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Remote sensing applied for the estimation of crop coefficient and detection of forest cover changes

Teledetección aplicada para la estimación del coeficiente del cultivo y detección de cambios en la cobertura boscosa

Sensoriamento remoto aplicado para estimar o coeficiente de cultivo e detectar mudanças na cobertura florestal

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Crop production

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Abstract

With the objective of applying remote sensing techniques for crop coefficient estimation and detection of changes in forest cover, in order to generate information that contributes to the sustainable management of agricultural and forestry resources, a study was conducted based on the theoretical foundations of agriculture 4.0, through the implementation of advanced technologies and intelligent data integration to optimize the entire agricultural production cycle. The methodology adopted includes the capture and processing of multispectral images from satellite platforms and unmanned aerial vehicles (UAVs), in order to obtain geometric and spectral information on various crops. Calculations of spectral indices (NDVI, NDMI, NDWI, Kc) and analysis of forest stand losses were performed using advanced software tools in GIS environment and the Google Earth Engine platform. The drone images made it possible to calculate the NDWI to classify soil moisture in high, moderate and low levels. Satellite images facilitated the identification of relationships between crop evaporation coefficient (Kc) and climatic parameters, as well as the detection of areas with forest losses in the Carrizal river basin. The results suggest strategies for the development of precision agriculture activities, promoting the substitution of conventional practices for sustainable development mechanisms based on geospatial technologies. This study contributes to the literature by demonstrating the application of advanced geospatial technologies to optimize agricultural production and sustainability.

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Resumen

Con el objetivo de aplicar técnicas de teledetección para la estimación del coeficiente del cultivo y la detección de cambios en la cobertura boscosa, de tal manera de generar información que contribuya al manejo sostenible de los recursos agrícolas y forestales se realizó un estudio con base en los fundamentos teóricos de la agricultura 4.0, mediante la implementación de tecnologías avanzadas y la integración inteligente de datos para optimizar el ciclo completo de producción agrícola. La metodología adoptada incluye la captura y procesamiento de imágenes multiespectrales provenientes de plataformas satelitales y de vehículos aéreos no tripulados (UAV), con el fin de obtener información geométrica y espectral de diversos cultivos. Se realizaron cálculos de índices espectrales (NDVI, NDMI, NDWI, Kc) y análisis de pérdidas de masas forestales utilizando herramientas avanzadas de software en ambiente GIS y la plataforma Google Earth Engine. Las imágenes de drones permitieron calcular el NDWI para clasificar la humedad del suelo en niveles alto, moderado y bajo. Por su parte las imágenes satelitales facilitaron la identificación de relaciones entre el coeficiente de evaporación del cultivo (Kc) y los parámetros climáticos, así como la detección de áreas con pérdidas de bosque en la cuenca del río Carrizal. Los resultados sugieren estrategias para el desarrollo de actividades en agricultura de precisión, promoviendo la sustitución de prácticas convencionales por mecanismos de desarrollo sostenible basados en tecnologías geoespaciales. Este estudio aporta a la literatura al demostrar la aplicación de tecnologías geoespaciales avanzadas para optimizar la producción agrícola y la sostenibilidad.

Palabras clave: índices espectrales, Kc, detección de cambios, UAV, GEE.

Resumo

Com o objetivo de aplicar técnicas de sensoriamento remoto para a estimativa do coeficiente de culturas e a detecção de mudanças na cobertura florestal, a fim de gerar informações que contribuam para o gerenciamento sustentável dos recursos agrícolas e florestais, foi realizado um estudo com base nos fundamentos teóricos da agricultura 4.0, por meio da implementação de tecnologias avançadas e da integração inteligente de dados para otimizar todo o ciclo de produção agrícola. A metodologia adotada inclui a captura e o processamento de imagens multiespectrais de plataformas de satélite e veículos aéreos não tripulados (VANTs), a fim de obter informações geométricas e espectrais de várias culturas. Os cálculos dos índices espectrais (NDVI, NDMI, NDWI, Kc) e a análise das perdas de povoamentos florestais foram realizados por meio de ferramentas de software avançadas em um ambiente de SIG e na plataforma Google Earth Engine. As imagens de drones permitiram que o NDWI fosse calculado para classificar a umidade do solo em níveis altos, moderados e baixos. As imagens de satélite facilitaram a identificação das relações entre o coeficiente de evaporação da cultura (Kc) e os parâmetros climáticos, bem como a detecção de áreas com perda de floresta na bacia do rio Carrizal. Os resultados sugerem estratégias para o desenvolvimento de atividades de agricultura de precisão, promovendo a substituição de práticas convencionais por mecanismos de desenvolvimento sustentável baseados em tecnologias geoespaciais. Este estudo contribui para a literatura ao demonstrar a aplicação de tecnologias geoespaciais avançadas para otimizar a produção agrícola e a sustentabilidade.

