Manglar 21(4): 443-451 (2024)

Delimitation of irrigation management zones in banana cultivation using satellite images and physical and chemical soil attributes

Delimitación de zonas de gestión del riego en el cultivo del banano mediante imágenes de satélite y atributos físicos-químicos del suelo

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ABSTRACT

In banana plantations, irrigation is managed in a homogeneous way, which is inadequate due to the variability of the soil in different areas, leading to significant losses in productivity. To address this issue, the delimitation of agricultural management zones (AMZ) was proposed, based on the spatial variability of the physical and chemical soil attributes, along with information obtained from spectral indices derived from satellite imagery. Additionally, the soil-climate-plant relationship was considered to improve the accuracy and reliability of the information. For this purpose, Sentinel-2 satellite images were processed, and various spectral indices were calculated using the Sen2R package. These indices allowed the generation of AMZ in QGIS using the Smart Map plugin. The satellite images facilitated the delimitation of homogeneous zones based on spectral information. Through a correlation matrix between the mean values of physical and chemical soil variables and the spectral indices per hectare, a correlation was identified between the water stress index and factors such as sand content, electrical conductivity, soil texture class, and available water. The geospatial analysis allowed for the accurate delimitation of irrigation zones, compared to those defined solely by the physical and chemical properties of the soil. The vegetation's response to soil characteristics, such as water retention capacity, cation exchange, and base assimilation in the soil, demonstrated the effectiveness of this delimitation.

Keywords: management zones, spectral indices; Smart map; Sen2r, Sentinel 2.

RESUMEN

En plantaciones de banano, el riego se gestiona de manera homogénea, lo cual resulta inadecuado debido a la variabilidad del suelo en diferentes zonas, lo que genera pérdidas significativas en la productividad. Para abordar este problema, se propuso la delimitación de zonas de manejo agrícola (ZM) basadas en la variabilidad espacial de los atributos físicos y químicos del suelo, junto con la información obtenida de índices espectrales derivados de imágenes satelitales. Además, se consideró la relación suelo-clima-planta para mejorar la precisión y confiabilidad de la información. Para ello, se procesaron imágenes satelitales del satélite Sentinel-2 y se calcularon diversos índices espectrales utilizando el paquete Sen2R. Estos índices permitieron generar las ZM en QGIS mediante el complemento Smart Map. Las imágenes satelitales facilitaron la delimitación de zonas homogéneas, basadas en información espectral. A través de una matriz de correlación entre los valores medios de las variables físicas y químicas del suelo y los índices espectrales por hectárea, se identificó una correlación entre el índice de estrés hídrico y factores como el contenido de arena, la conductividad eléctrica, la clase textural y la cantidad de agua disponible. El análisis geoespacial permitió realizar una correcta delimitación de las zonas de riego, comparada con las zonas definidas exclusivamente a partir de las propiedades físicas y químicas del suelo. La respuesta de la vegetación a las características del suelo, como la capacidad de retención de agua, el intercambio catiónico y la asimilación de bases en el suelo, mostró la eficacia de esta delimitación.

Palabras clave: Zonas de gestión; índices espectrales; Smart map; Sen2r; Sentinel 2.

Recibido: 24-08-2024.
Aceptado: 10-12-2024.

DOI: http://doi.org/10.57188/manglar.2024.048

INTRODUCTION

The cultivation of bananas (*Musa* spp.) is a basic source of food worldwide (Ghag & Ganapathi, 2017), as well as an important agricultural export product for many tropical countries, including Ecuador, where its commercialization in the international market is one of the country's most significant economic activities (Evans et al., 2020) Annual banana production increases by an average of 1.37 tons per hectare (Varma & Bebber, 2019), which is closely related to the increase in productivity, which is achieved through efficient, technician management that takes into account both the physiological needs of the crop and the soil and climatic conditions of the area in which it is grown (Panigrahi et al., 2021).

A good agronomic management of crops can be achieved with the delimitation of agricultural management units or agricultural management zones (MZs), which allow the optimization of resources; economic, social and environmental (X. Song et al., 2009). The importance of a differentiated management is due to the variability of the physical and chemical attributes of the soil, but also to irrigation, since in the banana crop, if managed incorrectly, it can generate losses in fruit mass of up to 65% (Panigrahi et al., 2021) or an increase in the incidence of insect pests and diseases, especially Black Sigatoka (*Mycosphaerella fijiensis* Morelet) (Yonow et al., 2019) In the province of El Oro, a large part of the irrigation systems are controlled by a manual operator, who without specific guidance causes by omission water wastage and inaccuracy in irrigation control, affecting crop productivity (Berrú-Ayala et al., 2020; Panigrahi et al., 2021).

