GEOSTATISTICAL ANALYSIS OF SOIL PROPERTIES OF THE KARSTIC SUB-HORIZONTAL PLAIN OF THE YUCATAN PENINSULA †

[ANÁLISIS GEOESTADÍSTICO DE LAS PROPIEDADES DE LOS SUELOS DE LA PLANICIE SUBHORIZONTAL KÁRSTICA DE LA PENÍNSULA DE YUCATÁN]

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SUMMARY

Background: In recently formed karst environments, as in the north of the state of Yucatan, Mexico, many chemical and physical properties of soils have a high spatial heterogeneity. However, this heterogeneity of the soil is not well-understood, which affects the agricultural use of the land. **Objective:** To identify the soil properties that best allow zoning, in order to select them for precision agriculture. **Methodology:** A plot was divided into 54 quadrants of 25 m^2 (5 x 5 m). In each quadrant, the properties of the soil described or analyzed were the stoniness, rockiness, depth, silt, sand, clay, particle density, bulk density, organic carbon, and field capacity. A georeferenced database of soil properties was built. Geostatistical analyzes were performed using ordinary kriging (parametric) and indicator kriging (probabilistic) interpolations. The precision of the interpolations was estimated. The soil property maps were constructed in Arc GIS. **Results:** The organic carbon, bulk density, rockiness, particle density, stoniness, silt, and sand were the soil properties with the best adjustment values between the theoretical and experimental models. In addition, those same soil properties had good, high, and very high correlations between data measured and data estimated with the interpolation. On the other hand, the depth, clay, and field capacity were the properties of soils with adjustment values lower than $r^2 = 0.8$, as well as with cross-validation values of less than r = 0.5. **Implications**: The probabilistic maps of soil depth allowed us to identify the areas with Nudilithic, Lithic, and other Leptosols. **Conclusion**: The percentage of organic matter and depth represent the two soil properties that could be best applied to conduct parcel zoning for the sake of achieving better precision agriculture.
Key words: Karst; Leptosols; Kriging; Semivariogram; Interpolation

RESUMEN

Antecedentes: En ambientes kársticos recientes, como en el norte del estado de Yucatán, México, muchas propiedades químicas y físicas de los suelos tienen una alta heterogeneidad espacial; sin embargo, esta heterogeneidad del suelo no se comprende bien, lo cual afecta el uso agrícola de los terrenos. **Objetivo**: Identificar las propiedades del suelo que mejor permitan la zonificación con la finalidad de seleccionarlas para hacer agricultura de precisión. **Metodología**: Una parcela se dividió en 54 cuadrantes de 25 m^2 (5x5 m). En cada cuadrante, las propiedades del suelo descritas o analizadas fueron: pedregosidad, rocosidad, profundidad, limo, arena, arcilla, densidad real, densidad aparente, carbono orgánico y capacidad de campo. Se construyó una base de datos georreferenciada de propiedades del suelo. Los análisis geoestadísticos se realizaron utilizando interpolaciones de kriging ordinario (paramétrico) y kriging indicador (probabilístico). Se estimó la precisión de las interpolaciones. Los mapas de las propiedades del suelo se realizaron en Arc Gis. **Resultados**: El carbono orgánico, densidad aparente, rocosidad, densidad real, pedregosidad, limo y arena fueron las propiedades del suelo con los mejores valores de ajuste entre los modelos teórico y experimental, además esas mismas propiedades del suelo tuvieron correlaciones buenas, altas, y muy altas, entre ambos datos medidos y estimados con la interpolación. Por otro lado, la profundidad, arcilla y capacidad de campo fueron las propiedades de los suelos con valores de ajuste menor que r^2= 0.8; así como con valores de la validación cruzada menos de r= 0.5. **Implicaciones**: Los mapas probabilísticos de profundidad del suelo permitieron identificar las áreas con Nudilithic, Lithic y otros Leptosols. **Conclusiones**: El porcentaje de materia orgánica y la profundidad son las dos propiedades del suelo que podrían funcionar mejor para hacer una zonificación de parcelas con el fin de lograr una mejor agricultura de precisión.
Palabras clave: karst; leptosoles; kriging; semivariograma; interpolación

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INTRODUCTION

In the last two decades, geostatistics has become a discipline widely used in environmental sciences, particularly in studies of spatial soil heterogeneity. Geostatistics assumes that the spatial distribution of the studied variable has a defined structure (Webster and Oliver, 1990). Geostatistics provides a set of statistical tools for incorporating the spatial coordinates of quantitative soil observations in data processing, allowing for the description and modeling of spatial patterns and the possibility of estimating the value of regionalized variables for unsampled sites or analyzed with an assessment of the uncertainty attached to these predictions (Goovaerts 1997, 1999). This is particularly important because laboratory analyses of some soil properties are expensive and time consuming (Nourzadeh *et al*., 2013; Delgado *et al.*, 2019).

