Relationship of Organic Matter Content with Spectral Indices in Soil Dedicates to Rice Cultivation



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Relación de la materia orgánica con índices espectrales en suelo dedicado al cultivo del arroz

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ABSTRACT: The determination of soil organic matter is a technique that is affected by the cost of reagents, specialized personnel and the time required. As a feasible tool for the determination of this chemical property, the use of remote sensing from digital image processing and the calculation of spectral indices is proposed. The objective of the research was to find the relationships of the organic matter (OM) content with the spectral index obtained by remote sensing and, given the relationship of OM with the fertility of a soil, to know its spatial variability in an area dedicated to rice cultivation. A systematic sampling was carried out in an area of 100 ha where 100 georeferenced points were selected at a distance between points of 100 m. The samples for the determination of the organic matter content were extracted at a depth between 0-0.20 m in a Chromic Vertisol. The spectral index NDVI, SAVI and the ClayIndex CI were calculated from a Landsat 9 image. Later, linear regression analyzes were performed between these indices and the organic matter content. The average values of organic matter, NDVI and SAVI were 3.81; 0.26 and 0.52%, respectively. The mean value for CI was 1.32. It was obtained that there is a high coefficient of determination with values close to 100 % and significant correlation between the spectral index and the organic matter content. The analysis of the spatial variability of the organic matter values was carried out with the Surfer 8 software and the model that best adjusted the experimental semivariogram was the exponential one. The results obtained are promising for the future estimation of the organic matter content from the spectral index in an agroecosystem dedicated to rice under the same edaphoclimatic conditions of the area.

Keywords: Kriging, Landsat, Remote Sensing.

RESUMEN: La determinación de la materia orgánica del suelo es una técnica que se ve afectada por el costo de los reactivos, del personal especializado y el tiempo requerido. Como herramienta factible para la determinación de esta propiedad química, se plantea el uso de teledetección a partir del procesamiento digital de imágenes y el cálculo de índices espectrales. La investigación tuvo como objetivo encontrar las relaciones del contenido de materia orgánica (MO) con los índices espectrales obtenidos mediante teledetección y, dada la relación de la MO con la fertilidad de un suelo, conocer su variabilidad espacial en un área dedicada al cultivo del arroz. Se realizó un muestreo sistemático en un área de 100 ha donde se seleccionaron 100 puntos georeferenciados a una distancia entre puntos de 100 m. Las muestras para la determinación del contenido de materia orgánica fueron extraídas a la profundidad entre 0-0,20 en un Vertisol Crómico. Los índices espectrales NDVI, SAVI y el ClayIndex CI se calcularon a partir de una imagen Landsat 9. Posteriormente fueron realizados análisis de regresión lineal entre éstos índices y el contenido de materia orgánica. Los valores medios de materia orgánica, NDVI y SAVI fueron de 3,81; 0,26 y 0,52% respectivamente. El valor medio para CI fue de 1,32. Se obtuvo que existe un alto coeficiente de determinación con valores cercanos al 100% y de correlación significativa entre los índices espectrales y el contenido de materia orgánica. El análisis de la variabilidad espacial de los valores de materia orgánica se realizó con el software Surfer 8 y el modelo que mejor ajustó el semivariograma experimental fue el exponencial. Los resultados alcanzados resultan promisorios para la estimación futura del contenido de materia orgánica a partir de los índices espectrales en un agroecosistema dedicado al arroz bajo las mismas condiciones edafoclimáticas de la zona.

Palabras clave: kriging, Landsat, teledetección, materia orgánica, índices espectrales.

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INTRODUCTION

The physical, chemical, ecological and biological degradation of soils affect their organic matter (OM) content according to Lal (2020) since it is linked to other physical, chemical and biological properties and processes that take place in the soil. Therefore, the OM content is a critical indicator of soil health due to the impact it produces on the aforementioned properties and processes (Doran & Zeiss, 2000; Lal, 2016).

