estimated with the regression kriging (RK) method, combining soil data and auxiliary information derived from a digital elevation model (DEM) and satellite images. Subsequently, the grouping of soil properties in raster format was performed with the fuzzy c-means (FCM) algorithm, whose final product resulted in a fuzzy soil class variation model at a semi-detailed scale. The validation of the model showed an overall reliability of 88% and a Kappa index of 84%, which shows the usefulness of fuzzy clustering in the evaluation of soil-landscape relationships and in the correlation with soil taxonomic categories.

Keywords: Fuzzy Logic; FCM Algorithm; Regression Kriging; Digital Soil Mapping; Soil Classes

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1. Introduction

Emerging technologies have created new opportunities to support quantitative soil survey methods that generate predictions with greater precision and accuracy. However, the needs of users of soil information are diverse. Knowledge of the spatial variation of soil properties should satisfy the requirements of agricultural and environmental models, strengthen decision making related to the spatial variation of some particular soil properties as well as visualize the behavior of several relevant soil properties together in a model of spatial variation of soil classes. In this regard, digital soil mapping allows the representation of the spatial variation of specific soil properties, and provides the possibility of integrating the various property models to obtain soil classes, in order to support decision making on soil conservation, watershed management and development of agro-environmental projects, among others.

At present, numerous statistical models have been applied for the interpolation of soil properties, among which geostatistical methods stand out, which are demanding in terms of the number of samples and the small geographical extension they represent. One of the most significant methodological developments for the prediction of soil properties are the predictive methods that combine multiple linear regression and interpolation of residuals[1,2]. This method of analysis, together with the development of geographic information systems (GIS), supported with auxiliary information of adequate spatial resolution (DEM and its derivatives, and satellite images), offers new opportunities

to produce edaphic information efficiently, in the shortest possible time. Similarly, fuzzy set theory[3] is one of the most important scientific advances used in soil classification. The algorithms developed under fuzzy logic have the ability to learn from the data provided and to process a large amount of complex and imprecise information. This feature makes it possible to explore and evaluate soil-landscape relationships in highly complex sectors such as mountainous areas.

The aforementioned techniques provide a broad scientific basis for strengthening CDS. The RK model can play an important role in geostatistics, because many covariates are available with the advancement in remote sensing and positioning technologies[2]. Many studies have shown that RK is easy to use and its accuracy often outperforms ordinary linear regression, ordinary kriging[4] and co-kriging. In this regard, Bishop and McBratney found that RK is more accurate in predicting soil CEC; it has been of great importance in predicting effective soil depth[5], and is most appropriate when auxiliary information can explain part of the variation in the estimated variable[6].

The most relevant applications of fuzzy logic in the edaphological field stand out in: a) soil classification[7–14]; b) soil survey and land assessment[15,16]; c) soil-landscape relationship modeling[17,18]; d) digital soil mapping[19–22]; e) soil property prediction[23,24]; f) zones for site-specific management[25]; g) landscape ecology[26]; h) soil quality assessment[27,28]; i) land cover change assessment[29].

In most of the cases studied where fuzzy logic is applied, a set of soil data obtained from a systematic sampling is initially grouped. Subsequently, the ordinary kriging or cokriging interpolation method is applied for the estimation of soil properties, and finally the values of the membership function are interpolated using the parameters obtained from the adjusted variograms for the prediction of soil properties. In other investigations, the algorithm is applied with the purpose of classifying the soil data set to generate important explanations about soil-landscape relationships, but without reaching the cartographic representation of soil classes.

The objective of this research was to produce a map of fuzzy soil classes by applying the FCM algorithm for the clustering of soil property prediction models in raster format, previously obtained with the kriging regression method. The algorithm allows the establishment of gradual boundaries between classes, which in turn can facilitate the establishment of correlations with geomorphological characteristics and taxonomic categories of soils in a sector of the upper Guárico River basin, specifically in the Caramacate River basin in Aragua State (Venezuela).