Currently, there is great concern for environments linked to the use of agrochemicals, which have been referred to with several names, including "precision agriculture" and "site-specific agriculture". In both, the goal is to use efficient agrochemicals, because, if used excessively, two things happen: a) Damage to the environment occurs, and b) farmers lose money by overuse the agrochemical (Flores, 2011; Sidorova *et al.*, 2012; Nourzadeh *et al*., 2013). It has been recognized that the properties of the soil and crops vary within fields (Beckett and Webster, 1971).

Understanding the spatial distribution and accurately mapping the soil properties are very important and useful for comprehensive soil management and environmental assessment, in order to achieve fertilization and nutritional management and environmental pollution control (Yemefack *et al.*, 2005). To achieve the aims of this type of agriculture, it is necessary to gain knowledge about the soil properties in a spatial context.

In karst environments, as in the state of Yucatan, Mexico, the soils have a high spatial heterogeneity (SH) in terms of different soil properties, such as organic carbon, stoniness, rockiness, the bulk density, the depth, nutrients, and others (Weisbach *et al.*, 2002; Bautista *et al.,* 2003; Shang and Tiessen, 2003; Bautista *et al.,* 2005; Flores, 2011; Bautista *et al.*, 2011). Additionally, the diversity of soil Maya names and their classification reflects the soil heterogeneity (Bautista *et al.*, 2003; Bautista and Zinck, 2010). SH should be taken into account when selecting plots for conducting agricultural experiments and/or using sophisticated statistical experimental designs and a large number of samples.

The aim of this study was to conduct an analysis of the spatial heterogeneity of soil in a recently formed karstic area to identify soil properties that enable better zoning, in order to select them for precision agriculture.

MATERIALS AND METHODS

Study site

The study area lies in a slightly undulating sub-horizontal karstic plain that covers the north of the Yucatán peninsula (Bautista *et al.* 2005). Dissolution depressions (i.e., sinkholes such as dolines and uvalas) alternate with rock-outcrop mounds, with 1–2 m of relative elevation (Bautista *et al.* 2015). Leptosols dominate the soilscape, with small inclusions of Cambisols (Bautista *et al.* 2011). The regional climate is hot sub-humid tropical with summer rains, and the vegetation is a seasonal dry forest (Delgado *et al.* 2017a).

The study was conducted in a 1350 m^2 parcel belonging to the Campus de Ciencias Biológicas y Agropecuarias from Universidad Autónoma de Yucatán, located in the municipality of Mérida Yucatán, México (20º51’57.36’’LN; 89º37’23.04’’LW). The plot was divided into 54 quadrants of 25 m^2 (5 x 5 m) each (Figure 1), used for agronomic experimentation (Bautista *et al.,* 2005).

The soil properties were described, including the stoniness (USDA, 2012; Bautista *et al.* 2016) and rockiness (USDA, 2012; Bautista *et al.* 2016), and the soil depth was measured. Samples were analyzed in the laboratory for silt, sand, clay (Okalebo *et al.* 1993), the particle density (Gandoy, 1992), the bulk density (Gandoy, 1992), organic carbon (Nelson y Sommers, 1982), and the field capacity (Gandoy, 1992).

Spatial analyses

A georeferenced database of soil properties was constructed. A geostatistical analysis using ordinary kriging and indicator kriging (only for the soil depth, because there are threshold values in the soil classification) interpolation was performed in terms of the distance with the Gamma Design Software (Robertson, 2008), following this sequence:

a) An exploratory data analysis with the aim of detecting atypical values or value errors, identifying the type of distribution values (fulfillment of the Gaussian data distribution), and detecting errors in the location of samples (Robertson, 2008).

b) Construction of experimental semivariograms and fit to a theoretical model of the spatial distribution (autocorrelation) of soil properties using

$$\gamma(h) = \frac{1}{2}\sum_{i=1}^{n}\left[Z(\chi_i) - Z(\chi_i + h)\right]^2,$$

where $\gamma(h)$ is the experimental semivariance value for all pairs at a lag distance h, $Z(\chi_i)$ is the parameter value of the point i, $Z(\chi_i + h)$ is the soil property value of other points separated from χ_i by a discrete distance h, χ_i is the georeferenced position where the $Z(\chi_i)$ values were measured, and n represents the number of pairs of observations separated by a distance h (Delgado *et al.*, 2010).