As a measure to mitigate these errors, precision agriculture has facilitated the automation of several processes in irrigation management with which the costs for the execution of procedures are reduced (Vélez et al., 2024), such as the delimitation of MZs with which the state of the vegetation and the variation present within a crop can be identified from spatial information obtained from satellite images, from which the yield or health of the vegetation can be estimated (HARRIS et al., 2005; Kureel et al., 2022) This information can be associated to the water conditions of the crop with which the water management of the crop can be focused (Erazo-Mesa et al., 2024; Gorokhova & Pankova, 2024). Additionally, it is important to consider that the water needs must be in function of the soil, climate and plant relationship, which will allow to increase the efficiency of irrigation management (Blum, 2011; Zinkernagel et al., 2020).

With the delimitation of the MZs, the technicians responsible for field management can make correct decisions (Sawadogo et al., 2023), considering the spatial variability of the physical and chemical attributes of the soil (Villegas Santa & Castañeda Sánchez, 2020), which are related to different physical properties of the soil such as: porosity, bulk density, texture and structure that influence the water retention capacity and availability of water for the crop (Coelho et al., 2019; Ding et al., 2020).

The literature reports delimitations of MZs using satellite images obtained from remote sensors as instruments to obtain information from an object at a distance in a manned or unmanned means of transport (MIAO et al., 2018) have been contrasted with MZs generated from physical (Igor et al., 2020), chemical (Ayele et al., 2019), hydric (Priori et al., 2020) and biological (Priori et al., 2019) properties, demonstrating their efficiency for the delimitation of MZs. The processing of remotely sensed information has been tested in several crops, including banana (Gomez Selvaraj et al., 2020; Wikantika et al., 2022), allowing the identification of plants by means of aerial imagery and machine learning methods and the identification of vegetation health (Cui et al., 2023; Wu et al., 2024). Precision agriculture and spectral indices obtained from satellite images make it possible to identify areas with lower productivity on a farm or to estimate crop yields using the normalized difference vegetation index (NDVI), the soil-adjusted vegetation index (SAVI) (Chlingaryan et al., 2018; El-Hendawy et al., 2019) to estimate soil moisture at field capacity and permanent wilting point using the water stress index (MSI) (Welikhe et al., 2017).

With the considerations described above, the general objective of this research is delimiting agricultural management zones (MZs), considering the spatial variability of soil physical and chemical attributes and the information of spectral indices calculated from satellite image data and the soil-climate-plant relationship to increase the reliability of the information.

METHODOLOGY

Study area

To define the irrigation management zones for banana cultivation, we worked with information from a banana farm in the coastal region of Ecuador located in the province of El Oro, Machala canton, farm "Las Mercedes" of the company PACIDEL S.A. with a surface area of 75 hectares, located at the geographic coordinates 3°15'59. 1 "S 79°53'43.2 "W the farm has the delimitation of productive lots according to the characteristics of the soil of variable texture which are mentioned in (Figure 1.), the period in which the study was developed was between the months of May to July 2022.

Satellite image processing

The images used were obtained through the Copernicus programmed of the European Space Agency, in Geo TIFF format (Level 1) and downloaded using the sen2r package in R version 4.2.2. The images were processed with the Sen2Cor package for the correction of the orthorectified level 2A images with reflectance levels below atmospheric (BOA). Images with reflectance levels above atmospheric (TOA) of levels 1C were not used in order to process information with better resolution, contrast and structure (Ranghetti et al., 2020).