2. Materials and methods

2.1 Description of the study area

The research was carried out in a sector of the upper Guárico river basin, specifically in the Caramacate river basin, which is located between the municipalities of Santos Michelena and San Sebastián de los Reyes in Aragua State (Venezuela), between the geographical coordinates 9.55 to 10.09° North and 67.12 to 67.03° West (**Figure 1**). The Caramacate river basin represents 8.5% of the upper Guárico river basin, of which it is a tributary. Although this basin supplies 60% of the water consumed by the Caracas metropolitan area, it is subject to intense environmental degradation processes and lacks sufficient information to support the implementation of management plans.

A sample of 6,760 ha was selected for the soil grouping test, where the landscape is dominated by mountain slopes with slopes of 40%. The geology is represented by metavolcanic rocks and basalts of the El Caño-El Chino formation, and by mafic metalliferous rocks of the El Carmen formation[30]. The zone's altitude ranges from 334 to 1,405 masl, with average annual precipitation ranging from 1,100 to 1,400 mm and average annual temperatures ranging from 22 to 26 ℃. Herbaceous vegetation occupies more than 50% of the sector's cover, as a result of extensive livestock use, overgrazing and annual burns. The soils are mostly Entisols, Inceptisols and Alfisols, whose variability has increased due to land use based on extensive cattle ranching and the incidence of mass movements[31].
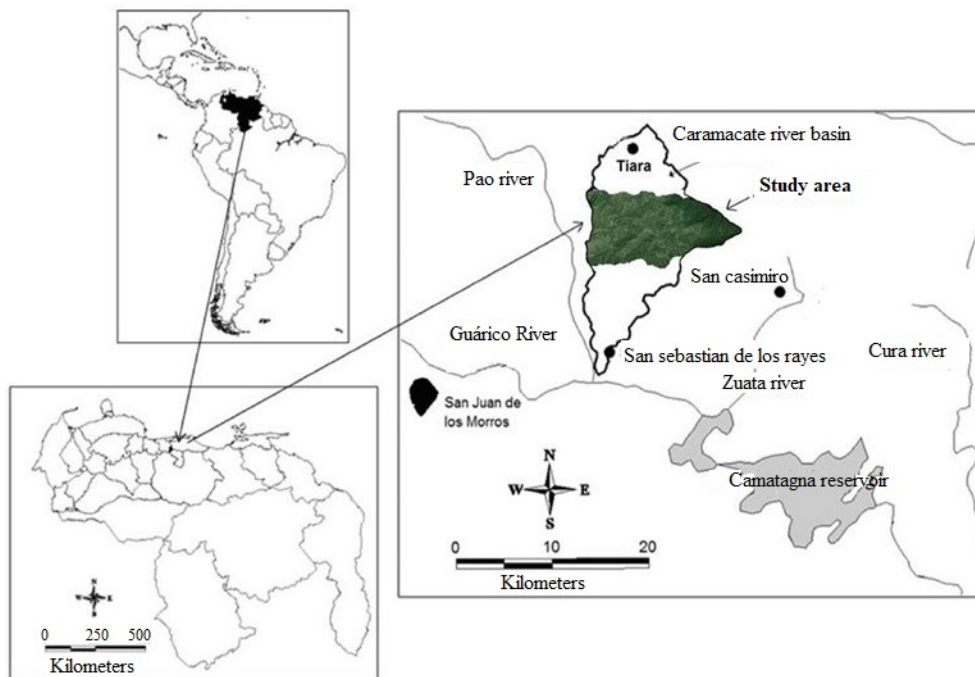
69

Figure 1. Relative location of the study area within the Guárico river basin, Aragua state, Venezuela.