As stated, the OM content therefore affects crop yields (<u>Reeves</u>, 1997). It is also known that the organic matter content is related to plant nutrition, to the global carbon cycle and it varies depending on the cropping system and climatic conditions (<u>Romanyà & Rovira</u>, 2011; <u>Mirzaee *et al.*</u>, 2016). For all the above, the OM content is considered as an indicator of soil fertility (Shibu *et al.*, 2006).

The traditional method for determining OM is that of <u>Walkley & Black (1934)</u>, however, for its use in large areas, it is a method that requires reagents and time of the samples in the laboratory, so it would be convenient to use methods indirect that allow their estimation once they are calibrated and validated.

In the 1990s, with the advancement of Geographic Information Systems (GIS) and remote sensing, new techniques have emerged to map the organic matter content of the soils through the use of multispectral images obtained from satellites (Gomez *et al.*, 2008; Sanka-Bhunia *et al.*, 2019).

The bands of the multispectral images most used for the determination of the organic matter content are infrared and red because it is a non-destructive, fast and reproducible physical method that has been extended to the prediction of other physical and biological properties of the soil (<u>Wang *et al.*</u>, 2018). Research has shown the feasibility of using images from Landsat TM and LiDAR satellites to predict soil properties at different scales (<u>Rasel *et al.*</u>, 2017).

In Holguín Municipality, Cuba, there is an area of 100 ha dedicated to rice cultivation which, in the future, could be extended to another 2000 ha in the same region depending on the fertility of these soils. Therefore, considering the OM content as an indicator to know the initial state of soil fertility in this region, in the present research, the study of the relationship of spectral index obtained from Landsat 9 images with the contents of OM. determined in the laboratory is carried out. The results obtained could be used for estimations in areas with the same characteristics as the one studied. In addition, the study of the spatial structure of the OM is carried out since the correct description of its spatial dependence is essential to know its degree of spatial continuity and the structure of its variability.

MATERIALS AND METHODS

The area selected for the investigation belongs to Guatemala Agricultural Company, CCS "Tomás Machado" in Cosme Herrera Town, located at $20^{\circ}44'54,601$ "N and $75^{\circ}50'43,743$ "W of Mayarí Municipality, Holguín Province (Figure 1). In it, more than 100 ha are dedicated to rice cultivation with very low productive results of 0.63 t·ha⁻¹, due to that, it has been fallow for three consecutive years, which could have improved its physical condition to be used in rice planting.





In the area of 100 ha mentioned above, a systematic sampling was carried out at 100 georeferenced points with a GPS with an appreciation of 3 m, at a distance between points of 100 m. The characteristic soil of the area is of the Chromic Vertisol type according to <u>Hernández et al. (2015, 2019)</u> with a slope of 2 %, so it can be considered flat. The samples were taken in the depth range between 0 to 0.20 m since the approximations made by spectral information from satellites to determine soil OM content have presented, in most of the studies, more precise relationships when samples are taken *in situ* in this depth range (<u>Denis et al., 2014</u>; <u>Angelopoulou et al., 2020</u>).

The analysis of the organic matter content was carried out in Camagüey Base Unit of Science and Technology following the Cuban Standard for the determination of soil organic compounds (<u>Norma Cubana (NC), 2014</u>).

Geostatistical Analysis

An exploratory data analysis was initially performed on the values obtained for organic matter, beginning with a univariate description. Measures of location, dispersion and shape were calculated, as well as the histogram and the normality curve. Structural analysis (variogram) of the data was performed to investigate if the values showed a spatial structure that would allow the use of the kriging interpolation technique, considered the best unbiased linear estimator (<u>Cressie, 1990</u>). Interpolation was performed by kriging to obtain maps of organic matter content at unmeasured points. Surfer 8 software (Golden Software, Inc.) was used.

