Active and Passive Remote Sensors in Citrus Crop Monitoring

Andrés-F Jiménez López, PhD.[1]; Fabián-R Jiménez López, MSc[2]; Fredy Hadid Villanueva de la Ossa[3]

[1]Faculty of Basic Sciences and Engineering – Macrypt - Farmtechnology – Universidad de los Llanos, Villavicencio, Colombia, ajimenez@unillanos.edu.co

[2] Engineering Faculty – Research Group I²E – Department of Electronic Engineering – Universidad Pedagógica y Tecnológica de Colombia, Tunja, Colombia, fabian.jimenez02@uptc.edu.co

[3]Faculty of Basic Sciences and Engineering – EISY - iCONBOT – Universidad de los Llanos, Villavicencio, Colombia, fhvillanueva@unillanos.edu.co

Abstract*– The observation of agricultural crop conditions through satellite platforms has been of vital importance for the development of decision-making systems in the field. Passive sensors determine land surface conditions by measuring the reflectance of solar radiation, while radar satellites emit their own radiation. Active satellites can acquire information even under cloudy conditions, unlike passive satellites, which lose functionality. The purpose of this work is to study the use of both types of satellites for analyzing vegetation cover in citrus crops and to evaluate the possibility of replacing passive sensor data with active data, along with training recurrent neural networks, particularly Long Short-Term Memory (LSTM). Preliminary results indicate that time series from both types of satellites provide relevant information for crop management. The development of a software tool for downloading and generating time series of remote sensing data for specific locations is presented, using a plugin developed in QGIS and Python. Future research will focus on developing a methodology for fusing data from both types of information acquisition technologies for citrus crops.

Keywords-- Precision Agriculture, Citrus, Artificial Intelligence, Optical Sensors, Remote Sensing.

I. INTRODUCTION

There is currently a pressing need to achieve sufficient and efficient agricultural production to meet global food demands, taking into account environmental, soil, and plant conditions [1]. Climate variability has led to the adoption of practices tailored to immediate conditions [2]. For this reason, it is essential to understand the behavior of various variables over time, particularly those related to soil water content dynamics and its availability in water sources, carbon dynamics, production yields, land use, and the cultivated lands conditions. This understanding is crucial for defining strategies to mitigate the impacts of climate change [3].

Data collected through remote sensing enables crop monitoring by providing information on plant phenological changes [4]. This technology allows the spatiotemporal analysis at several spatial and spectral scales, ranging from a few centimeters to several kilometers [5]. Photosynthetic and optical properties can be studied using optical remote sensors in satellites, such as LandSat, MODIS, Spot, Sentinel-2, QuickBird, among others [6]. These parameters can be associated with both spectral signatures and vegetation indices, which are derived from operations between spectral bands [7].

Satellite imagery from the optical spectrum has facilitated the creation of crop type maps [8] and the estimation of biophysical parameters related to plant development [9]. However, the most evident drawback of these sensors is the impact of cloud cover on the collected data [10].

Using electromagnetic models, data from satellites equipped with Synthetic Aperture Radar (SAR) have enabled the study of various frequencies and incidence angles for the temporal analysis of agricultural crops [11]. SAR systems have also been used to create vegetation type maps [12]. Nevertheless, SAR data have been less frequently employed than optical data for crop studies due to the complexity of data analysis and the limited availability of such imagery in previous years [13]. This limitation was addressed in 2014 when the European Space Agency began capturing images from the Sentinel-1 satellite, offering high spatial and temporal resolution. This satellite provides multi-temporal SAR (C-band) image series with a 12-day interval, further improved with the launch of Sentinel-1B in 2016, reducing the temporal resolution to six days. Continuing with optical data acquisition systems, the European Space Agency also launched the Sentinel-2A satellite in 2015, with a temporal resolution of 10 days, enhanced to five days with the launch of Sentinel-2B [14].

Other satellites, such as MODIS and Landsat 8, have also continued their optical spectrum data collection activities [15]. The temporal data from these satellites offer an opportunity for crop monitoring, with these systems expected to remain operational until 2030. Additionally, a next generation of Sentinel satellites is planned beyond this year, ensuring the capacity to monitor and study the Earth's surface over the long term [16].