Palavras-chave: índices espectrais, Kc, detecção de mudanças, UAV, GEE.

Introduction

Recent advances in geospatial technologies provide new options in agricultural sciences (Fuentes-Peñailillo *et al*., 2024; Masi *et al*., 2023). According to Kganyago *et al.* (2024) and Karunathilake (2023), remote sensing has the potential to evolve adaptive agricultural practices by providing continuous information on crop status at various scales. This is especially crucial in a context of historically generated weather patterns on land. However, in Ecuador, where a large part of the population depends on agricultural activities, research in these areas is scarce.

One of the challenges facing remote sensing is the analysis of crop moisture. Basharat *et al*. (2023), Chen and Liu (2020), and Mehedi *et al.* (2024) explored low-cost geospatial techniques to increase agricultural yields and reduce environmental impact.
Quantification of 'plant water stress' is proposed as an indicator to improve irrigation practices by considering the interaction between soil water availability, atmospheric demand and plant physiology.

Munaganuri and Yamarthi (2024) proposed an innovative approach based on remote sensing and artificial intelligence to optimise irrigation, using convolutional neural networks to classify remotely sensed images and capture crop water requirements. Unmanned aerial vehicles (UAVs) have also been used extensively in precision agriculture. Manfreda and Dor (2023) provided a review on the history, commercial, social aspects and current applications of UAVs in agriculture. Work has also been developed for the estimation of crop Kc from the Leaf Area Index (LAI) to improve water balance calculations (Eliades *et al*., 2022).

Soil moisture has been studied using multispectral UAV and satellite imagery, together with artificial intelligence algorithms. Bai *et al*. (2021), Datta and Faroughi (2023) and Ge *et al*. (2021) presented research that has advanced soil moisture prediction at various depths. Wu *et al*. (2024) were able to predict moisture at 5, 10, 20 and 40 cm depth in citrus orchards using multi-modal remotely sensed UAV data. Khose and Mailapalli (2024) confirmed that the ratio vegetation index (RVI) has the greatest potential for estimating surface soil moisture using UAV imagery and machine learning algorithms.

In the context of remote sensing, several satellites orbit the Earth providing multispectral images. In this research, Sentinel-2 imagery, available through the European Space Agency's Copernicus platform, was used. De la Guardia *et al*. (2024) used Sentinel-2 and ERA-5 Land data to calculate the evapotranspiration of a bean crop in Brazil. Sabie *et al*. (2024) used Landsat Sentinel-2 (HLS) data to calculate crop coefficients and estimate evapotranspiration at the field level, with high agreement between calculations and field data.

In addition, cloud computing elements were considered to analyse multi-temporal datasets such as MODIS Land Cover Type (MCD12Q1) and Hansen Global Forest Change (2000-2021) products in monitoring the dynamics of different forest types and canopy cover, facilitating image identification and calculation of multi-temporal spectral indices. Del Valle and Jiang (2022), Kumari *et al*. (2024), Lemesios and Petropoulos (2024) and Yi *et al*. (2024) highlighted the importance of the Google Earth Engine (GEE) platform for the identification of multi-temporal images of vegetation types and forest cover, using historical remotely sensed data.

Considering the potential of these geospatial technologies in agriculture, the objective of this study was to apply remote sensing techniques for crop coefficient estimation and forest cover change detection in order to generate information that contributes to the sustainable management of agricultural and forestry resources.