The experimental semivariogram γ (h) was obtained from expression (1) (Journel & Huijbregts, 1978).

$$\gamma(h) = \frac{1}{2Np(h)} \sum_{i=1}^{Np(h)} \left[Z(x_i) - Z(x_i + h) \right]^2 \quad (1)$$

Where Np(h) is the number of pairs of observations separated by distance h, Z(xi) is the value of the variable at site xi and Z(xi + h) is the value of the variable at a site located at a distance h from site xi.

The adjustment of the experimental semivariogram to theoretical models was carried out, obtaining the one with the best adjustment according to the methodology proposed by Legrá-Lobaina & Atanes-Beatón (2010). In this, the semivariogram is generated from the adaptation of its scope, plateau, nugget effect and its model, which allows obtaining local corrections of the variability of the magnitude under study.

Once the theoretical model was established, the values of the nugget effect (Co) were found, which is the lowest value of the semivariance and the maximum semivariance $(C_0 + C_1)$. On the other hand, C_1 is the difference between the maximum semivariance and the value of the pip effect. In order to quickly obtain quantitative information on the spatial dependence of the OM variable, the Degree of Spatial Dependence (GDE) proposed by <u>Cambardella et al. (1994</u>), was also calculated, which is defined by expression (2).

$$GDE(\%) = \left(\frac{C_o}{C_0 + C_1}\right) * 100 \quad (2)$$

<u>Seidel & Oliveira (2014)</u> propose the following categories for the GDE: strong spatial dependence

(GDE > 75 %), moderate spatial dependence (25 <GDE \leq 75 %) and weak spatial dependence (GDE \leq 25 %). To also take into account the effect of the model used to fit the experimental variogram as well as all the other characteristics of the semivariogram, the spatial dependence index of the model (IDE) proposed by <u>Seidel & Oliveira (2014)</u> and <u>Seidel & Oliveira (2016)</u>, which is given by the following expressions for the spherical, exponential and Gaussian models, respectively.

$$IDE_{esf\,\acute{e}rico}(\%) = 0.375 * \left(\frac{C_1}{C_0 + C_1}\right) * \left(\frac{a}{0.5MD}\right) * 100 \quad (3)$$

$$IDE_{exponencial}(\%) = 0.317 * \left(\frac{C_1}{C_0 + C_1}\right) * \left(\frac{a}{0.5MD}\right) * 100$$
(4)

$$IDE_{gausiano}(\%) = 0.504 * \left(\frac{C_1}{C_0 + C_1}\right) * \left(\frac{a}{0.5MD}\right) * 100 \quad (5)$$

Where the practical range is *a*. MD is the maximum distance. The coefficients that appear at the beginning of each model according to <u>Seidel & Oliveira (2014)</u>, are known as the Model Factor (FM) and express the strength of the special dependency that a given model can achieve, so the higher its value, the greater the strength of the spatial dependency of the model. <u>Seidel & Oliveira (2016)</u> propose, according to the IDE values, the classification presented in <u>Table 1</u>.

Satellite Image Processing

An image of April 26, 2022, belonging to the Landsat 9 OLI/TIRS 2 satellite (LC09_L2SP_011046_20220426_20220428_02_T1) of the United States Geological Survey on path 011 row 046 was used and was projected on the WGS 84 System UTM Zone 18 North in the QGIS 3.10 "A Coruña" software and spectral index of soil and vegetation were determined (Table 2), after performing the atmospheric correction to eliminate the effect of clouds on the image.

For the extraction of the digital values of the image, the layer of sampling points was used in the ArcGIS 10.5 software and an Excel database was created with said information for each calculated spectral index. In the Statgraphics Plus software, the exploratory and linear regression analysis was carried out between the values of OM and the spectral index of soil and vegetation.