In temporal data analysis from SAR and optical systems, it is necessary to correct faulty data that inaccurately describe field variable behavior. These procedures include the use of special bands containing pixel quality information or data smoothing methods in time series [17]. This article focuses on the study of data correction methods in time series and procedures for fusing SAR and optical data to improve the periodicity of temporal data for certain crop parameters. The article is organized as follows: the next section outlines the methodology of the work conducted, followed by the implementation of algorithms, preliminary results, and conclusions.

II. Methodology

A. Study Area

The study area for this research corresponded to a citrus crops, particularly Tahiti acid lime, in a 4-hectare field located at coordinates 4°2'22.96"N, 73°15'13.10"W, in the Puerto Colombia district, along the Villavicencio - Puerto López route, Colombia (Figure 1).

B. Data Processing

Figure 2 illustrates a time series of data acquired from the Sentinel-2 satellite. In the series, one of the measured values is erroneous. Using the time series data acquired by Landsat 8, it is possible to replace the incorrect value. Figure 3 shows a real-world scenario where data from both satellites may be affected by cloud cover or other factors. In this case, the erroneous data cannot be easily replaced using the other time series.

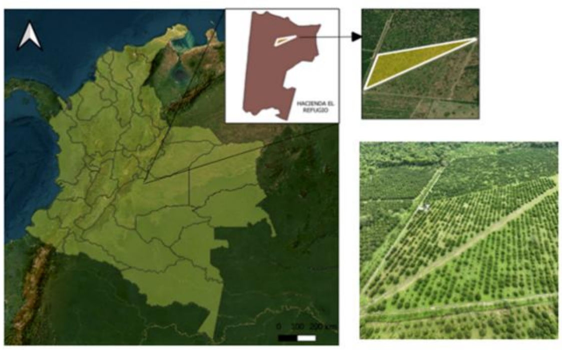

Fig. 1 Study area. Hacienda el refugio. Source: Authors.

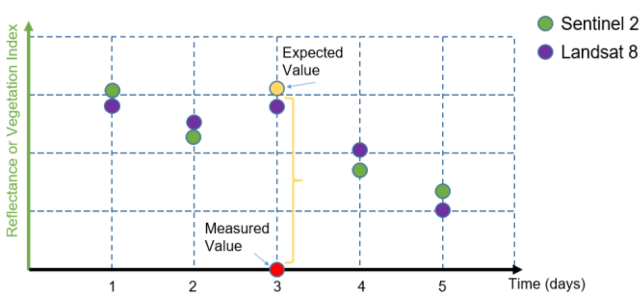

Fig. 2 Replacing missing data methodology using different optical time series. Source: Authors.

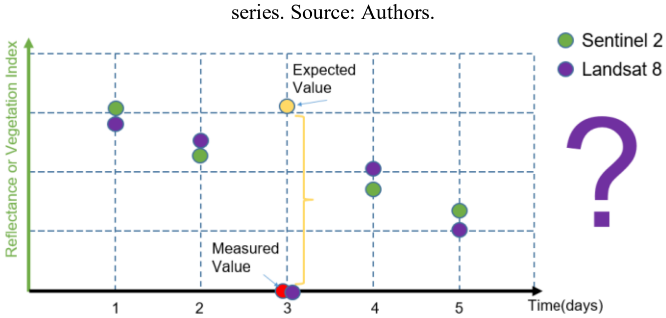

Fig. 3 Challenges in determining missing values in optical time series. Source: Authors.

This research aims to address this difficulty by replacing erroneous data in the Sentinel-2 time-series with data from the Sentinel-1 SAR satellite, which is not affected by cloud cover, as shown in Figure 4.

Fig. 4 Determining missing values in optical time series using SAR Data. Source: Authors.

Before replacing values using data from other time series, a procedure is applied to calculate the erroneous pixel value based on its nearest neighbors, as described by Equation (1) and illustrated in Figure 5.

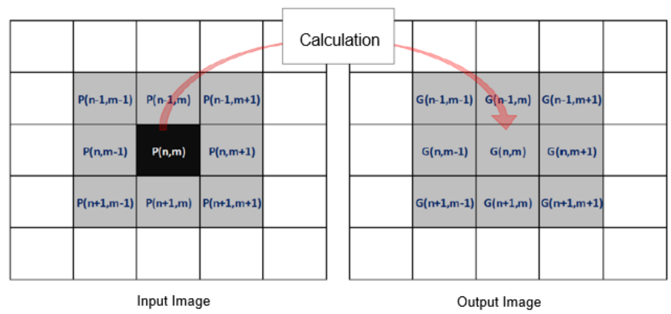

Fig. 5 Determining erroneous pixels using nearest neighbor data. Left: Input Image, Right: Output Image. Source: Authors.

$$G_{n,m} = \frac{\sum_{1}^{n} Good\ Quality\ Pixel}{Number\ of\ Good\ Quality\ Pixels} \quad (1)$$

C. Convolutional Neural Network

To predict missing time series values, the use of a LSTM (Long Short-Term Memory) neural network is proposed. This deep learning model can learn the time series behavior using previous data over long or short periods, enabling the prediction of missing values (Figure 6).