Materials and methods

Location of the study area

The research was carried out in agricultural sectors of the Province of Manabí, Ecuador (Figure 1).

Traditional crops of the region and forested areas located within the Portoviejo and Carrizal Chone river basins were selected.

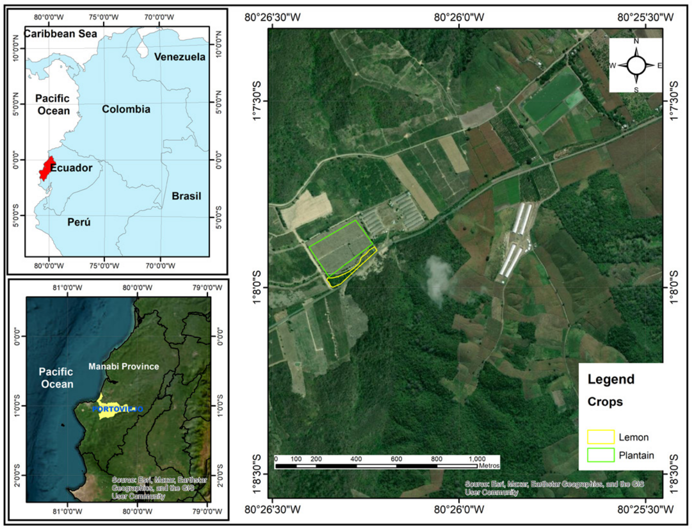

Figure 1. Location of the study area in the Province of Manabí, Ecuador.

Photogrammetric flight for the capture of aerial images

On September 17, 2023, in the middle of the dry season for the study area, in the Ecuadorian coastal region, a photogrammetric flight was carried out over an area of approximately 10 ha. The Ebee SQ Agricultural Drone (SenseFly, Switzerland) was used, instrumented with the Parrot Sequoia multispectral camera, which captures RGB images and the green, red, red edge and near infrared bands. The flight was planned with Emotion AG software, where the area of interest, flight path, height at 95 metres above the ground and an overlap of 80 % between the photographs were defined. At the end of the flight, the data were downloaded and the images were processed in the PIX4D photogrammetry software to generate orthomosaics, point clouds, spectral bands, digital terrain and surface models.

Six ground control points (GCP) were defined to support the photogrammetric flight. The points were distributed strategically, uniformly covering the flight area to guarantee adequate precision in the adjustment of the images obtained. To obtain the precise coordinates of the control points, RTK (Real-Time Kinematic) equipment (Topcon model GR-5, Japan) was used, which allowed centimetric precision to be achieved in the location of the points. The coordinates were registered in the geodetic system with the support of the permanent station REGME POEC 42008M003, located in Portoviejo, guaranteeing consistency with the official cartography of Ecuador and remote sensing data.

The GCPs were manually entered into the project, specifying their precise coordinates obtained with the high precision GPS. Within Pix4D, the GCPs were manually marked on various images where they were visible to correctly align and georeference the model, adjusting the positions of the images according to the control points.

Downloading Sentinel 2 imagery

Sentinel-2 imagery was downloaded from the Copernicus Open Access Hub, selecting parameters such as date, geographic extent and cloud cover (<30 %), focusing on a lemon crop in Santa Ana, Manabí. The images were processed in ArcGIS, calculating spectral indices (Table 1) with map algebra tools, providing relevant information on vegetation and crop conditions.

Table 1. Spectral indices calculated with the multispectral images.

Index name	Formula	Reference
Normalised Difference Vegetation Index	NDVI	Toosi, *et al*. (2022)
Normalised Difference Humidity Index	NDMI	Mc Feeters (1996)
Normalised Water Differential Index	NDWI	Mc Feeters (1996)
Evapotranspiration	Kc	Terink *et al*. (2015)

Soil and crop water conditions

ArcGIS software tools were used to analyse the green, red, red-edge and near-infrared bands captured by the eBee SQ agricultural drone (SenseFly, Switzerland). Moisture indices (NDMI and MDWI) and crop evaporation coefficient (Kc) were calculated using the equations shown in Table 1. The indices and Kc were calculated for each 10 m resolution cell, using the multispectral bands of the Sentinel image, and then averaged for each plot, according to crop. Subsequently, descriptive statistical analyses of the indices were carried out to assess the water conditions of the soils and crops.