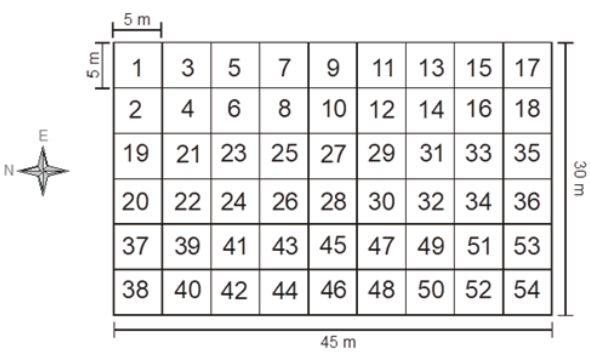

Figure 1. Plot under study, showing the distribution of sampling quadrants.

The structural parameters of the semivariogram describing the model were as follows: (a) The nugget variance (C_0), which is the y-intercept of the semivariogram model representing the variation in soil parameters not spatially dependent over the range examined, and reflecting both the spatial variation in soil parameters at shorter distances than the minimum sample spacing and the unexplained soil parameter variance; (b) the sill (C_0 + C), which indicates the asymptote of the curve where the structural variance reaches its maximum values because it remains constant; and (c) the range, which indicates the distance value (meters) at which the maximum soil parameter variance is reached, thus defining the area of influence of the autocorrelation.

The theoretical model which best adjusts to the experimental semivariogram is that with the lowest value of the residual sum of square (RSS), and the largest determination coefficient (r^2) (Webster and Oliver,1990).

The estimation of the data was conducted using ordinary kriging and indicator kriging interpolation.

Ordinary kriging is the technique that provides the best unbiased linear estimator, as well as an estimation error known as the kriging variance, which depends on the correlation structure chosen, based on the theoretical model and the locations of the original data. The interpolation attributes a weight to each observed value while considering the geometric characteristics of the data. By minimizing the estimation variance, the optimal use of the available information is guaranteed (Webster and Oliver,1990). Soil parameter estimates were obtained by punctual kriging using the following equation:

$$Z(\chi_0) = \sum_{i=1}^{n}\lambda_i Z(\chi_i),$$

where λ_i is the optimal weight selected to minimize the estimation variance, $Z(\chi_i)$ is the observed value of the soil parameter, and $Z(\chi_0)$ is the optimal and unbiased estimate of the soil parameter.

Before the data were used, log transformation was conducted for the bulk density, rockiness, depth, and clay data. The particle density, organic carbon, stoniness, silt, sand, and field capacity data were processed without transformation.

The accuracy of the estimates was achieved using cross validation, the correlation coefficient (r), the mean error (ME), the root mean square error (RMSE), and the normalized root mean squared error (NRMSE) between measured and estimated soil parameter values (Delgado *et al.* 2010).

In cross-validation, r values must be positive because the correlation is directly proportional. The ME is used for determining the degree of bias in the estimates and it is calculated as

$$ME = \frac{\sum_{i=1}^{n}\hat{Z}(\chi_i) - Z(\chi_i)}{n},$$

where n is the number of samples, $\hat{Z}(\chi_i)$ is the estimated value, and $Z(\chi_i)$ is the measured value of the soil parameter.

The root RMSE is a frequently used measure of the differences between values estimated by a model and the values measured; it is a good measure of precision and serves to aggregate the individual differences or residuals into a single measure of predictive power. The RMSE provides a measure of the error size that is sensitive to outliers in the estimates and is calculated by

$$RMSE = \sqrt{\frac{\left[\sum_{i=1}^{n} \hat{Z}(x_i) - Z(x_i)\right]^2}{n}},$$

where n is the number of samples, $\hat{Z}(x_i)$ is the estimated value of the soil parameter, and $Z(x_i)$ is the measured value of the soil parameter.

The NRMSE is the RMSE divided by the range of observed values:

or: $NRMSE = \frac{RMSE}{(x_{màx}) - (x_{mìn})}$.

Lower values indicate less residual variance.

This statistic provides a comprehensive approach for the evaluation of kriging interpolations, in order to select the best soil parameter for mapping the spatial variability of soil heterogeneity in a parcel of Yucatan.

Indicator kriging (IK) is a non-parametric geostatistical method. It makes no assumption of normality, and a binary transformation (0-1 indicators) of data is used to make the predictor less sensitive to outliers. IK builds the cumulative distribution function at each point, based on the behavior and correlation structure of indicator-transformed data points in the neighborhood. IK can be used to estimate the proportion of values that exceed critical concentrations of HM by incorporating the uncertainty of the value of variables at unobserved locations. After the cumulative distribution function is built, it must be post processed to produce a probability map (Goovaerts 1997, 1999; Antunes and Albuquerque 2013).