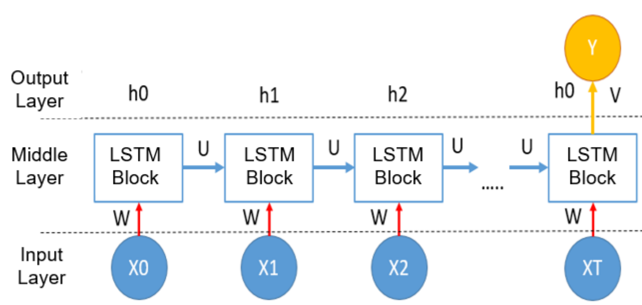

Fig. 6 Long Short-Term Memory Neural Network. Source: Authors.

Figure 7 outlines the general methodology used to train the model. Initially, optical sensor images are acquired, and the pixels corresponding to the study area are identified. The values are extracted and analyzed to determine if they are erroneous. If errors are detected, corrections are made. If no errors are found, the time series is generated. Subsequently, using the SAR data time series, the training and validation process begins, with the output being the optical spectrum time series data. This methodology aims to improve the quality of remote sensing time series data and explore the possibility of fusing optical and SAR technologies.

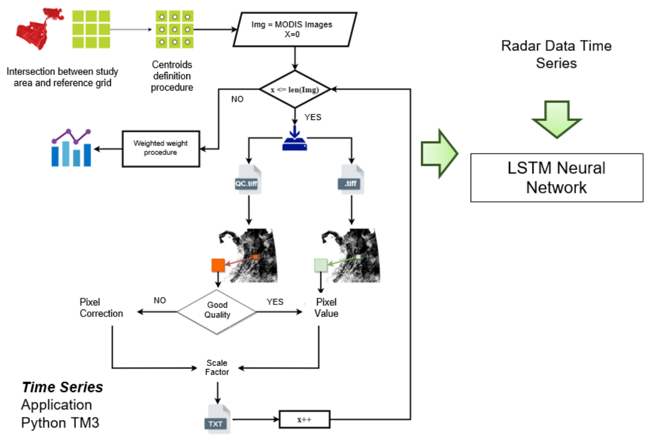

Fig. 7 Methodology for pixel data correction and LSTM model training. Source: Authors.

III. Results

D. Graphical User Interface

Figure 8 presents the graphical user interface (GUI) developed in Python and QT5 to download and process data in remote sensing time series. The interface allows the selection of one or more plots for which the time series procedure will be applied, including the erroneous values identification. This process involves two steps: first, evaluating defective pixels, and second, assigning values from different data sources.

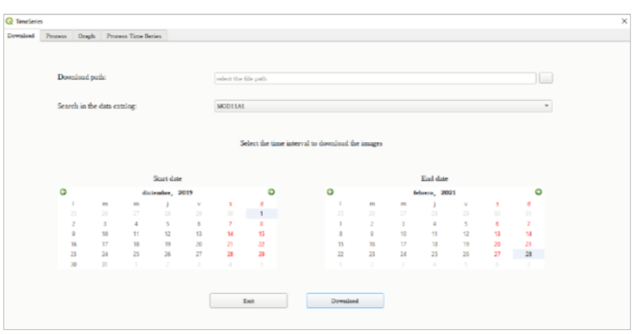
Fig. 8 Graphical User Interface. Source: Authors.

E. Pixel Value Association with Vector Polygons

Figure 9 illustrates the mechanism for associating pixel values with the vector polygons of the study plots. The left side shows the study area without the intersection procedure, while the right side demonstrates the intersection using a reference grid.


Fig. 9 Left: Study area without intersection procedure. Right: Intersection using a reference grid. Source: Authors.

F. Centroid Determination for Time Series Extraction

Figure 10 depicts the procedure for determining plots centroids. This step establishes the geographic positions from which pixel values in the time series will be extracted.