 TABLE 1. Classification of the IDE spatial dependency index for the Spherical, Exponential and Gaussian models

Model	Spatial dependence Index (IDE %)			
	Strong	Moderate	Weak	
Spherical	> 15	Entre 7 y 15	≤ 7	
Exponential	>13	Entre 6 y 13	≤ 6	
Gaussian	> 20	Entre 9 y 20	≤ 9	

RESULTS AND DISCUSSION

Exploratory Analysis of the Variables under Study

<u>Table 3</u> shows the statistics of the variables analyzed. The average OM content was found to be 3.81 % with minimum and maximum values of 1.65 % and 6.75 %, respectively. That could be associated with the fact that the area has remained fallow for three years and the possible presence of grazing animals at some points, which leads to the incorporation of OM into the soil by the decomposition of their excreta.

The median showed a trend of 3.74% with a standard deviation of 1.25%, with a standard error in its determination of 0.12% in the permissible ranges in which the unit of measurement of this property oscillates. The coefficient of variation indicated that the values of OM vary moderately for 32.80% according to <u>Wilding (1985)</u>. Alexakis *et al.* (2019) refer that the coefficient of variation reflects the distribution of each soil property and can have characteristic spatial patterns for each experimental area. <u>Ayoubi *et al.* (2011)</u> obtained a moderate variation with a coefficient of variation of 32 % and 34 % in the sites where they sampled the OM content and refer that this variation depends on the accumulation of water on the soil cover.

The asymmetry and kurtosis, both in the OM content of the soil and in the determined spectral index, is in the range of -1 to 1 which indicates that the values do not follow a normal distribution (<u>López-Granados *et al.*</u>, 2005).

The average value of NDVI was found to be 0.26, which ranges from -1 to 1 and agrees with what was stated by <u>Rawashdeh (2012)</u> that for this index, values from 0 to 0.5, there is scarce vegetation and coincides

with the current state of the study area. The SAVI vegetation index reported an average of 0.52, closely related to the average index obtained from NDVI and the corresponding vegetation status classification.

Joko-Prasetyo *et al.* (2020) use the NDVI and SAVI as indicators of the state of aridity in Indonesia, obtaining values similar to those found in this research and pointing out that they are areas with low vegetation cover where photosynthetic activity is decreasing and, therefore, the values fluctuate between 0.1 and 0.5.

In line with the type of soil in the study area (Vertisol), characterized by having a high content of monmorillonite-type clays (<u>Hernández et al., 2015</u>, 2019), the CI yielded mean values greater than 1 with 1.32. The results obtained coincide with what was stated by <u>Boettinger et al. (2008)</u> who report that the multispectral images of the Landsat satellite in its near-infrared bands can be used to identify the parent material of the soil.

Geostatistical Analysis

Figure 2 illustrates the experimental and theoretical semivariogram of the values obtained from OM in the study area, which had a better fit to an exponential model, agreeing with studies previously carried out by Reza *et al.* (2016); Bogunovic *et al.* (2017); Durdevic *et al.* (2019). They report that most of the soil properties, when performing a structural analysis, have a better fit to an exponential model.

Jian-Bing *et al.* (2006) and Rawashdeh (2012) when studying the spatial variability of chemical properties of the soil, obtained similar results. They refer that OM, pH, electrical conductivity, assimilable potassium and total carbonate had a better fit to an exponential model. In Figure 2, according to the

Spectral Index	Equation	Reference
Normalized Difference Vegetation Index Vegetación (NDVI)	$\frac{B_{NIR} - B_{Red}}{B_{NIR} + B_{Red}}$	(7) <u>Rouse <i>et al.</i> (1974)</u>
Clay index (CI)	$\frac{B_{NIR}}{B_{SWIR2}}$	(8) <u>Boettinger <i>et al.</i></u> (2008)
Soil Adjusted Vegetation Index (SAVI)	$(B_{NIR} - B_{Red})^*(1+L))/(B_{NIR} + B_{Red} + L)$	(9) <u>Huete (1988)</u>

TABLE 2. Spectral index of determined soil and vegetation

L=1 effect of soil correction; BNIR is the infrared band of the sensor; BRed is the red band of the sensor; SWIR2 is the shortwave infrared band of the sensor.