IK was only used for the soil depth, considering that there are thresholds of 5 cm for Nudilithic Leptosols, 10 cm for Lithic Leptosols, and 25 cm for other Leptosols (IUSS, 2015).

RESULTS

Descriptive statistics of soil parameters

The skewness values of the soil parameters closer to 0 (<0.25) were obtained for clay, the bulk density, the field capacity, stoniness, and the particle density; that is, the properties were symmetric. Conversely, the values higher to 1 were obtained for depth, rockiness, and sand, and these properties were clearly non-symmetric. The soil parameter with a kurtosis value close to 3 was obtained for rockiness; the highest values, and thus farthest away from 3, were the depth and stoniness. Parameters with the greatest number of different values for the mean and median were obtained for rockiness, silt, and sand (Table 1).

Table 1. Descriptive statistics of soil parameters.

Parameter	Difference Mean- median	Skewness	Kurtosis	Minimum value	Maximum value	s
Organic Carbon (%)	1.5	0.60	-0.49	3.88	21.83	4.7
Bulk Density (mg mL^{-1})	0	-0.04*	-1.01	0.46	0.94	0.12
Rockiness (%)	6.57	2.05*	3.60	5	70	14.5
Particle Density (mg mL^{-1})	0.08	-0.25	-1.09	1.08	2.57	0.40
Stoniness (%)	0.1	0.16	-1.45	10	80	23.9
Silt (%)	3.28	-0.50	-1.01	0	45	12.6
Sand (%)	2.87	1.37	1.58	15	79	14.1
Depth (cm)	1.81	2.14*	6.51	1	54.75	9
Clay (%)	0.59	-0.03*	-0.47	10	67	14.6
Field Capacity (%)	0.39	0.14	-0.62	26.50	47.40	4.88

* = Log transformation data.
The parameters with a similar mean and median were the bulk density, particle density, and stoniness.

Table 2. Characteristics of semivariogram models.

Parameter	Model	Nugget (%)	Sill	Range (m)	Structural Variance (%)	Model r^2
Organic Carbon (%)	Spherical	10	0.22	14.6	90	1
Bulk Density (mg mL^{-1})	Spherical	15	4.8E-0003	15.9	85	1
Rockiness (%)	Spherical	10	0.59	20.9	90	0.99
Particle Density (mg mL^{-1})	Spherical	14	0.165	23.5	86	0.96
Stoniness (%)	Exponential	0	607.9	21.6	100	0.95
Silt (%)	Exponential	14	166	24.1	86	0.91
Sand (%)	Spherical	2	145.4	15.3	98	0.86
Depth (cm)	Spherical	8	0.5	10.5	92	0.8
Clay (%)	Exponential	0	0.18	12.1	100	0.8
Field Capacity (%)	Exponential	0	21.75	9.1	100	0.7

Structural Analysis for soil parameters

The experimental semivariograms fit spherical or exponential models. The soil parameters had r^2 values ranging from 0.7 to 1, the structural variance had values ranging from 85.4% to 99.99%, the nugget variance had values ranging from 0.01% to14.6%, and the range had values ranging from 10.25 to 24.1 m (Table 2).

The models with the highest values of r^2 semivariogram models were organic carbon, the bulk density, rockiness, the particle density, stoniness, and silt (Table 2 and Figures 2, 3). All of the experimental semivariograms, except for field capacity, were adjusted to the theoretical model.

The r values of cross-validation of the interpolations ranged from 0.09 to 0.77. Considering the association (r) between estimated and observed values, the parameters with a high precision were sand and the particle density ($r \geq 0.75$), whereas those with a good accuracy were organic carbon, the bulk density, and stoniness ($r \geq 0.65$). The parameters with little association were the field capacity and clay ($r \leq 0.5$).

The medium error (ME) values of the interpolations ranged from 0.00 to 2.19. In relation to the ME, the parameters without bias were the bulk density and particle density; on the other hand, the parameters with a very high bias were clay and stoniness. The root mean squared error (RMSE) of the interpolations ranged from 0.09 to 14.86. The parameters with the lowest RMSE were the bulk density, particle density, and stoniness, and the parameters with the major size errors were clay and rockiness. The normalized root mean squared error (NRMSE) values of the interpolations ranged from 0.00 to 0.26. The parameter without residual variance was stoniness and those with major residual variance were clay and silt. Therefore, the parameters with the most precise estimates, considering at least three of the statistical indices, were the particle density, bulk density, and stoniness, whereas, the least accurate parameter was clay (Table 3).