2.2 Prediction of soil properties

Soil properties were estimated by applying the spatial prediction model called regression kriging (RK) or residual kriging, based on the combination of the ordinary kriging technique and multiple linear regression. This statistical model allowed the integration of the regression values of edaphic variables and environmental attributes with the interpolation values of the residuals of this regression[32]. The RK algorithm considers the local correlation between environmental variables and the unsatisfactory goodness of fit of spatial variation models for a given data set. The auxiliary variables were derived in previous studies, starting from a digital elevation model of 8 m resolution(altitude(msnm), slope(rad), slope orientation(rad), topographic moisture index,arearecapture(m^2), perfildecurvature(m.m^{-2}), plane of curvature(m.m^{-2}), relative position) and the red and infrared bands of a SPOT(NDVI) satellite image, at 15 m spatial resolution[33]. Additionally, a precipitation map estimated by ordinary kriging was used[34].

With RK, models were generated for the variation of nine (9) soil properties, organized according to their nature in: a) morphological: thickness of horizon A (Esp A), thickness of solum (Esp AB), effective depth (PEF); b) physical: coarse skeleton (%EG), sand (%a) and clay (%A), and c) chemical: organic carbon content (%CO), percentage of saturation with bases (PSB) and pH of the soil in water (1:1). In the prediction of edaphic properties, 100 soil profiles were used to generate the models (75%), and 33 profiles were used for validation (25%). The validation of soil properties indicated that the agreement index between the estimated values and the observed values exceeded 72% on average, with a degree of agreement of 61% for morphological variables, 74% for physical variables, and 84% for chemical variables. These variables were used as input parameters to the network.

2.3 Prediction of soil classes

The Fuzzy C-means (FCM) algorithm, implemented in the FuzME program by Minasny and McBratney, was used to generate the digital fuzzy soil class model.

2.3.1 Fuzzy C-means algorithm (FCM)

The FCM fuzzy classification algorithm is also called Fuzzy k-Means, and produces an unsupervised classification of individuals into fuzzy classes. The FCM optimally divides a dataset into a number of classes and computes the memberships of each of the elements to each of the categories. The algorithm

70

requires a previous training process with a certain number of classes and diffusivity coefficients. Generally, it ends when it reaches the maximum number of iterations or when the result of one iteration and the previous one is less than or equal to the convergence coefficient, which are user-defined learning parameters.

The objective of the FCM algorithm[35,36] is to minimize the weighted root mean square sum of the distances between the points Zk and the center of the class Ck, and the distances ik, are weighted with the membership value i,k. Therefore, the objective function is:

$$J(Z;U,C) = \sum_{j=1}^{n} \sum_{k=1}^{c} (\mu_{ik})^{\phi} d_{ik}^{2}$$

(1)

where $Z = \{Z_1, Z_2, \ldots, Z_n\}$ is the data to be classified, $U = [\mu_{ik}]$, is the fuzzy partition matrix of Z, $C = [c_1, c_2, \ldots, c_c]$ is the vector of centroids or patterns of the classes to be determined, d_{ik}^{2} is the squared distance between ik, and (1) is a weighting exponent that determines the degree of fuzziness of the resulting classes.

The membership function μ from the i-th object to the k-th cluster in the ordinary fuzzy k-means algorithm employs the distance d used for similarity, and the fuzzy exponent to determine the diffusivity magnitude:

$$\mu_{ik} = \left[(d_{ik})^2 \right]^{-1/(\phi-1)} / \sum_{k=1}^{c} \left[(d_{ik})^2 \right]^{-1/(\phi-1)}$$

(2)

Once the membership intensities have been determined, the centroids of the classes (c_k) are calculated by means of the following equation:

$$c_k = \sum_{i=1}^{n} (\mu_{ik})^{\phi} x_i / \sum_{i=1}^{n} (\mu_{ik})^{\phi}$$

(3)

As for the initialization process, the FCM works by means of an iterative procedure that starts with a random distribution of the objects to be classified into k classes. Given the distribution of the classes, the center of each is calculated as the average of the attribute values of the objects. In the next step, the objects are redistributed among the classes according to their relative similarity. The similarity index is usually a distance measure (d) such as the Euclidean, Diagonal or Mahalanobis distance[37].