Climatological conditions

Data from the La Teodomira Meteorological Station, belonging to the hydrometeorological network of the Portoviejo river basin of the National Institute of Meteorology and Hydrology of Ecuador, were analysed.

Loss of forest masses

Using the Google Earth Engine platform, a JavaScript code was programmed to analyse forest stand loss. The Hansen Global Forest Change 2000-2023 collection was accessed, which provided layers on forest cover (trees over 5 metres), vegetation loss (Loss) and gain (Gain). The affected area was quantified and represented on a thematic map, assessing its influence on erosion processes.

Results and discussion

Close remote sensing

As a result of this research, high-precision photogrammetric products with a resolution of 2 $cm.pixel^{-1}$ were generated. The data obtained allowed the production of orthophotos, spectral bands, point clouds and digital terrain and surface models.

Soil and crop water conditions

The orthophoto (Figure 2a) shows a soil under different moisture conditions, partially covered by pine nut and cocoa crops. Normalised Difference Wetness Index (NDWI) values (Figure 2b) ranged from -0.530059 to -0.866279, where minimum values represent vegetation, intermediate values indicate soils with high or moderate moisture, and maximum values reflect dry soil (Table 2).

The Natural Breaks method, built into Arcgis tools, is based on natural groupings inherent in the data. Classes are created so that similar values are grouped together and differences between classes are maximised.

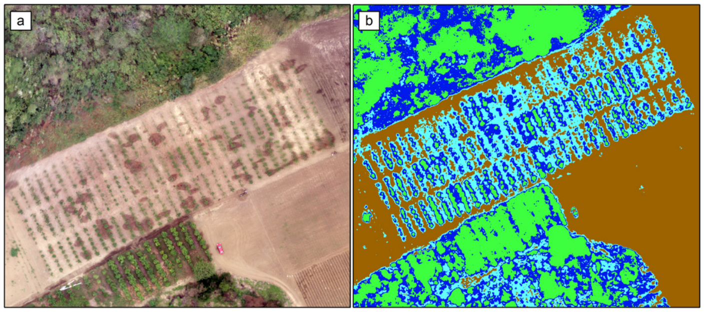

Figure 2. a) RGB photo ortho generated by Pix4D software and b) Normalised Difference Wetness Index (NDWI).

Table 2. Reclassification of the normalised difference humidity index.

Color	NDWI Range	Clasification
	≤ -0.593540	Vegetation
	-0.593540 -0.517160	Soil with high humidity
	-0.517160 -0.435378	Soil with moderate moisture
	≥ -0.435378	Dry soil

Features are divided into classes whose boundaries are set where there are relatively large differences in data values. In this case it was verified by fieldwork and visual interpretation of the orthophoto, that the classes defined in Table 2 correspond to the coverages visualised in the verification.

The method of classification of natural changes (Natural Breaks) made it possible to differentiate the coverages according to the NDWI ranges. These results are in agreement with the studies of Chandramohan *et al*. (2024) and Judge *et al*. (2021), who used different data sources to measure soil moisture.

Remote sensing

Sentinel 2 images (Figure 2a) were found with cloud cover below 30 % for 11 months of the year, allowing NDVI to be calculated (Figure 3b).

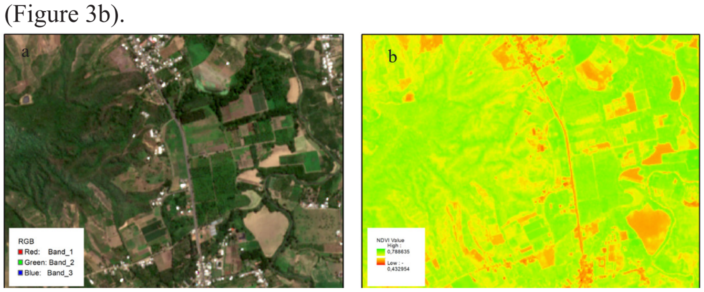

Figure 3. a) Sentinel 2 image and b) NDVI for the study area in Manabí Province, Ecuador.