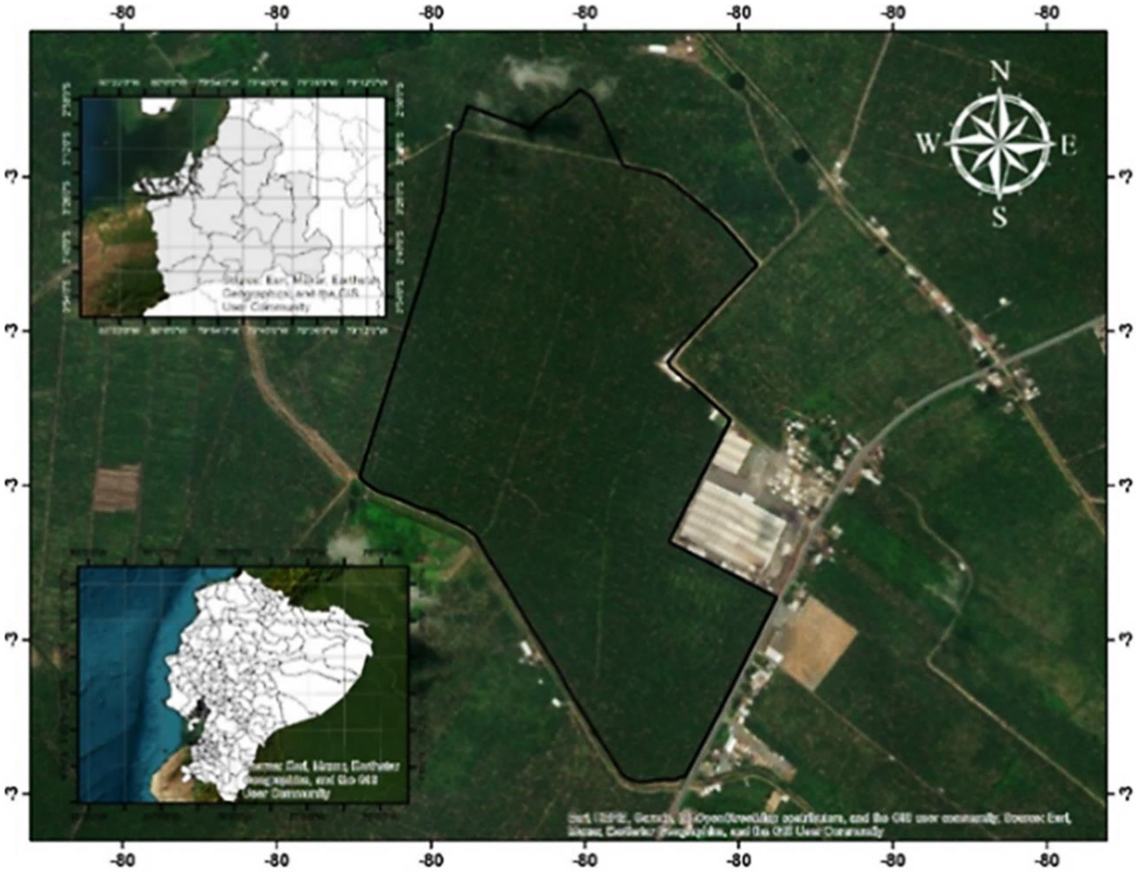

Figure 1. Spatial location of the study area.

our images were selected using a KLM and the EarthExplorer interface, and a Shapefile was included to delimit the farm in the download. For image processing, the image was cropped with a mask layer on the farm and the resolution between bands was adjusted to 10 meters. Normalized land cover index (NDVI), normalized difference adjusted index (SAVI) and MSI water stress index (Cohen et al., 2013) were selected using the following equations:

NDVI=((NIR-RED))/((NIR+RED))

where: NDVI is the Normalized Difference Vegetation Index; NIR the near-near infrared region; RED the red region. In Sentinel 2 the NIR corresponds to band 8 (spectral resolution of 0.78 - 0.90 µm) and RED to band 4 (spectral resolution of 0.65 - 0.68 µm).

The Soil Adjusted Vegetation Index (SAVI) has a slight variation of the traditional NDVI formula to avoid distortions in the analysis values when vegetation is located on exposed soils (Rhyma et al., 2020). Conditions such as temperature or humidity can influence the working bands analyzed and thus the results provided by the indicator. In this case, the SAVI vegetation index will try to avoid this influence of the soil on the results by adding an additional factor (L) in the NDVI equation that will allow working in scenarios where vegetation development is incipient.

SAVI=((NIR-RED))/((NIR+RED+L))*(1+L)

Water Stress Index (MSI) for canopy water deficit analysis, productivity prediction and biophysical modelling (Welikhe et al., 2017). The interpretation of the MSI is reversed relative to other aquatic vegetation indices; thus, higher values of the index indicate higher plant water stress and, in inference, lower soil moisture content. Values of this index range from 0 to more than 3, with the common range for green vegetation being 0.2 to 2.