Table 3. Statistics of cross-validation between measured and estimated values for different quality water parameters.

Parameter	r	ME	RSME	NRMSE
Sand (%)	0.77	-0.29	9.03	0.14
Particle density (mg mL^{-1})	0.75	0.00	0.26	0.18
Organic Carbon (%)	0.68	0.05	3.46	0.19
Bulk density (mg mL^{-1})	0.67	0.00	0.09	0.19
Stoniness (%)	0.66	-1.85	0.27	0.00
Rockiness (%)	0.6	-0.32	11.77	0.18
Silt (%)	0.6	-0.31	10.44	0.23
Depth (cm)	0.5	-0.89	9.96	0.19
Field capacity (%)	0.37	-0.11	2.96	0.14
Clay (%)	0.09	2.19	14.86	0.26

CV = Cross validation; ME = medium error; RSME = root mean squared error; NRSME = normalized root mean squared error.

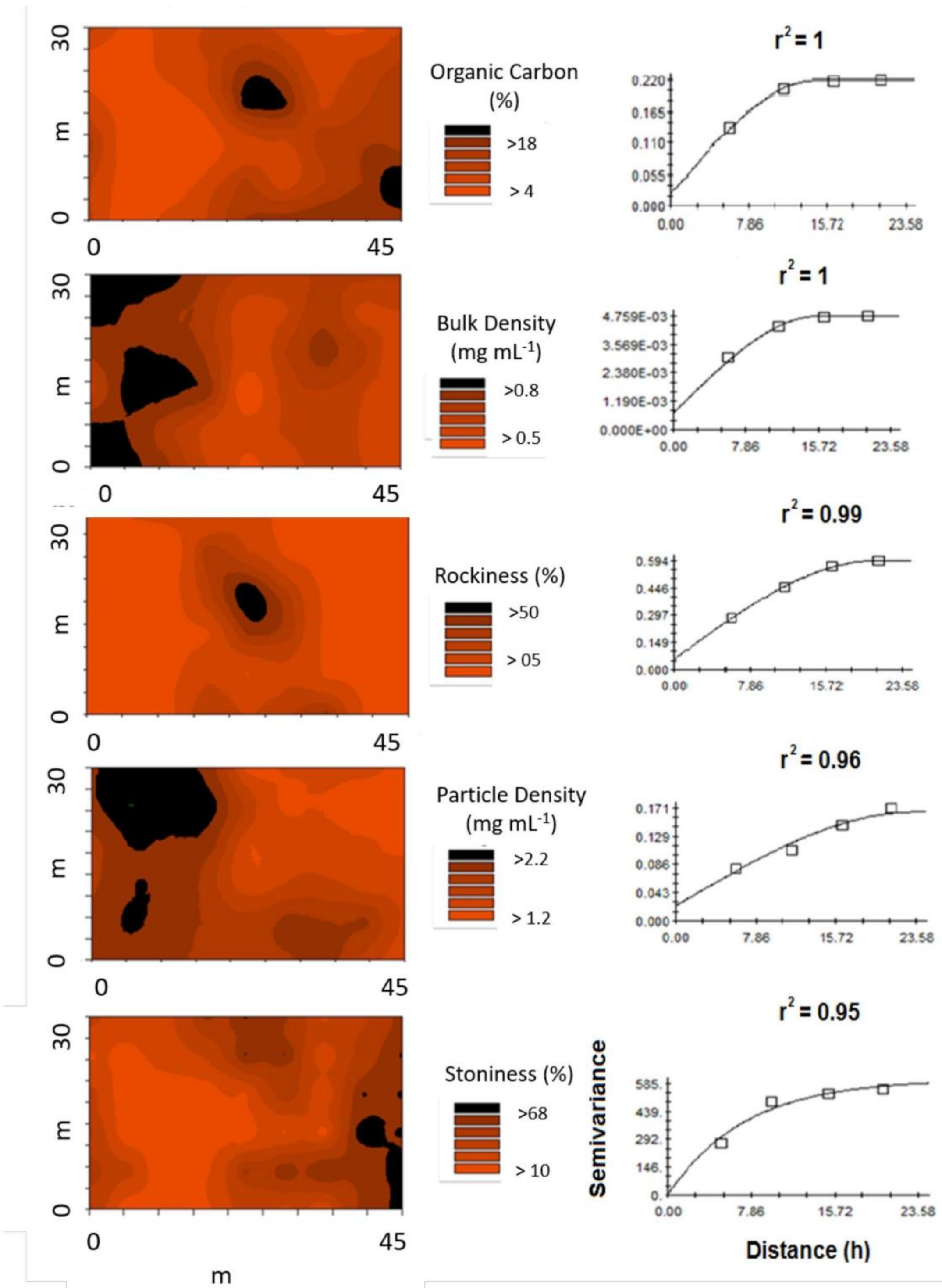

Figure 2. Graphic representation of the soil property models and their experimental and model semivariograms.