Crop evapotranspiration coefficient of lemon crops

The crop coefficient (Kc) reflects the water requirements at each stage of lemon development, and is key for irrigation planning and design in the studied area. For a comprehensive understanding of the data, in terms of the inter-annual variability of Kc, it is essential to consider its relationship with the phenological stages of the crop and how these are affected by the annual weather conditions.

The data in Table 3 show the interannual variations of Kc for the lemon crop, highlighting the month of March with 0.25 indicating the lowest water requirements, for the final months of harvest or the beginning of a new phase of vegetative development, when the crop reduces its transpiratory activity, as the fruits have been removed and there is a period of recovery.

On the other hand, the maximum Kc value (0.62) was recorded during August, indicating high water requirements in conditions of low rainfall and high evapotranspiration, in addition to the fact that the crop is in a critical phase of fruit development, where a peak in Kc is observed due to the high water demand to sustain the rapid growth of the fruit.

The decrease in Kc values during September to November is explained by the fact that the crop is generally at an advanced stage of fruit development or ripening. As the fruits reach the right size and enter the ripening stage (September to November), vegetative growth decreases, reducing transpiration and hence Kc.

The variation of the crop coefficient (Kc) throughout the year is crucial for optimising agricultural irrigation scheduling. This parameter, which reflects the ratio between reference evapotranspiration (ETo) and crop evapotranspiration, varies according to rainfall, temperature and plant development stage, allowing irrigation to be adjusted more efficiently (Das *et al*., 2023).

According to Lobos *et al*. (2017) the water demand of a crop is mainly determined by two factors, the climatic conditions of the sector and the level of development of the plants. The development stage of the crop is defined by the crop coefficient (Kc), which indicates the water consumption of a plant according to its phenological stage.

Toosi *et al*. (2022) report a good number of investigations that relate the Kc with the phenological development of the crop, highlighting that the crop coefficient (Kc) varies significantly throughout its phenological cycle, as it reflects the water needs of the crop according to its development. For lemon during the early stages, such as initial growth and vegetative development, the Kc is low due to the limited water demand of the young plants. As the crop progresses to active growth and ripening stages, Kc increases, reflecting a higher water demand caused by increased transpiration and photosynthesis.

In this context, the use of the normalised difference vegetation index (NDVI) has been consolidated as an effective tool to estimate the Kc of lemon at different phenological stages. This is because NDVI

Table 3. Climatic data from the INAMHI Teodomira Station and crop coefficient (Kc), calculated with the multispectral bands of the Sentinel image.

Month	Jan	Feb	Mar	Apr	May	Jun	Aug	Sep	Oct	Nov	Dec
Prec (mm)	83.9	92.6	217.4	47.3	32	1.7	0.3	0.6	0.2	0	33.3
Temp (°C)	27.35	26.65	27.75	27.75	26.75	26.65	26.75	26.35	26.5	25.85	26.3
Hum (%)	80	83	84	84	85	84	83	80	79	78	78
Eva (mm)	99	85	130.2	120	89.6	91.7	115.5	137.6	144.3	134.5	122.4
NDVI	0.91	0.57	0.36	0.49	0.59	0.48	0.42	0.47	0.47	0.32	0.31
Lemon Kc	0.40	0.26	0.25	0.41	0.32	0.39	0.62	0.37	0.35	0.38	0.41

measures the amount and vigour of vegetation, correlating directly with the level of evapotranspiration and hence with the Kc of the crop. Recent research has shown that there is a significant correlation between NDVI values and Kc in lemons, especially during the active growth and ripening stages, allowing for more accurate and efficient water management (Ippolito *et al*., 2023).

Forest cover loss

Figure 4 shows, in red polygons, the areas where losses of vegetation cover were recorded, according to the calculations made in the Hansen Global Forest Change collection for the period 2000-2023. The sum of the area of the polygons with forest stand loss resulted in 58 km², which represents 21 % of the native forest stand in the study area, located in the upper and middle parts of the Carrizal river basin.