MSI=MidIR/NIR

To avoid errors due to overlapping satellite images in the study area, spectral index data were filtered for each situation assessed. Values in a 10 m band around the perimeter of the area and the areas where fruit processing and housing takes place, especially at the edges of the area that were close to other plantations, were excluded. This procedure allowed for the normalization of NDVI and SAVI data, as well as productivity data, and allowed for an accurate comparison between these parameters. This methodology was used to ensure the accuracy and reliability of the results (Damian et al., 2020).

Delimitation of management zones using satellite images

To define the management zones, a combination of three spectral indices (NDVI, SAVI and MSI) obtained from the average of four nearby satellite images was used. The average values of each index were processed using the Smart-map plug-in of QGIS version 3.22.11 (Pereira et al., 2022). First, data including the coordinates extracted from the image and the index values were loaded. Then, the management zones window was reviewed, the data were interpolated, and the number of classes generated was identified. In this case, three zones with several iterations equal to 500 were adjusted according to the FPI and NCE values. This methodology was applied following the methodology described in the document (Balafoutis et al., 2017).

Delimitation of Management Zones by physical-chemical properties

The management zones were determined using the soil characteristics provided by the company PACIDEL S.A. For this purpose, the farm was delimited by means of a planimetric survey and sampling points were generated within each hectare. ArcGIS image processing tools, including kriging-based interpolation models and Voronoi polygon division, were used to create the management zones (Villaseñor et al., 2021).

Soil characteristics and adjustment of water requirements

To determine the irrigation needs of the banana crop, the CROPWAT software was used, based on the crop requirements (30). These calculations were carried out to compare previous water applications, as well as to adjust them according to the climatology of the area and the physical and chemical properties of the soil. To gather information on climatology, the meteorological yearbooks of the nearest meteorological station of the National Institute of Meteorology and Hydrology (INAMHI), with station code M0292 (Luna-Romero et al., 2018) were consulted (Table 1). This station is located at an altitude of 5 m above sea level, at latitude 3.17°S and longitude 79.54°W. As for the calculation of the effective precipitation of the crop using the FAO/AGLW method, where the effective precipitation is calculated by the formula 0.6*P -10/3 when the monthly precipitation is less than or equal to 70/3 mm and varies from 0.6 to 0.8*P-24/3 when the monthly precipitation is greater than 70/3 mm implemented in the same CROPWAT software (Villazón Gómez et al., 2021) the irrigation programming in the characteristics of the crop was carried out using the data obtained from the FAO manual 56 (Valle Júnior et al., 2021) due to the fact that it is a perennial crop the irrigation programming of the crop was carried out by calculating the phase of the crop at 365 days, Kc (crop coefficient) of the crop 1.10 root depth of the crop of 0.70 m, critical exhaustion level 0.65, yield response 1.35 and crop height of 3 m, because the soil characteristics are variants on the farm was determined to perform the calculations of the sheet time and frequency of irrigation through the Excel software package Office, based on this background is performed pro-average calculation of irrigation needs per month.

Table 1

Climatology of the study area station M0292. T °C (Temperature), RH (Relative Humidity), VW (Wind Speed), Evap (Evaporation), PP (Precipitation), H (Heliophany)

Months	T (°C)	HR (%)	VW (km h^{-1})	Evap (mm mes^{-1})	PP (mm mes^{-1})	H (h día^{-1})	PP (mm día^{-1})
January	26.83	80.05	1.19	112.55	102.67	3.32	3.31
February	27.06	79.95	1.19	107.94	164.80	3.55	5.89
March	27.34	79.05	1.26	124.42	130.85	4.45	4.22
April	28.69	79.33	1.25	123.57	85.33	4.49	2.84
May	26.63	81.33	1.13	97.43	28.75	3.57	0.93
June	25.19	85.00	1.08	75.57	14.36	2.34	0.48
July	24.33	85.14	1.02	73.94	10.41	2.31	0.34
August	23.60	86.14	1.06	71.18	13.27	2.08	0.43
September	23.95	86.32	1.07	71.39	11.46	1.60	0.38
October	23.94	85.70	1.78	65.36	16.70	1.08	0.54
November	24.47	84.70	1.14	71.91	76.63	1.49	2.55
December	25.89	81.05	1.19	98.43	39.50	2.64	1.27