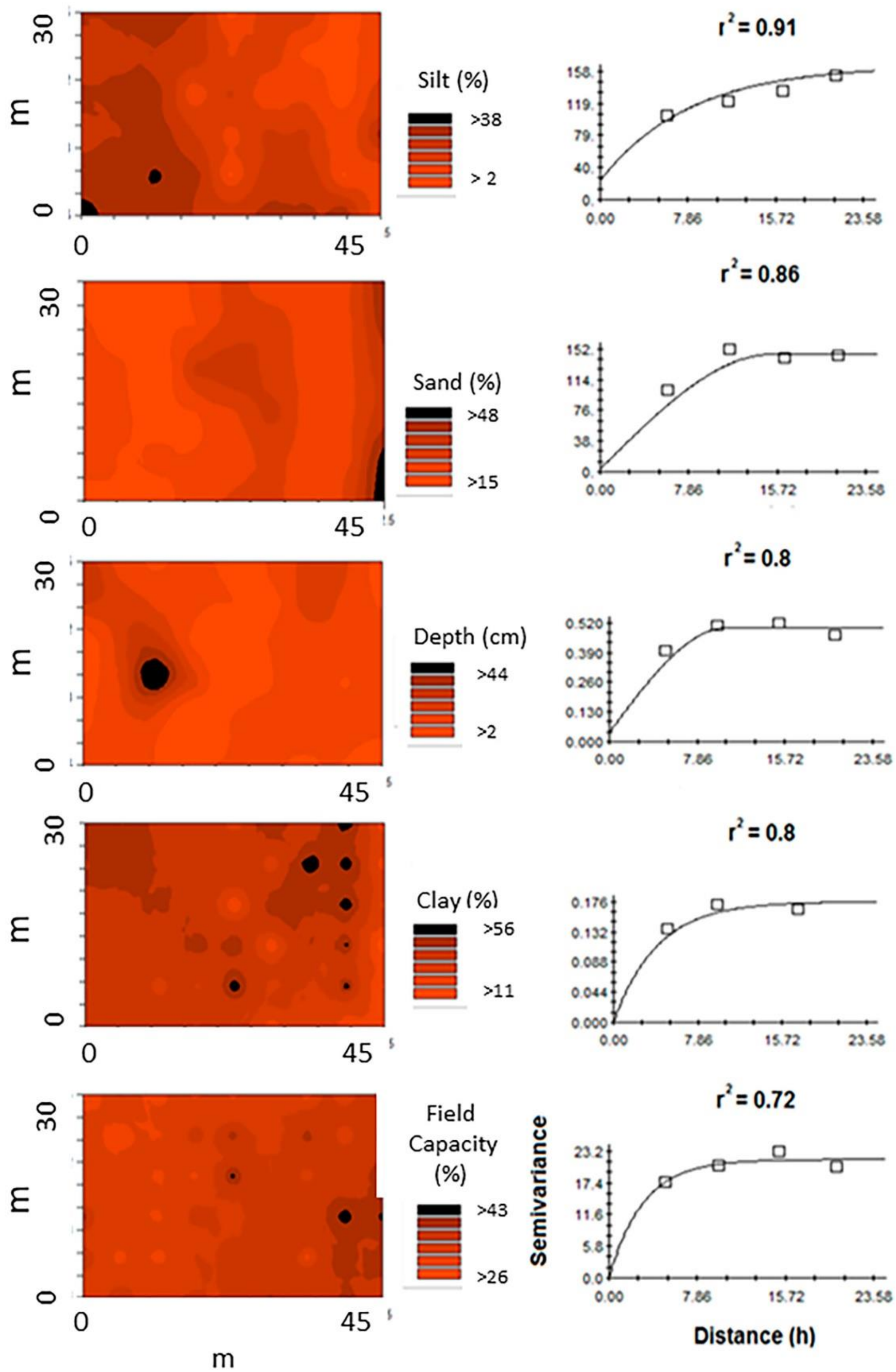

Figure 3. Graphic representation of the soil property models with their respective experimental and model semivariograms.

