

Optimization of water resource management in crops using satellite technology and artificial intelligence techniques

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ABSTRACT

This study aims to optimize water consumption in avocado crops through the application of satellite technology, machine learning algorithms, and precise climate data from the climate hazards group infrared precipitation with stations (CHIRPS) system. Crop classification in satellite images is conducted using the random forest algorithm, enabling detailed categorization of cultivated areas, urban land, soil, and vegetation, with a specific focus on avocados due to their high-water demand. Given its economic importance and status as one of the most water-intensive crops, avocado cultivation presents a critical challenge for agricultural sustainability. To validate predictive models and ensure classification accuracy, advanced evaluation methodologies such as the confusion matrix and Cohen's kappa index are utilized, quantifying the precision and reliability of the results. This estimation of water consumption under deficit and surplus conditions offers key insights for efficient water management in avocado cultivation. The results generated can enhance agricultural efficiency by aligning water use with the crop's actual requirements, thereby contributing to the reduction of its water footprint.

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1. INTRODUCTION

Agriculture plays a crucial role in the global economy and food security by providing the necessary resources to sustain a growing population [1]–[4]. However, demographic expansion and climate change pose significant challenges for managing natural resources, particularly water [5], [6]. As food demand increases, so does the pressure on water systems, which are already reaching critical limits in many regions worldwide. Agriculture is one of the most water-intensive activities, particularly for specific crops that require substantial amounts of this resource to develop [7], [8]. The current situation calls for innovative and sustainable approaches that optimize water use while maintaining agricultural productivity without compromising natural resources for future generations.

Among agricultural practices that significantly impact water consumption, avocado cultivation has become one of the most relevant cases [9]–[11]. This tropical fruit is highly valued worldwide for its nutritional benefits and has experienced a remarkable increase in demand, leading to substantial expansion in cultivation areas [12]. According to the Food and Agriculture Organization of the United Nations (FAO) in its report Major Tropical Fruits: Market Analysis, global per capita avocado consumption has increased by 39.9% over the last decade, underscoring the popularity and rapid growth of this product [13]. Mexico is the world's leading producer and exporter of avocados, accounting for 45.95% of the global supply, with most production concentrated in the state of Michoacán, followed by Jalisco and other states [14].

Michoacán, which contributes 75% of the national avocado production, faces significant environmental issues due to the expansion of this crop, including the disruption of hydrological processes caused by high water consumption. Studies indicate that each kilogram of avocado has an average global water footprint of 1,132 liters during its cultivation period, with an additional 849 liters required to dilute contaminants generated during production [15]. In four municipalities within Michoacán's avocado-growing region, the average water requirement is 1,181.6 liters per kilogram, ranging from 782.9 liters under rainfed conditions to 1,580.4 liters with irrigation [16]. This context underscores the need for monitoring and analytical tools that can support decision-making to sustainably manage avocado cultivation and minimize its environmental impact.

Avocado cultivation, particularly in regions like Michoacán, has undergone intensive expansion due to its high profitability and increasing international demand. However, this expansion has significantly increased water usage in areas with limited water resources, generating environmental and social tensions. The intensive extraction of water for irrigation, combined with the conversion of forests and natural lands into agricultural areas, has altered local hydrological processes, degraded soils, and reduced biodiversity.

Climate change exacerbates these issues by intensifying droughts and increasing precipitation variability, which reduces water availability and threatens the sustainability of crops. According to the report *Climate Change 2014: impacts, adaptation, and vulnerability* by the intergovernmental panel on climate change (IPCC), agriculture not only faces challenges such as resource scarcity and greenhouse gas emissions but must also play an active role in climate change mitigation through sustainable practices and innovative technologies.

In this context, it is essential to develop technological tools that enable efficient and sustainable monitoring of water use and land cover [17]–[19]. The use of satellite data and machine learning algorithms, such as random forest, presents a promising solution for identifying critical water consumption areas, accurately classifying agricultural land, and assessing environmental impact. These technologies facilitate informed decision-making and can guide the implementation of strategies that mitigate the negative impacts of intensive avocado production. Without a comprehensive approach that integrates technological innovation and sustainable resource management, the problems associated with intensive avocado cultivation are likely to worsen, jeopardizing both the sector's economic viability and long-term environmental conservation.