perty	Mean	SD	SE (%)	CV	Min.	Max.	Median	Asymmetry	Kurtosis
М	3.81	1.25	0.12	32.80	1.65	6.75	3.74	0.49	-0.17
OVI	0.26	0.06	0.01	21.74	0.11	0.43	0.25	0.34	0.89
VI	0.52	0.11	0.01	21.74	0.22	0.85	0.51	0.34	0.89
CI	1.32	0.04	3.5E-03	2.67	1.21	1.39	1.32	-0.74	0.96
	perty PM DVI AVI CI	perty Mean M 3.81 DVI 0.26 AVI 0.52 CI 1.32	perty Mean SD DM 3.81 1.25 DVI 0.26 0.06 AVI 0.52 0.11 CI 1.32 0.04	perty Mean SD SE (%) DM 3.81 1.25 0.12 DVI 0.26 0.06 0.01 AVI 0.52 0.11 0.01 CI 1.32 0.04 3.5E-03	perty Mean SD SE (%) CV M 3.81 1.25 0.12 32.80 DVI 0.26 0.06 0.01 21.74 AVI 0.52 0.11 0.01 21.74 CI 1.32 0.04 3.5E-03 2.67	perty Mean SD SE (%) CV Min. M 3.81 1.25 0.12 32.80 1.65 DVI 0.26 0.06 0.01 21.74 0.11 AVI 0.52 0.11 0.01 21.74 0.22 CI 1.32 0.04 3.5E-03 2.67 1.21	perty Mean SD SE (%) CV Min. Max. M 3.81 1.25 0.12 32.80 1.65 6.75 OVI 0.26 0.06 0.01 21.74 0.11 0.43 AVI 0.52 0.11 0.01 21.74 0.22 0.85 CI 1.32 0.04 3.5E-03 2.67 1.21 1.39	perty Mean SD SE (%) CV Min. Max. Median M 3.81 1.25 0.12 32.80 1.65 6.75 3.74 DVI 0.26 0.06 0.01 21.74 0.11 0.43 0.25 AVI 0.52 0.11 0.01 21.74 0.22 0.85 0.51 CI 1.32 0.04 3.5E-03 2.67 1.21 1.39 1.32	pertyMeanSDSE (%)CVMin.Max.MedianAsymmetryM3.811.250.1232.801.656.753.740.49OVI0.260.060.0121.740.110.430.250.34AVI0.520.110.0121.740.220.850.510.34CI1.320.043.5E-032.671.211.391.32-0.74

TABLE 3. Statistics of the variables determined

OM: organic matter; SD: standard deviation; SE: standard error; CV: coefficient of variation; Min: minimum; Max: maximum.

obtained range of 600 m, it can be established that in samples taken at distances less than this one, their values will be spatially related, while those taken at greater distances are not related, due to the fact that the semivariance is made equal to the sample variance (Kerry & Oliver, 2007).

The degree of spatial dependence (GDE) was 43.75%, which corresponds to the classification proposed previously by <u>Cambardella *et al.* (1994)</u> as moderate spatial dependence ($25 < \text{GDE} \le 75\%$) and according to the classification of the effect of the adjusted exponential model, an SDI value of 16.36 % implies a strong spatial dependence (<u>Table 1</u>) as it is greater than 13 %. These values reflect that the spatial dependence is controlled by intrinsic and extrinsic factors influenced by inappropriate agricultural practices in the soil (<u>Liu *et al.*</u>, 2014</u>). The existing spatial structure allows the use of kriging as an interpolation technique that will allow the preparation of the OM map by estimating values at unmeasured points.

Figure 3 shows the distribution of the OM content obtained by kriging, where the highest values of OM are found to the north with darker tones in an irregular transept in the study area while the lowest values are in the center with lighter shades. It is possible that these higher OM values in this area are associated with the presence of peasant cattle as the area is fallow.