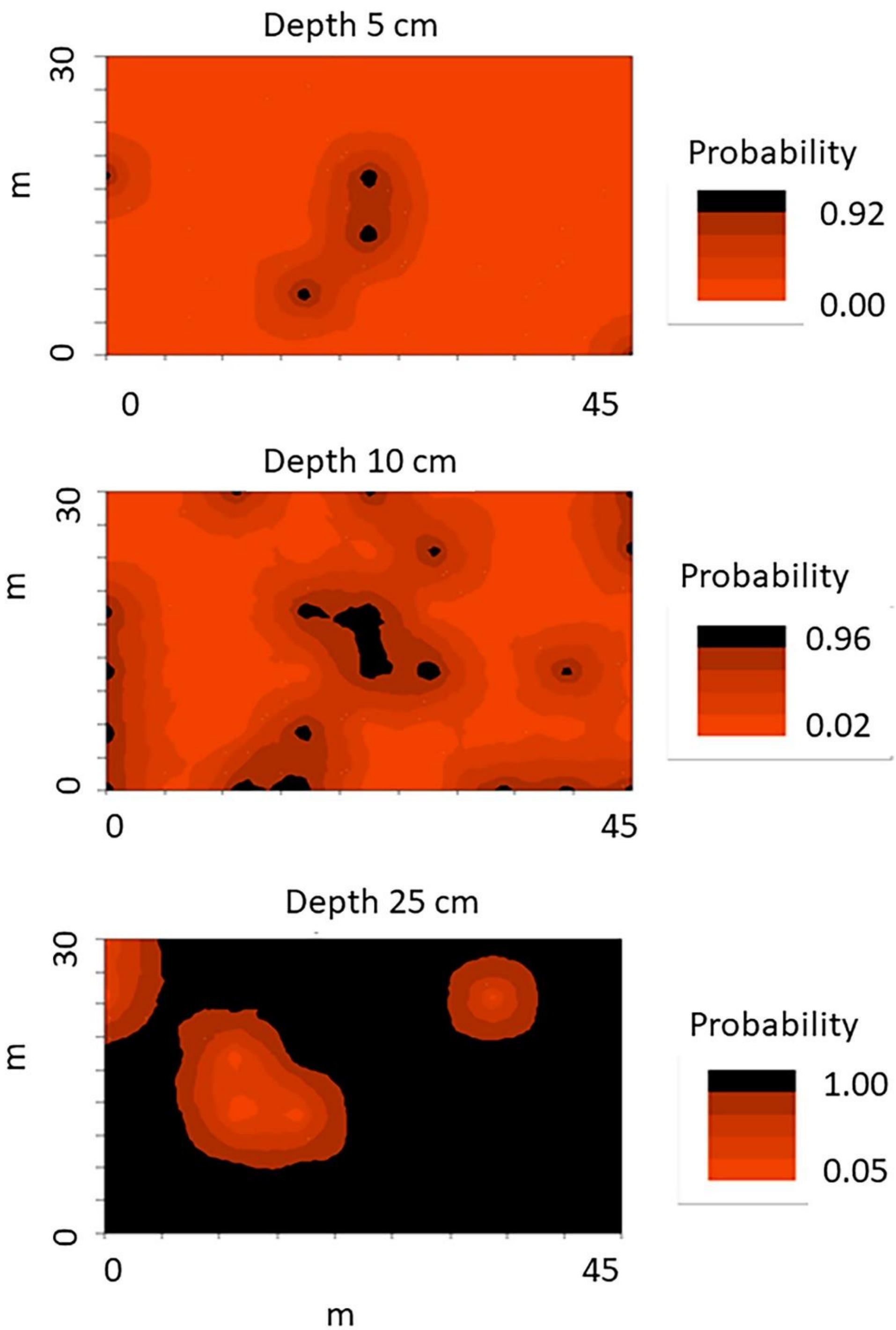

Figure 4. Probability depth soil diagrams for three different cut offs (5, 10, and 25 centimeters) showing their probabilities in each diagram.

Maps with ordinary Kriging

The graphic representation obtained with the interpolation shows that higher percentages of stoniness (>68%), carbon organic (>17) (Figure 2), sand (>67%), and the field capacity (>43%) (Figure 3) can be found in the southeast. Additionally, higher percentages of organic carbon and rockiness (>51%) can be found in the central part.

The parameters particle density and bulk density (Figure 2) have higher values in the west of the parcel and there are similarities with sites with a major depth (>40 cm). At such sites, there are lower percentages for rockiness, stoniness, organic carbon, the field capacity, and sand.