This research focuses on the geospatial classification of avocado cultivation areas through machine learning techniques and satellite image analysis [20]–[22]. The main objective is to delineate cultivated areas to enable precise monitoring of water consumption associated with this crop, facilitating the adoption of sustainable water management strategies. To achieve this, satellite and climatic data from platforms such as Google Earth Engine (GEE) [23], [24] and climate hazards group infrared precipitation with stations (CHIRPS) will be utilized, processed through a machine learning model [25], [26]. The obtained data will be used to accurately estimate water usage and evaluate the sustainability of current practices, aiming to optimize resources and reduce the environmental impact of avocado cultivation in vulnerable regions.

This article is organized into the sections: **Materials and Methods**: this section presents the flow diagram of the methodology carried out; it also briefly describes the data, tools, and procedures employed in this research. Additionally, it explains the importation of climate data from CHIRPS and moderate resolution imaging spectroradiometer (MODIS) and the calculation of water balance metrics. **Theory and Calculations**: provides the theoretical basis and formulas used in the calculation of the water balance and other metrics of interest, grounding the methods for data processing and analysis. Details on the incorporation of climate data from CHIRPS and MODIS are also included. **Results and Discussion**: this section presents the findings of the proposed model, including the accuracy in classifying avocado cultivation areas, the estimation of water consumption, and the associated environmental impact. The results are discussed in relation to previous studies, and the effectiveness of the approach in water management is analyzed. **Conclusions**: Summarizes the contribution of the study and proposes recommendations for future research and sustainable management practices in agriculture.

2. MATERIALS AND METHODS

GEE, a cloud-based platform, was used for processing and analyzing large geospatial datasets, including accessing satellite imagery and conducting large-scale analyses. Landsat 8 images (30m spatial resolution) were used for land cover analysis, capturing data in multiple spectral bands suitable for vegetation index calculations and classification. Images were obtained via GEE. Precipitation data were sourced from CHIRPS, combining satellite estimates and station data for daily precipitation records.

The implemented methodology integrates standardized approaches in remote sensing with the novel application of machine learning algorithms for water resource management in crops. The justification for these methods lies in their ability to efficiently process large volumes of geospatial and climate data, enabling

accurate land cover classification and reliable estimation of water consumption, thereby validating their suitability for study replication in other agricultural regions.

Normalized difference vegetation index (NDVI) band data from MODIS were used to estimate water consumption, providing insights into vegetation health. Sentinel-2 and Landsat images were imported into GEE, applying cloud filters and selecting optimal dates to create a mosaic image for accurate land cover classification. The study area, including urban areas, crops, and vegetation, was delineated using geometries in GEE. Bands B4 (red), B5 (near-infrared), and B3 (green) generated RGB composites to highlight landscape features. NDVI and soil adjusted vegetation index (SAVI) were calculated as inputs for the random forest model to enhance differentiation between land cover types. A supervised training dataset was created with samples of land cover classes (urban, trees, soil, avocado), identified with specific colors in GEE as shown in Figure 1.

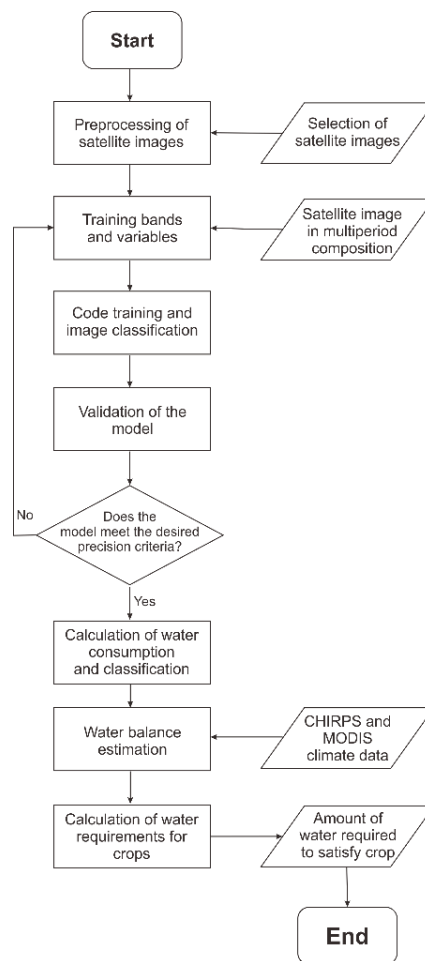


Figure 1. Methodological flow for crop classification and water balance estimation using satellite images

The random forest algorithm, known for combining multiple decision trees from random sub-samples, was used. Its ensemble architecture improves accuracy and stability, especially in noisy datasets. The technique uses Bagging and random subspace methods to avoid overfitting. The classifier was trained using the supervised data, fine-tuned with selected spectral bands and vegetation indices NDVI, and SAVI. The model used 100 trees to generate a classified image assigning a land use category to each pixel.