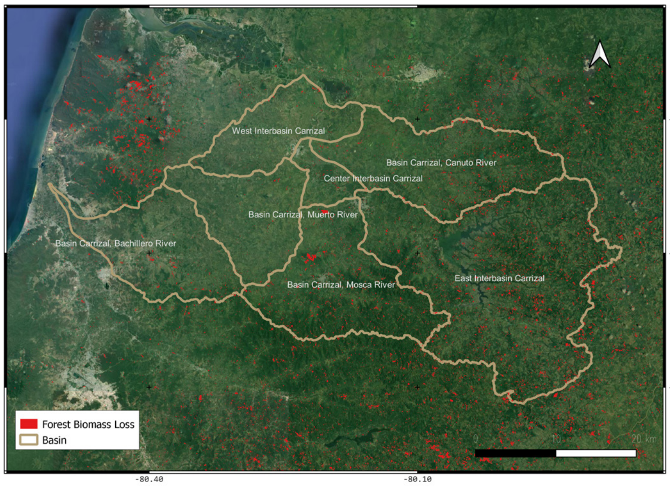

Figure 4. Spatial distribution of forest cover loss in the Carrizal river basin.

The loss of vegetation cover found in this study is directly related to deforestation, associated with the expansion of the agricultural frontier, which has profoundly affected hydrological processes, reducing the capacity of the basins to regulate the water cycle.

The loss of these 58 km² of forest could be influencing the reduction of water retention capacity in the forest, increasing surface runoff and the risk of erosion and flash floods (Elogne *et al*., 2023).

Additionally, considering the reports of Pedroza-Parga *et al*. (2022), a significant increase in soil erosion due to the loss of vegetation mass can be expected. According to the authors, areas with vegetation loss show a sediment erosion of 58.6 $t.ha^{-1}$, while areas with intact vegetation show lower values of approximately 26.3 $t.ha^{-1}$.

These results underline that vegetation on the soil surface helps to reduce flow velocity and particle removal, confirming that proper vegetation management positively influences hydrological processes, particularly infiltration, runoff and topsoil protection.

In the Carrizal river basin, the loss of forest cover is driving erosion in the upper and middle reaches of the drainage sub-basins. The resulting erosive processes generate large amounts of sediment that accumulate in the drainage network and reach the mouth of the Chone River estuary in Bahía de Caráquez. This accumulation of sediments in the watercourses has diverse hydrological consequences, affecting the dynamics of the ecosystems and the safety of the hydraulic infrastructure.

Strategies for precision agriculture

Remote sensing-based precision agriculture offers a key opportunity to improve the agricultural sector in the province of Manabí, Ecuador. This technology allows continuous monitoring of crops, using satellite imagery to detect problems such as water stress and deforestation. By obtaining accurate data on crop health, cover and water conditions, farmers can make informed decisions to apply inputs more efficiently, optimising the use of resources such as water and fertilisers.

In addition, remote sensing facilitates agricultural planning by being a tool for analysing soil conditions, which can help identify critical areas, providing real-time information that enables preventive measures to be implemented. In this way, the technology improves decision-making and the competitiveness of the sector, favouring more sustainable practices and increasing farmers' resilience.

Conclusions

Close remote sensing with unmanned aerial vehicles (UAVs) was very useful in generating very high spatial resolution orthophotos of the order of 2 $cm.pixel^{-1}$, which can be a very useful input in decision making related to the optimal use of water resources.

Normalised Difference Wetness Index (NDWI) values, calculated with spectral bands from a photogrammetric flight, ranged from -0.53 to -0.86, where minimum values represent vegetation, intermediate values represent high and moderate moisture soils, and maximum values represent dry soil.

The minimum (0.23) and maximum (0.62) Kc values for the lemon crop indicate the water consumption needs of the plant according to its phenological stage, with the minimum value coinciding with the final stage of harvest and the maximum with the time of fruit development. Remote sensing was optimal for the analysis of environmental conditions through the use of multispectral images from the Sentinel 2 satellite.

The Carrizal river basin has experienced a substantial loss of forest mass of 58 km², representing a 21 % decrease in native forest over a 20-year period.

The monitoring of agricultural activities and environmental conditions, using remote sensing techniques, integrates data sets that allow the various stakeholders to make informed, optimal and timely decisions in time and space to promote the sustainable development of the region.

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