The silt map shows that higher percentage values are distributed in the west, principally in the southwest; these coincide with the major percentages of the particle density, bulk density, and depth. In the east, the sites with lower percentages of silt have a major percentage of clays. Moreover, where we saw a higher percentage of rockiness, we found lower percentages for the depth, particle density, bulk density, clay, and silt (Figures 2, 3).

Probabilistic depth map

The probability of finding soils with a depth of 0 to 5 cm or Nudilithic Leptosols in the parcel is higher in the central-south area of the parcel and in the west, while the probability of finding soils with a depth of 0 to 10 cm (Nudilithic Leptosols and more Lithic Leptosols) is higher in the central, north, south, extreme west, northeast, and southeast areas. The probability of finding soils with a depth of 0 to 25 cm (Nudilithic Leptosols, Lithic Leptosols, and other Leptosols) is high in the majority of the parcel, except in the north-east, central-west, and northwest (Figure 4) (IUSS, 2015). This means that depths greater than 25 cm are found at these sites.

DISCUSSION

This work followed the recommendations for the preparation of digital soil maps (Minasny and McBratney, 2016), and consisted of three components: a) A georeferenced database with the properties of the soils; b) data processing, which required geostatistical techniques, software, and hardware; and c) the output in the form of soil maps using geographic information systems.

The digital soil maps at the plot level produced in this work allow a vision of the soil as a continuum (Heuvelink and Webster, 2001) compared to the maps traditionally made by experts, using Mayan wisdom and technical knowledge (Bautista *et al.,* 2005), in which the soils seem like puzzle blocks.

The effect of stoniness on soils is controversial. In a positive way, stoniness can reduce the erosive effect of rain and help to prolong humidity (Querejeta *et al*., 2007). However, stony conditions make it difficult to plant crops and reduce the fertility in shallow soils (Magier and Rabina, 1984).

The depth digital soil map reveals that in the plot under study, within the sub-horizontal karst plain, the soils exhibit wide spatial variability, with Nudilithic Leptosols, Lithic Leptosol, other Leptosols, and Cambisols (IUSS, 2015), which has not previously been reported in a spatial way.

Table 4. Proposed land agricultural classes in karstic areas.

Parameters	Maya name (Bautista *et al*. 2010)	WRB (IUSSS, 2015)	Agricultural Class
Depth 0-5 cm	Chaltún	Nudilithic Leptosol	V
Depth 5-10 cm	Hay lu’um	Lithic Leptosol	IV
Stoniness ≥ 60%	Chochol lu’um Chich lu’um	Skeletic Leptosol Hyperskeletic Leptosol	III
Depth 10-25 cm	Ma taan Chak lu’um	Other Leptosols Cambisols	II
Depth 25-43 cm	Chak lu’um Taantaan lu’um	Cambisols	I

The high spatial heterogeneity of soil properties was consistent with the high diversity of Maya milpa crops in the karst lands of the Yucatán Peninsula (Terán and Rasmussen, 1994).

The percentage of carbon is often taken as an indicator of the soil fertility. However, in the case of karst areas, the percentage of carbon tends to be higher in soils with lower amounts of fine earth, that is, a shallower depth, greater rockiness, and greater stoniness (Bautista *et al*., 2016). What happens is that, in karst areas, the amount of organic carbon must be taken into account and not the concentration (percentage). In this way, the amount of organic carbon (kg/m^2) can be used as an indicator of fertility (Delgado *et al*., 2017b).

For agricultural technicians who do not know both, Maya Soil Classification (Bautista and Zinck, 2010; Estrada-Medina *et al*., 2013) or the International Classification of Soils (IUSSS, 2015) are recommended for using the five classes of agricultural suitability of land for recently formed karstic areas (Table 4).

CONCLUSIONS

The use of geostatistical techniques allowed us to document the high spatial heterogeneity of soil properties in a sub-horizontal karst plain. The highest precision maps developed with ordinary kriging interpolation were those for sand, the particle density, organic carbon, the bulk density, and stoniness. The use of the kriging indicator allowed us to identify the surface of the Nudilitic Leptosols, Lithic Leptosols, and other Leptosols. Both soil maps for the depth and stoniness allowed us to identify five classes of different agricultural qualities for the sub-horizontal karst plain of the Yucatan peninsula.

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Conflict of interest statement. The author declares that there is no conflict of interest.

Compliance with ethical standards. The research presents original data that have not been submitted to other journals at the same time.

Data availability. Data are available from the corresponding author (leptosol@ciga.unam.mx) upon reasonable request.

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