Evaluation metrics including the confusion matrix, kappa index, User Accuracy (UA), and Producer Accuracy (PA) were. A validation dataset was generated by sampling Landsat images to compare original and validated classifications. Validation variables were marked with specific colors: turquoise ("ValUrban"), purple ("ValTrees"), red ("ValSoil"), green ("ValAvocado"). (See Appendix C for Confusion Matrix, Appendix D for Accuracy Metrics). The area of each class was calculated in square meters based on Landsat's 30 m² per pixel resolution and converted to hectares.

To ensure replicability, the research procedure followed a detailed sequence. First, satellite images were imported into GEE, applying cloud filters and selecting optimal dates for mosaic creation.

Subsequently, NDVI and SAVI vegetation indices were calculated as inputs for the random forest model. A supervised training dataset was created from land cover class samples, identified with specific colors in GEE. The random forest classifier was trained and fine-tuned with the selected spectral bands and vegetation indices, generating a classified image. Finally, evaluation metrics such as the confusion matrix and kappa index were used to validate classification accuracy.

NDVI data (MODIS) and precipitation data (CHIRPS) were processed via GEE. Daily water consumption was calculated as the difference between daily evapotranspiration (derived from NDVI) and daily precipitation. Monthly water consumption was calculated as a sum of daily values. This monthly image, multiplied by the land cover classification, isolated consumption for the avocado area. Based on SAGARPA data (10.7 tons/ha yield), a consumption of 12,643,120 liters/ha was assumed. This was multiplied by the total avocado area to estimate total water required.

Random forest was chosen for its ability to handle large datasets and perform multiclass classifications. It creates an ensemble of decision trees, assigning pixels to categories (urban, trees, soil, avocado) via voting. It reduces variance and is robust against overfitting in satellite image classification. The confusion matrix compares model predictions with reference data. Rows represent actual classes, columns represent predicted classes. Model accuracy is evaluated using this matrix. Diagonal elements show correct classifications; off-diagonal show errors.

3. RESULTS AND DISCUSSION

The random forest classification model achieved robust performance with an overall accuracy of 85.82% and a kappa index of 0.81. This aligns with findings in [27] on the algorithm's effectiveness with multi-source or noisy satellite data. The accuracy ensures reliable identification of land use areas: avocado cultivation (5,116 hectares), urban areas (1,877 hectares), forests (4,136 hectares), and barren lands (2,590 hectares). The Kappa value of 0.81 validates the model's robustness.

The findings of this study, demonstrating high accuracy in avocado crop classification and quantification of its water demand, have significant implications for sustainable agricultural management. They highlight the insufficiency of natural precipitation to meet avocado's water needs, underscoring the reliance on external water sources and the pressure on water resources in producing regions. In the future, these results can serve as a basis for developing early warning systems and more precise planning tools that guide decisions on water resource allocation and the implementation of efficient irrigation practices.

For the avocado class, user's accuracy (UA) was 92.16% and producer's accuracy (PA) was 96.91%, highlighting model reliability for this specific, water-intensive crop. An estimated annual production of 54,739 tons of avocados provides key data for agricultural planning. The study identified an annual water demand of 64,679,992,757 liters for avocado cultivation. This contrasts with the calculated net water gain/loss from precipitation and evapotranspiration in the avocado region, which was negative (-25,260,356 liters), indicating actual water losses likely due to factors like runoff or high evapotranspiration rather than infiltration. This negative balance underscores the crop's reliance on external water sources beyond local precipitation capture within the root zone as shown in Figure 2.



Figure 2. Satellite image of the city of Uruapan

The high accuracy (85.82%) and kappa index (0.81) achieved by the random forest model demonstrate the viability of using machine learning and satellite imagery (Landsat 8, MODIS in Figure 3) for detailed land cover classification, particularly for identifying specific crop types like avocado. The high UA (92.16%) and PA (96.91%) for the avocado class further boost confidence in the results specific to this target crop. An effective discussion of the results reveals that the model's ability to accurately identify avocado

areas (UA 92.16%, PA 96.91%) is crucial for understanding the water impact of this crop. The identification of a substantial annual water demand for avocado (approximately 64.7 billion liters for 5,116 hectares) in contrast to a negative water balance (-25.3 million liters) provides a clear context about the need for supplementary irrigation and the vulnerability of water resources, Figure 4 shows the classification area. This finding contradicts the idea that precipitation alone can sustain the crop in the region, providing valuable information for water managers.