Relationships between Spectral Index and Organic Matter Content

<u>Table 4</u> presents the statistics of the linear regression analysis between the OM content of the soil and the spectral index of soil and vegetation. There is a high correlation of 0.98 between the OM content of the soil, the NDVI and the SAVI, which may be because both indexes use the red and infrared bands of the sensor for their determination.

The CI had a correlation of 0.94 with respect to the OM content of the soil. The determination coefficient yielded values close to 100%, the NDVI model vs. O.M (%) 95.61%, SAVI vs. O.M (%) 95.66% and CLAY INDEX vs. O.M (%) of 88.92 %. Therefore, it can be affirmed that the spectral index used can predict the OM content, with an error in its forecast in all cases within the permissible ranges in which the determined variables are measured (Ayoubi *et al.*, 2011).

Correlation coefficient close to 1.0; of 0.86 and 0.90 were found by <u>Wang *et al.* (2018)</u> with the use of Landsat 8 OLI/TIRS images with the processing of the red and infrared bands of the sensor, they obtained a strong determination of 92 % in the relationship between the OM content of the soil and the combination of sensor bands.



FIGURE 2. Experimental and theoretical semivariogram of the OM values obtained.



FIGURE 3. Map of the organic matter content obtained by kriging.

Xu et al. (2023) report that the use of remote sensing establishes a strong relationship between the data captured by the sensor and the OM of the soil with a strong linear relationship between the NDVI variables and index obtained by a digital elevation model (DEM), while no positive relationship was found with the Sentinel 2 spectral bands. Previous studies have shown that the relationship of soil OM content through remote sensing cannot be seen as a methodology that is generalized to various environments, but rather which is unique for each study site, and depends on the type of sensor used, the characteristics of the soil, the relief and the climate (Lamichhane et al., 2019).

On the other hand, <u>Prudnikova & Savin (2021)</u> found a negative relationship between the CI and the OM content of the soil with a coefficient of determination for the rainy season of 81 % and of 84 % in the dry season, respectively when using

Statistics	NDVI vs. O.M (%)	SAVI vs. O.M (%)	CLAY INDEX vs. O.M (%)
r ²	0.98	0.98	0.94
\mathbb{R}^2	95.61	95.66	88.92
Standard Error	0.26	0.26	0.01
EAM	0.19	0.19	0.01
Durbin-Watson	2.26 (P=0.08)	2.26 (P=0.08)	1.96 (P=0.37)
Equation of the model	OM = -1.78 + 21.68*NDVI	OM = -1.78 + 10.84*SAVI	OM= 1.22 + 0.03*CI

TABLE 4. Statistics of the linear regression analysis between the organic matter content of the soil and the spectral index of soil and vegetation

r²: Correlation coefficient; R²: Coefficient of determination; EAM: Mean Absolute Error.

Sentinel 2 to estimate the OM content of an Albic Luvisols in Russia.

There are references to other investigations in which estimates of the organic carbon content of the soil are made (Sodango *et al.*, 2021). This chemical element derived from the OM content of the soil (<u>Rasel *et al.*</u>, 2017) is estimated from spectral vegetation index, in which, when using the NDVI with mean values of 0.49 (dense vegetation) a correlation of 0.74 is reached (<u>Sankar-Gouri. *et al.*</u>, 2019).

CONCLUSIONS

Organic matter showed mean values of 3.81 % with adjustment of the experimental semivariogram to an exponential model with a degree of spatial dependence (GDE) of 43.75 % (moderate spatial dependence) and a strong index of spatial dependence according to the model used (IDE $_{model}$) of 16.36 %. The highest OM values were found to the north of the area. The use of the NDVI, SAVI and CI spectral index showed linear regression analysis statistics that make it possible to estimate the organic matter content of the soil. Correlation values of 0.98 were found for the NDVI and the SAVI while for the CI it was 0.94, while the determination showed values close to 100%. The results obtained in this research demonstrate the potential of remote sensing as a feasible and low cost tool in its acquisition for the estimation of soil OM in Vertisol chromic soil on fallow.

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