2.3.2 Number of fuzzy classes

To obtain the best fuzzy class model, an inductive approach was used, based on the procedure, which relates the Fuzziness Performance Index (FPI) and the modified partition entropy (MPE) to the number of classes. These parameters are obtained using the Fuzzy c-Means (FCM) algorithm of the Fuzme 3.5 program[38].

The selection of the optimal number of classes in FCM was performed by repeating the classification for a range of number of classes. For each clustering obtained, two classification parameters are generated, such as the FPI and the modified partition entropy (MPE). The FPI estimates the degree of diffusivity generated by each specific number of classes. Mathematically, it is defined as:

$$FPI = 1 - [(cF - 1)/(c - 1)]$$

(4)

where: c is the number of classes and F is the partition coefficient calculated as:

$$F = (1/n) \sum_{i=1}^{n} \sum_{k=1}^{c} (\mu_{ik})^2$$

(5)

F is conceptually comparable to the ratio of the set of variances within classes to the variance between classes and is close to 1 for the most significant clustering. In the present study, the clustering of maps in raster format was performed by previously establishing the following parameters: a) number of classes (c = 6 to 12), b) fuzzy exponent = 1.1 to 1.6 with increments of 0.1; c) a maximum of 50 iterations, and d) stopping criterion (ε = 0.0001). The metric distance used was that of Mahalanobis, which takes into consideration the correlation found between some properties present between soils and landscapes of the studied area.

2.3.3 Evaluation of the soil class model

For the evaluation of the reliability of the soil classes, confusion matrices were developed and calculations of the overall accuracy (EG)[39] and the Kappa(k) index[40] were performed. The Kappa concordance index is used as a method to evaluate multicategorical classifications, allowing to determine to

what extent the observed concordance is superior to that expected to be obtained by pure chance, and is defined as follows:

$$k = \sum_{c=1}^{n} f_o - \sum_{c=1}^{n} f_e \, / (n - \sum_{c=1}^{n} f_e)$$

(6)

where f_o is the sum of the observed frequencies on the main diagonal of a cross-tabulation, f_e is the sum of the expected frequencies on that diagonal, and n is the total number of cases (categories).

The overall accuracy of the model (EG) was obtained from the number of well-assigned classes versus the total number of categories (n) used in the calibration or validation of a model, with respect to the frequencies observed in the main diagonal of the confusion matrix, with the following formula:

$$EG = \sum_{c=1}^{n} (f_o \, / \, n)$$

(7)

The soil map validation module of the digital soil mapping software SoLIM Solutions was used to calculate the indices used. The validation was performed with an independent dataset of soil profiles used in the prediction of soil classes. Thirty-three soil profiles were used and the morphological, physical, and chemical variables were validated.

3. Results and discussion

3.1 Number of diffuse soil classes

For the soil fuzzy classes, the FCM algorithm indicated that 10 categories were optimal for grouping the soil property maps. The combination of the number of classes and the FPI parameter presented an inflection point showing the most suitable number of classes, characterized by the highest internal organization of the fuzzy classes. The central concepts of each of the soil fuzzy classes are shown in **Table 1**, where it can be corroborated that all the classes present differences among themselves, according to the contribution of the centroids of the soil property values.

Table 1. Centroids of the representative diffuse soil classes of the Caramacate River basin, integrated with FCM

Class	Eng A	Eng AB	PEF	%EG	%A	%a	PSB	pH	%CO
A	15	15	43	40	25.6	24.0	63	5.43	1.90
B	18	36	74	26	33.0	28.8	56	5.29	1.88
C	18	43	89	20	25.8	26.9	53	5.27	1.90
D	17	45	80	30	27.0	28.6	45	5.26	1.90
E	20	58	72	18	24.4	35.3	56	5.32	1.87
F	17	43	79	26	23.8	27.1	53	5.09	1.87
G	23	98	116	8	25.0	26.7	58	5.36	2.10
H	21	86	95	15	23.2	25.7	51	5.29	2.34
I	18	85	80	27	21.4	28.7	50	5.16	2.49
J	18	107	111	21	35.7	28.2	45	4.65	2.57

Eng A: thickness A (cm), Eng AB: solum thickness (cm), PEF: effective depth (cm), EG: coarse skeleton, A: sand, a: clay, PSB: percentage of saturation with bases, CO: organic carbon, phin water (1:1).