Table 2

Water requirements as a function of climatic conditions in study area M0292. Kc (crop coefficient), ETc (crop evapotranspiration), Pref. effect (effective precipitation), Req.irrigation (irrigation requirement)

Moths	Stage	Kc	ETc mm día^{-1}	ETc mm dec^{-1}	Prec. efec mm dec^{-1}	Req.Riego mm dec^{-1}	Req.Riego mm día^{-1}
January	Start	1.1	3.2	33.5	19.4	14.1	1.4
February	Start	1.1	3.4	32.1	36.0	0.3	0.0
March	Start	1.1	3.7	38.0	26.9	11.1	1.1
April	development	1.1	3.5	35.2	14.7	20.6	2.1
May	development	1.1	2.8	29.1	2.5	26.6	2.7
June	development	1.1	2.2	22.1	0.0	22.1	2.2
July	development mediation	1.1	2.1	21.4	0.0	21.4	2.1
August	development mediation	1.1	2.1	21.9	0.0	21.9	2.2
September	development mediation	1.1	2.1	21.4	0.0	21.4	2.1
October	Finish	1.1	2.1	21.7	0.1	21.6	2.2
November	Finish	1.1	2.2	21.7	12.5	9.2	0.9
December	Finish	1.1	2.4	25.0	4.7	20.3	2.0

Based on all these antecedents and mathematical modelling and the USDA Soil Water Characteristics (Saxton & Rawls, 2006) the needs for which irrigation time maps were obtained adjusted to daily irrigations and time intervals between 30 - 50 minutes depending on the texture every 3 days for which 15% more or less of the interval obtained was adjusted so that the irrigation management in situ is easy to use for the operators and to avoid making manual mistakes. Additionally, the adjustment of the irrigation time by textural class is taken into consideration, to better understand and manage irrigation.

Statistical analysis and comparison of the results

Before comparing the results, outliers were manually removed from the attribute table in each index by generating raster histograms, due to the influence of roads, key roads and constructions within the banana plantations. To identify the correlation between the chemical physical variables of the soil with the values determined in the spectral indices, by means of the Voronoi maps in the ARCGIS software (Song et al., 2015; Tian, 2021) of the most important properties for irrigation issues, the data will be extracted by polygons obtained especially on the textural class and from these to know what is the relationship between the data obtained from the satellite images, The raster images were cut and the values were extracted for each site in order to locate an average value for each zone as well as for the physical and chemical conditions of the soil, and correlation was carried out using the R software packages corrplot, tidyverse and their complements. Additionally, to verify the reported values of the MSI, the maps were compared with the values of the volumetric moisture content by means of the TRD 350 probe of Espectrum Technologie s.Inf (Adla et al., 2020) and related it to the water retention capacity of the soil.

RESULTS AND DISCUSSION

The once the average raster files for each index were elaborated, the image was cut and the values of each pixel were converted to points and processed in Smart-map and the outliers, extremes or oultiers were eliminated (Pereira et al., 2022), because the outliers were previously eliminated, the distribution of the data in an exponential manner was maintained, for each index giving a representation of the outliers produced by the constructions eliminated from the zoning.

Prior to data cleaning the data were interpolated and the semi variance model was fitted to the exponential model in order to generalize the isotropic variogram (Figure 2 and Figure 3.), the R2 values were adjusted to 0.91 for the NDVI, 0.81 for the SAVI index and finally 0.87 for the MSI, the data were homogeneously fitted with a good correlation coefficient to be able to process the data between the spectral indices (Pereira et al., 2022).