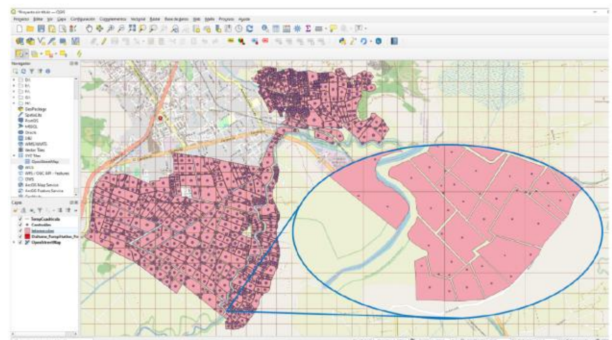
Fig. 10 Centroid determination for generalizing time series extraction. Source: Authors.

G. Time Series Extraction and Error Identification

Figure 11 shows a time series extracted from satellite images downloaded using the developed GUI. Erroneous data points, which are set to zero, are identified and must be replaced with data from another satellite.

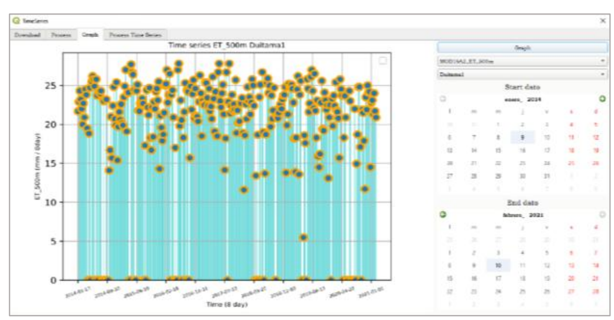
Fig. 11 Time series of optical satellite data. Source: Authors.

H. Data Imputation and Smoothing

Figure 12 displays the results of modifying the studied time series. The erroneous values were replaced using data imputation techniques, and a smoothing procedure was applied to the time series.

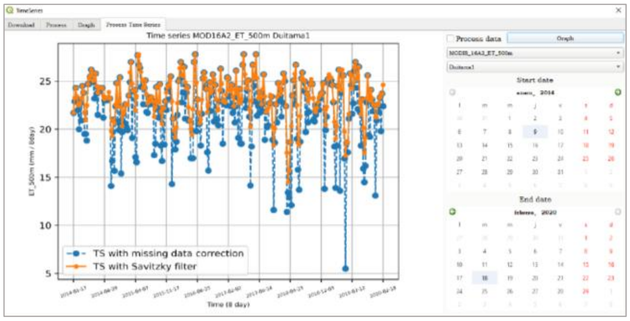

Fig. 12 Smoothing and data imputation using python algorithms. Source: Authors.

ACKNOWLEDGMENT

This research was conducted by the Macrypt, Dynamic Systems, and Precision Agriculture research groups at the Universidad de los Llanos, in collaboration with the I2E research group at the Universidad Pedagógica y Tecnológica de Colombia. The study is funded by the Universidad de los Llanos (DGI) - Colombia, under the project: Analysis of Temporal and Spatial Characteristics of Agricultural Crop Parameters Using Synthetic Aperture Radar and Optical Remote Sensing Data (C07-F02-004 2024 FCBI). A.F. Jiménez expresses his gratitude to the Department of Boyacá and MinCiencias – Colombia for their support through the scholarship program No. 733 - 2015.

IV. CONCLUSIONS

The study highlights the potential of remote sensing technologies using satellites for analyzing large-scale agricultural crops. Images from passive satellites can be combined to generate time series, enabling detailed crop development analyses. However, challenges such as cloud cover and other factors that introduce errors in the acquired images often remain uncorrected.

This research is now beginning to explore the fusion of images from passive and active satellites. This approach aims to evaluate the performance of deep learning models in determining missing data and improving the quality of time series. The integration of these technologies could significantly enhance the accuracy and reliability of crop monitoring systems.

The use of Python and QT3 plugins for QGIS applications demonstrates the benefits of automating procedures, as evidenced in this work. This automation not only increases efficiency but also enhances the versatility and capability of geospatial data analysis, paving the way for more advanced and scalable agricultural monitoring solutions.

REFERENCES

[1] C. Cruz-Cárdenas, L. Zelaya, G. Sandoval, D. Santos, E. Rojas, I. Chávez Díaz and S. Ruíz. Utilización de microorganismos para una agricultura sostenible en México: consideraciones y retos. Revista mexicana de ciencias agrícolas, 12(5), 899-913, 2021.