Class A groups superficial or shallow soils and have a very thin A horizon. They have a silty-loam surface texture, with a moderately acid pH, a high base-saturation exchange complex, and an abundant amount of coarse fragments on the surface. Classes B and C are characterized by grouping soils of moderate depth, with a thin surface horizon of loam to clay loam textures. Both differ in the thickness of the solum, in the effective depth and in the coarse skeleton content of the surface layer. Chemical properties are similar, with a strongly acidic pH and an exchange complex with moderate to high saturation of exchangeable bases. Class D, E and F soils have a solum of variable thickness, with a thin A horizon. They have textures ranging from clay loam to loam with few to frequent coarse fragments on the surface; they are of moderate pH strongly acidic and medium saturation with bases. Classes G and H include very deep to deep soils, with a very coarse solum, loam and silt loam surface texture respectively, with few coarse surface fragments, have a coarse A horizon with high CO contents. The soils are moderately to strongly acidic pH, with moderate PSB in the exchange complex. Classes I and J include deep to very deep soils, with a well-developed solum, loamy to clay loam surface texture, with frequent coarse surface fragments, have a thin A horizon with high CO contents. Soils of both classes are strongly acidic

pH, with moderate PSB in the exchange complex.

3.2 Fuzzy soil class model

The integration of the soil properties data in raster format allowed obtaining models of spatial variation of the values of the membership function for each soil class. These maps are an intermediate product of the FCM algorithm, whose output is expressed in raster format and reflects the spatial variation of the degrees of membership between 0 and 1, where light colors represent absolute membership and dark colors indicate non-membership of the class. Of the ten models obtained, **Figure 2** spatially represents the membership functions of four representative soil classes (A, D, G and J), which show the similarity with the geographical pattern discriminated in the digital model of diffuse soil classes (**Figure 3**).
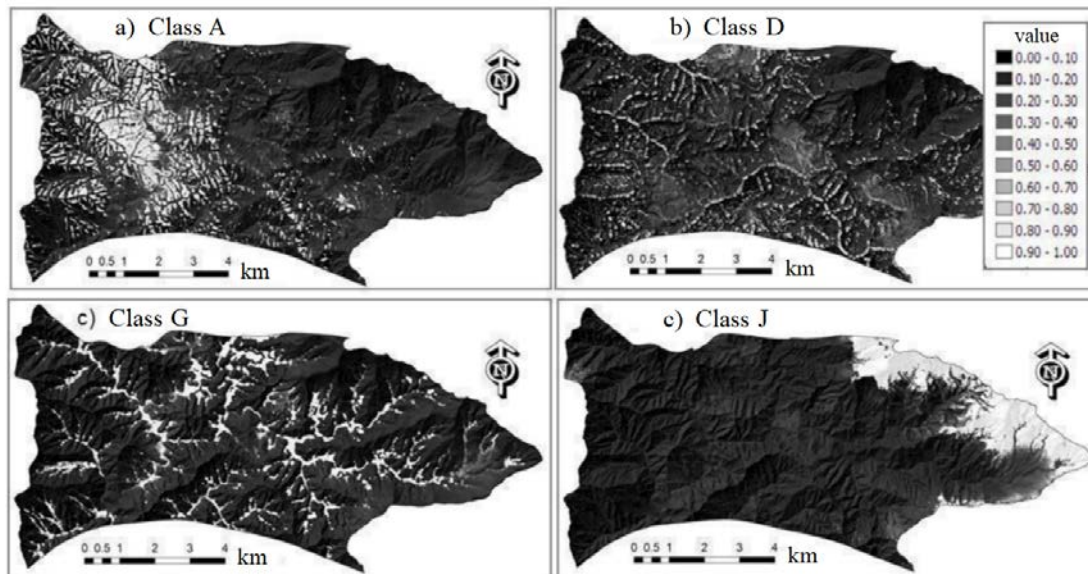