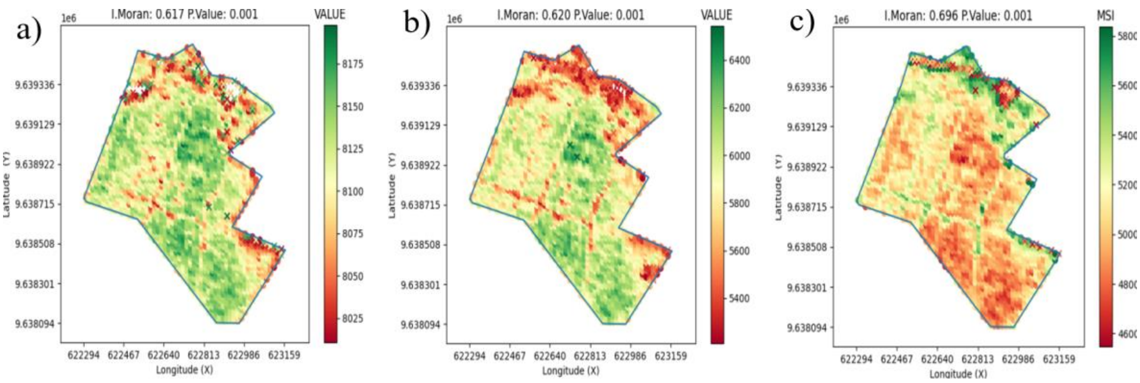

Figure 2. Removing outliers and cutting the extension of the farm "Las Mercedes". From left to right the a) NDVI, b) SAVI and c) MSI index showing the oultiers to be removed.

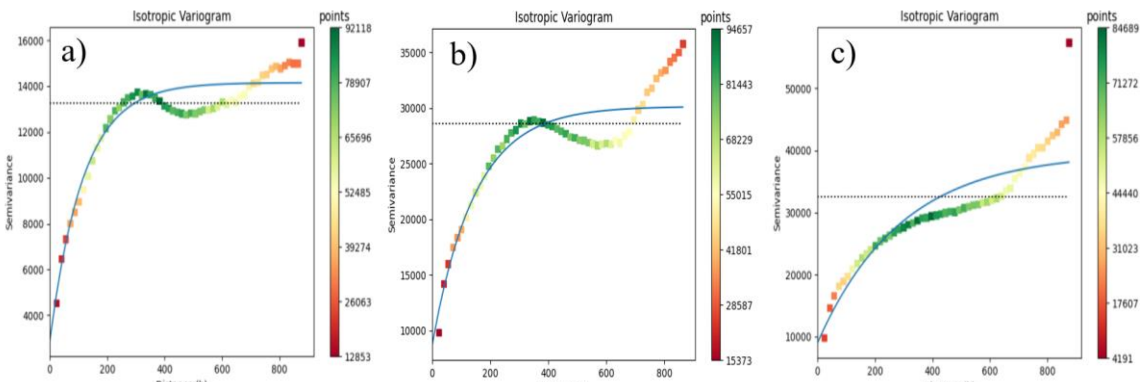

Figure 3. Distribution of the isotropic variograms with the distances h and the distribution of the exponential variance. From left to right the a) NDVI, b) SAVI and c) MSI index showing the oultiers to be suppressed.

Based on the models to generate the number of classes for NDVI, SAVI and MSI were grouped and intercepted into 3 classes, these results were the same when generating the management zones by the physical chemical attributes of the soil in which the fuzzy K-means test and calculates the FPI (Fuzzy Performance Index) and NCE (Normalized Classification Entropy) indices, which are widely recommended in the literature to define the appropriate number of MZs found the grouping for 3 clusters with each other (Figure 4.). The spectral indices allowed estimation of the health of the vegetation (Cohen et al., 2013), especially in relation to the hydric conditions of the crop.

Finally, generated the group number and with interactions adjusted to 500 between them, homogeneous zones were generated to the zones generated by the same kriging interpolation model from variables and spectral information obtained from Sentinel 2 satellite images, the variations between spectral indices were not variants between them, but they were significantly related to the management zones (Figure 5). The spectral indices associated with vegetation health allowed the generation of management zones (Damian et al., 2020) contrasted with the results currently obtained, with NDVI and SAVI being the most closely related, varying from the zones obtained from the physical and chemical soil conditions.

An overview of the physical and chemical parameters of the soil were better associated with the spectral indices than with the management zones generated from the physical and chemical properties of the soil. This can be verified with the retention capacity from the spatial behavior of the usable water in the 60 cm and with the textural class of the soil as well as with the water stress index; on-site visits to the farms contrasted the assumptions reviewed, as the areas of greater water stress had greater water infiltration (Figure 6).