Figure 3. Satellite image of the city of Uruapan, with the area of interest delineated using multispectral composition

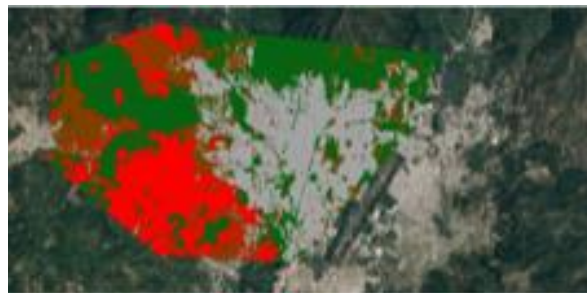


Figure 4. Satellite image of the city of Uruapan, with the area of interest delineated through the obtained classification. The class representation includes: avocado crops in red, urban area in gray, barren lands in brown, and forest area in green

The calculated annual water demand for the identified 5,116 hectares of avocado is substantial (approx. 64.7 billion liters). Critically, the water balance calculation for the avocado area showed a net loss (-25.3 million liters), indicating that natural precipitation retained within the system is insufficient to meet the crop's needs, confirming its high-water demand and reliance on irrigation, likely from external sources. This highlights the pressure on water resources, consistent with concerns raised about avocado farming in regions like Michoacán.

The findings of this research reaffirm and expand existing knowledge on water management in agriculture, particularly for high-demand crops like avocado. Previous research has highlighted that agriculture is one of the most water-intensive activities, and avocado cultivation is a relevant case due to its high water demand. This study adds a specific quantification of water consumption and an analysis of the negative water balance in the study area, which complements reports on the avocado water footprint by providing a direct assessment of the insufficiency of local precipitation to meet crop needs. This underscores the critical importance of satellite technology and machine learning for sustainably monitoring and managing the environmental impact of agricultural expansion.

The study quantifies the water footprint based on crop yield and area, providing a specific estimate for the region. However, it's noted that this estimate primarily reflects the 'blue water' (irrigation) and 'green water' (effective rainfall) components. The calculation does not explicitly incorporate the 'grey water' footprint, which represents the volume needed to dilute pollutants from agricultural inputs like fertilizers. While [15] estimated an additional 849 liters/kg for pollutant dilution, the study acknowledges the practical difficulty in verifying if water is specifically allocated for this, suggesting pollutants often accumulate in local water bodies instead. This implies the environmental impact might be underestimated if only direct consumption is considered.

The findings underscore the importance of implementing water-saving strategies like irrigation optimization, rainwater harvesting, and improving soil infiltration to mitigate the high-water demand. The methodology provides a valuable tool for monitoring land use change and water consumption, supporting informed decision-making for sustainable agricultural planning and water resource management. The approach is replicable for other regions or crops, promoting more resilient agriculture facing climate change.

4. CONCLUSION

This study successfully established an effective methodology using satellite data (Landsat 8, MODIS, CHIRPS) and machine learning (random forest) for classifying agricultural land cover, specifically avocado crops, and estimating associated water consumption. The high classification accuracy (85.82% overall, 0.81 kappa) provides reliable data for water management and agricultural planning. The results quantify the significant water demand of avocado cultivation in the study area (approx. 64.7 billion liters annually for 5,116 ha) and highlight a negative water balance within the crop zone, emphasizing reliance on external water sources. This underscores the vulnerability of water resources in regions with high-demand agriculture.

While the grey water footprint associated with pollutant dilution adds another layer to the environmental impact, its practical application in water allocation remains uncertain in the study region. Therefore, adopting sustainable practices like efficient fertilizer use, crop rotation, and improved irrigation is crucial to mitigate overall environmental effects, including water quality impacts.

The developed approach demonstrates the potential of integrating remote sensing and artificial intelligence (AI) for sustainable agriculture, providing valuable tools for monitoring environmental impacts and informing policy development for balancing agricultural production with environmental conservation. This methodology is replicable and scalable, offering a pathway toward more resilient and resource-efficient agriculture in the face of climate change.

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