Figure 2. Maps of membership function values for some fuzzy soil classes. The degrees of membership vary between 0(black) and 1(white).
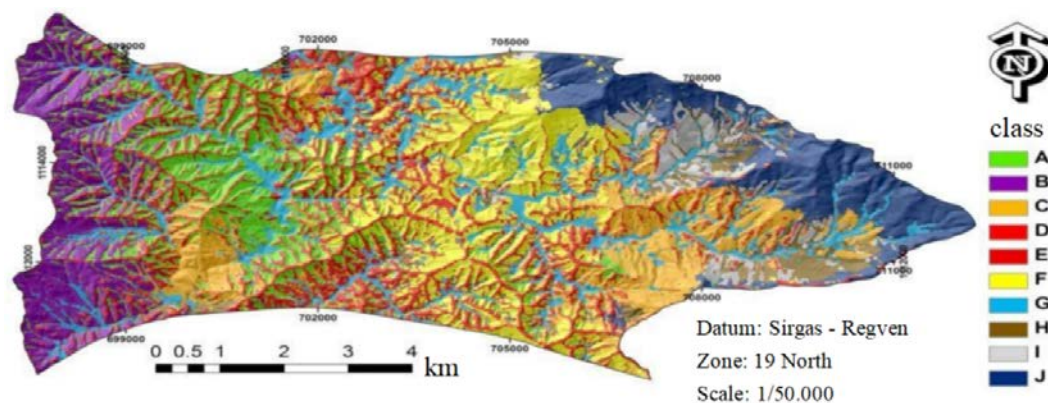

Figure 3. Digital model of diffuse soil classes in a sector of Caramacate, upper Guárico river basin.

The values of the degrees of belonging to each soil class obtained with the fuzzy clustering method, allowed corroborating the influence provided by the information of the minimum spatial units (pixel), whose geographical expression is given by the limits of the auxiliary variables derived from the DEM and the satellite image. In this sense, most of the classes are represented physiographically by a diversity of mountain landscape slopes, with different orientations and relative heights (A, B, C, E, H, I, J).

In this regard, class A represents the type of relief of slopes that predominantly occupy the eastern sector, with a gradual gradient towards the central region and very little representation in the western

73

region of the studied area, and class J is represented by mountain slopes with the highest altitude of the sector, where the land cover is dominated by forest vegetation. In contrast, classes D and E correspond to relief types of ridges and beams of the dominant mountain landscape units in the entire sector evaluated, and class G corresponds to the meadows of intramountain valley landscapes, whose course drains in a north-south direction. Under the fuzzy sets approach, the variation structure of soil classes allowed the evaluation of soil-landscape relationships, and facilitated the correlation with taxonomic categories at the family level of particle size classes in the study area (**Table 2**).

At the slope level, the low stability and susceptibility to mass movements have promoted the occurrence of soils with little to moderate pedogenetic development (Typic Haplustepts intermixed with Lithic Ustorthents). These classes occupy an area equivalent to 59.6% of the evaluated area in the zone. This situation contrasts slightly with the dominant mountain landscape slopes in the northeastern region of the study area, where pedogenetic processes are highly influenced by the combined action of relief, vegetation and climate. In this sector, the distribution of soil classes is characterized by the dominance of the taxonomic subgroups Typic Haplustalfs and Ultic Haplustalfs (corresponding to 15.3% of the studied area).

On the ridges and slope beams there are also soils of incipient development, which present variable depths; with a dominance of the Lithic Haplustepts subgroup, mixed with soils of the large Ustorthents group. This group occupies about 19.8% of the soils present in geomorphological positions. In the meadows of the intramontane valleys, localized accumulation processes occur, creating a stable surface with sufficient time for the development of a Cambrian endopedon, with soils of the Typic Haplustepts subgroup occupying 5.3% of the area considered.