[2] A. Beltran. Plataformas tecnologicas en la Agricultura 4.0: Una mirada al desarrollo en Colombia. Journal of computer and electronic science, theory and applications, 3(1), 9-18, 2022.

[3] H. Saad El Imanni, A. El Harti, and J. Panimboza. Investigating Sentinel-1 and Sentinel-2 Data Efficiency in Studying the Temporal Behavior of Wheat Phenological Stages Using Google Earth Engine. Agriculture, 12(10), 1605, 2022.

[4] I. Dronova and S. Taddeo. Remote sensing of phenology: Towards the comprehensive indicators of plant community dynamics from species to regional scales. Journal of Ecology, 110(7), 1460-1484, 2022.

[5] B. Duchemin, R. Fieuzal, M.A. Rivera, J. Ezzahar, L. Jarlan, J.C. Rodriguez, ... C. Watts. Impact of sowing date on yield and water use efficiency of wheat analyzed through spatial modeling and FORMOSAT-2 images. Remote Sens. 7 (5), 5951–5979. 2015.

[6] X. Wang, Y. Zhang and K. Zhang. Automatic 10 m Forest Cover Mapping in 2020 at China's Han River Basin by Fusing ESA Sentinel-1/Sentinel-2 Land Cover and Sentinel-2 near Real-Time Forest Cover Possibility. Forests, 14(6), 1133, 2023.

[7] Y. Zeng, D. Hao, A. Huete, B. Dechant, J. Berry, J. Chen .. and M. Chen. Optical vegetation indices for monitoring terrestrial ecosystems globally. Nature Reviews Earth & Environment, 3(7), 477-493, 2022.

[8] A. Tariq, J. Yan, A. Gagnon, M. Riaz and F. Mumtaz. Mapping of cropland, cropping patterns and crop types by combining optical remote sensing images with decision tree classifier and random forest. Geo-Spatial Information Science, 26(3), 302-320, 2023.

[9] I. Guechi, H. Gherraz and D. Alkama. Correlation analysis between biophysical indices and Land Surface Temperature using remote sensing and GIS in Guelma city (Algeria). Bulletin de la Société Royale des Sciences de Liège, 2021.

[10] J. Li, Z. Wu, Z. Hu, J. Zhang, M. Li, L. Mo and M. Molinier. Thin cloud removal in optical remote sensing images based on generative adversarial networks and physical model of cloud distortion. ISPRS Journal of Photogrammetry and Remote Sensing, 166, 373-389, 2020.

[11] H. McNairn, A. Kross, D. Lapen, R. Caves, J. Shang. Early season monitoring of corn and soybeans with TerraSAR-X and RADARSAT-2. Int. J. Appl. Earth Obs. Geoinf. 28, 252–259, 2014.

[12] S. Adeli, B. Salehi, M. Mahdianpari, L. Quackenbush, B. Brisco, H. Tamiminia and S. Shaw. Wetland monitoring using SAR data: A meta-analysis and comprehensive review. Remote Sensing, 12(14), 2190, 2020.

[13] N. Bhogapurapu, D. Mandal, Y. Rao and A. Bhattacharya. Soil Moisture Estimation for Wheat Crop Using Dual-Pol L-Band SAR Data. In 2020 IEEE India Geoscience and Remote Sensing Symposium (InGARSS) (pp. 33-36). IEEE, 2020.

[14] S. Felegari, A. Sharifi, K. Moravej, M. Amin, A. Golchin, A. Muzirafuti and N. Zhao. Integration of Sentinel 1 and Sentinel 2 satellite images for crop mapping. Applied Sciences, 11(21), 10104, 2021.

[15] F. Zhou and D. Zhong. Kalman filter method for generating time-series synthetic Landsat images and their uncertainty from Landsat and MODIS observations. Remote Sensing of Environment, 239, 111628, 2020.

[16] Q. Zhao, L. Yu, Z. Du, D. Peng, P. Hao, Y. Zhang and P. Gong. An overview of the applications of earth observation satellite data: impacts and future trends. Remote Sensing, 14(8), 1863, 2022.

[17] W. Yang, S. Wang, Y. Fang, Y. Wang, and J. Liu. Band representation-based semi-supervised low-light image enhancement: Bridging the gap between signal fidelity and perceptual quality. IEEE Transactions on Image Processing, 30, 3461-3473, 2021.