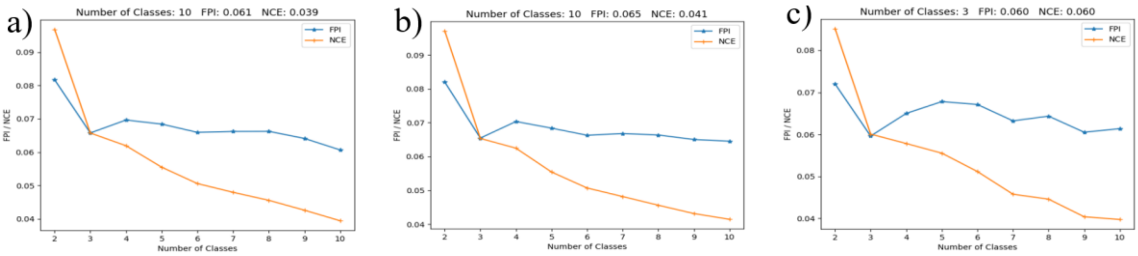

Figure 4. Number of classes or groups generated in each spectral index. From left to right the a) NDVI, b) SAVI and c) MSI indexes showing the oultiers to be suppressed.

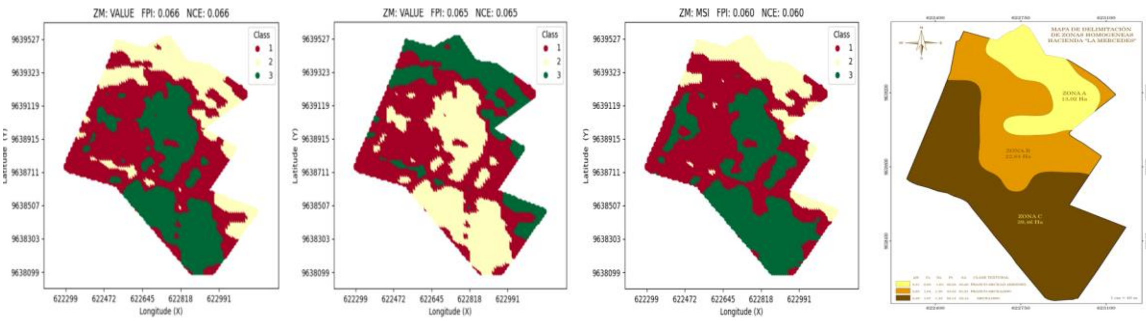

Figure 5. Agronomic management zones generated from spectral indices and soil physical and chemical properties. a) Irrigation Management Zones a) NDVI, b) SAVI, c) MSI and d) Management zones based on the physical and chemical characteristics of the soil.

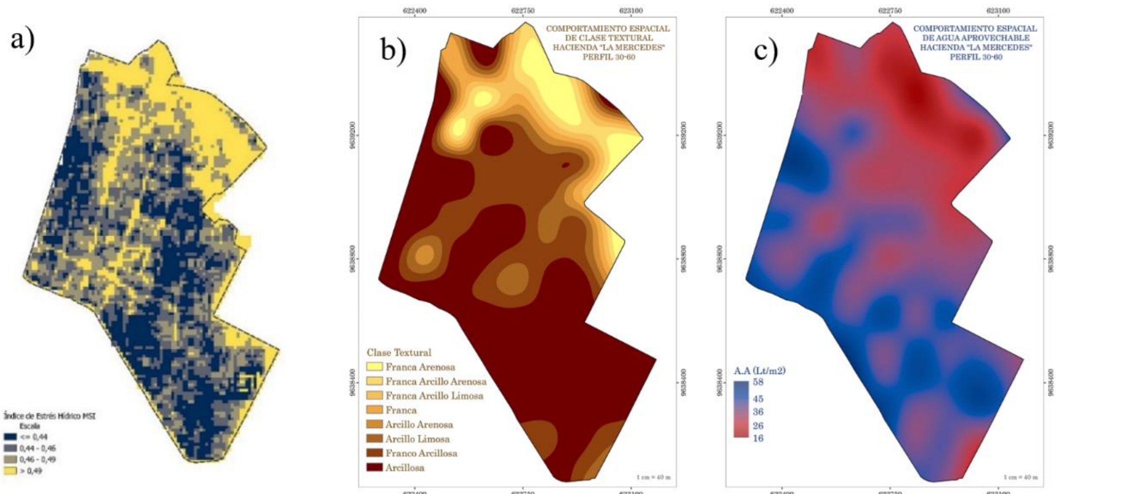

Figure 6. Soil physical properties associated with agricultural management zones. From left to right a) water stress index (MSI), b) soil textural class and c) usable water in the soil A.A (Lt/) with TDR 350.