Table 2. Correlation between fuzzy classes and soil taxonomic categories

Class	Correlated family	Physiography	Surface area (%)
A	Lithic Ustorthents, coarse frank	Slopes	10.5
B	Typic Haplustepts, fine loam	Slopes	12.2
C	Lithic Haplustepts, coarse lithic loam	Slopes	10.7
D	Lithic Haplustepts, coarse lithic loam	Crests	12.6
E	Typic Haplustepts, fine loam	Ridges, beams	7.2
F	Lithic Haplustepts, fine lithic loam	Slopes	11.6
G	Typic Haplustepts, fine loam	Vegas	5.3
H	Typic Dystrustepts, fine loam	Slopes	14.6
I	Typic Haplustalfs, fine loam	Slopes	4.1
J	Ultic Haplustalfs, fine	Slopes	11.2

Source: Soil survey staff, 2014

3.3 Evaluation of the reliability of fuzzy soil classes

The results of the evaluation of the soil classes indicated that most of them have a reliability equivalent to 88%, where the reference classes have been well classified (**Table 3**). The exception is presented by classes D, E and H (Lithic Haplustepts and Typic Haplustepts in beams and ridges), where some soils were not classified in that category (false negatives), so they are confused with other classes (slopes), according to the accuracy of the producer. Similarly, the user's accuracy in terms of the percentage of each diffuse class that has been correctly classified is indicative of the soils classified erroneously (error of commission). The most striking case is presented by classes A, E and G (Lithic Ustorthents and Typic Haplustepts on slopes, ridges and meadows), where some soils were classified in some classes and actually belong to others (false positives).

The other statistic derived from the integral information of the error matrix, and which corroborates the degree of agreement between the classes of the model considered, is the Kappa coefficient, whose result was 0.84. This index indicates that the fuzzy class model presents a substantial strength of agreement with respect to the reality of the soil classes present. This means that the matrix used is 84% better than the one that could result from applying another classifier that randomly assigns the fuzzy classes.

Table 3. Assessment matrix for diffuse soil classes

Estimated class	Class observed						Total	EU
	A	D	E	F	G	H		
A	5	0	1	0	0	0		0.83
D	0		0	0	0	0		1.00
E	0	1		0	0	0		0.92
F	0	0	1		0	0	5	1.00
G	0	0	0	0	1	1		0.50
H	0	0	0	0	0			1.00
Total	5	5			1	5		
EP	1.00	0.80	0.92	1.00	1.00	0.80		

Overall reliability: 0.88; Kappa: 0.84; EP: producer's accuracy; EU: user's accuracy.

The results of the validation of the fuzzy set approach used showed that it is an alternative for the generation of soil classes, especially in areas of high geomorphological and edaphological complexity. These results are slightly superior to those obtained by Yang *et al.*, Zhu *et al.* and McKay *et al.*, in the prediction of soil types at the subgroup and soil series level. The aforementioned authors applied approaches based on knowledge of soil-environment relationships, and obtained digital models with an accuracy of 72%, 76%, 73.7% respectively, and concluded that the validation results were quite acceptable for an initial soil map with data limitations.

4. Conclusions

The number of classes derived discriminated the spatial variation existing in the soils, which highlights the importance of the application of fuzzy set theory in areas of high complexity, to obtain internally homogeneous classes.

The approach based on the integration of soil properties generated with the application of the FCM algorithm allowed the establishment of correlations between local soil classes with taxonomic families, achieving a reliability of 88%.

The grouping of soils through the application of fuzzy set theory generated a gradual variation pattern in mountain areas, becoming an alternative for the evaluation of the variation structure of soils and an option for the support of digital soil mapping in mountain areas.

Conflict of interest

The authors declare no conflict of interest.

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75

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