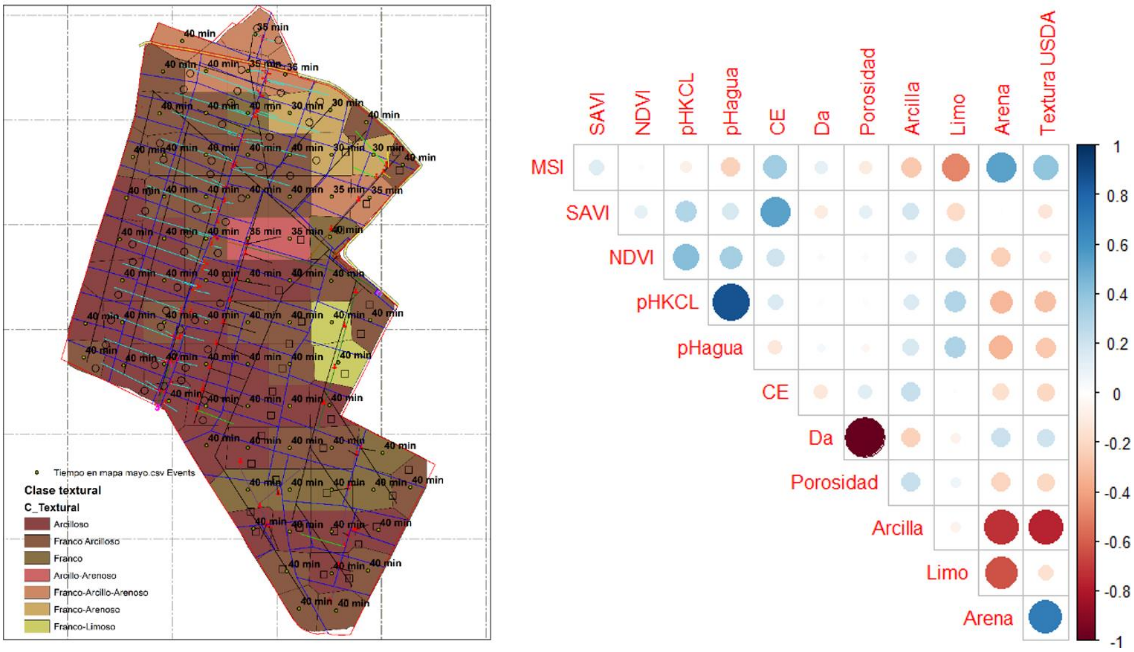

Figure 7. Irrigation scheduling as a function of soil adjusted to management zones and correlation matrix.

Based on these management zones, better irrigation scheduling can be made by adjusting the level of depletion based on crop textural classes in order to allow for efficient crop management adjusted to daily irrigations (Mndela et al., 2023). However, once the adjustments were made and applied within the farm, it was complicated to manage irrigation due to the process involved for the irrigators of the farms to be able to move between valves to open the irrigation modules (Figure 7), so it would be convenient to automate the opening of the valves according to a module opening design that helps to reduce water consumption (Berrú-Ayala et al., 2020). The values were positively associated with the water stress index, because the higher the water stress the higher the sand content in the study area or site, while the clay content decreases with which the soil conditions can be related especially to the water retention capacity of the soil particles, as well as the electrical conductivity (CE) conditions which will influence the productivity of the zones (Verheijen et al., 2019), while the NDVI and SAVI spectral indices were better associated with the EC of the soil and the pH.

CONCLUSIONS

The management zones generated from the NDVI, SAVI and MSI spectral indices by processing information from satellite images made it possible to describe three management zones generated by comparing the j-means model with the management zones created by the physical and chemical properties of the soil. However, these were more associated with the water assimilation capacity and physical properties obtained at 60 cm depth, specifically with the textural class.

The spatial behavior of water use obtained with the TDR 350 probe resembled better with the zones generated from satellite images than with the physical and chemical properties of the soil. The management zones and the physical characteristics of the soil associated with the irrigation requirements could not be managed correctly due to the difficulty of programming the irrigation modules manually, so it is recommended that this process be automated in order to manage irrigation more efficiently and reduce water consumption.

ACKNOWLEDGEMENTS

The authors would like to thank all the members of the "GRUPO EMPRESARIAL SÁNCHEZ" for their contributions for the collection of information and the use of physical and chemical analyses provided by the company PACIDEL S.A., as well as the Technical University of Machala for the use of equipment for the development of the research.

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