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LONG-TERM SOIL MOISTURE ASSESSMENT USING THE OPTICAL TRAPEZOID MODEL FOR SUSTAINABLE AGRICULTURE AND ENVIRONMENTAL MANAGEMENT IN THE WESTERN PROVINCE OF SRI LANKA

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ABSTRACT

The assessment of soil moisture plays a crucial role in various environmental and agricultural applications. This study conducts a thorough spatial analysis of soil moisture in Sri Lanka's Western Province from 2015 to 2024 using the OPtical TRApezoid Model (OPTRAM). Based on GeoTIFF images processed through Google Earth Engine and visualized in QGIS, the analysis revealed soil moisture values ranging from 0 (completely dry) to 1 (fully saturated). Significant temporal and spatial fluctuations were identified, with high soil moisture levels in Kalutara and Galle during 2015-2016, followed by a decline due to urbanization and land use changes in the subsequent years. By 2023, areas of low soil moisture had expanded across Colombo, Gampaha, Kalutara, and Galle. These results provide critical insights for water resource management and agricultural planning, illustrating the value of remote sensing in tracking long-term soil moisture dynamics.

Keywords: OPTRAM, Soil Moisture Dynamics, GIS, Remote Sensing, Temporal Analysis

1. Introduction

Soil moisture plays a critical role in agriculture, water management, and environmental science due to its impact on groundwater recharge and rainfall patterns, which in turn influence the broader hydrological cycle (Pandey, Putrevu, & Misra, 2021). Effective irrigation practices, crucial for crop development and output, rely heavily on accurate soil moisture monitoring (Water Management, 2024). Beyond agriculture, soil moisture is integral to environmental management, affecting weather patterns and climate models, making it a vital factor in studies on climate change (Huang, Xie, & Wang, 2015). The ability to evaluate soil moisture accurately enables better decision-making in agricultural planning and water resource management, thereby enhancing the sustainability of these practices (Burdun, 2020).

The traditional methods of measuring soil moisture, such as ground sensors and manual sampling, are labor-intensive, time-consuming, and only provide coverage over small areas (Singh, Gaurav, Sonkar, & Lee, 2023). These limitations have spurred the adoption of remote sensing technologies, which offer a more efficient and extensive means of estimating soil moisture (Bekele, Gela, Mengistu, & Derseh, 2023). Using satellite and aerial imagery, remote sensing techniques such as the Normalized Difference Vegetation Index (NDVI), Synthetic Aperture Radar (SAR), and the Soil Moisture Active Passive (SMAP) mission enable comprehensive, long-term monitoring of soil moisture dynamics across wide areas, contributing significantly to our understanding and management of soil moisture (Xu, Qu, Hao, & Wu, 2020; Li, Leng, Zhou, & Chen, 2021).

Comparing the various methods, the OPtical TRApezoid Model (OPTRAM) emerges as a particularly effective remote sensing technique for estimating soil moisture content. OPTRAM uses optical satellite data to calculate a Soil Moisture Index (SMI), which ranges from 0 (dry) to 1 (fully saturated) (Sadeghi, Babaeian, Tuller, & Jones, 2017). This model, by utilizing the trapezoidal feature space of shortwave infrared (SWIR) reflectance versus NDVI, offers a detailed analysis of soil moisture levels (Sadeghi, 2023; Babaeian, Sadeghi, Franz, Jones, & Tuller, 2018). The long-term soil moisture maps generated by OPTRAM provide consistent and thorough overviews of soil moisture fluctuations, which are essential for identifying patterns, making informed decisions, and planning for water resource management and agricultural productivity (Chen,2020).

The research paper "Long-Term Soil Moisture Assessment Using the Optical Trapezoid Model for Sustainable Agriculture and Environmental Management in the Western Province of Sri Lanka" aims to comprehensively assess both spatial and temporal fluctuations in soil moisture levels from 2015 to 2024. By analyzing OPTRAM-based GeoTIFF images, this study will explore the regional distribution of soil moisture over time, assess the effects of land use changes and urbanization on soil moisture, and detect annual trends in soil moisture fluctuation. The findings are expected to provide valuable insights into enhancing water resource management and promoting sustainable agricultural practices in the region.

2. Literature Review

The gravimetric method is widely regarded for its precision in measuring soil moisture and is often considered the industry standard. This method involves drying soil samples and calculating moisture content by weight, offering highly accurate results. However, it is labor-intensive and not feasible for large-scale applications. Ground-based sensors, while useful for continuous monitoring, also have limitations in terms of geographical coverage. They typically collect data from a limited number of locations, which may not represent a larger region comprehensively (Rasheed, 2022; Susha Lakshmi, 2014).

Remote sensing techniques, particularly satellite images, offer a significant advantage in soil moisture mapping by providing extensive spatial coverage and periodic updates on soil moisture conditions. This capability is especially valuable in areas like the Western Province of Sri Lanka, where large and often inaccessible regions require consistent monitoring. Remote sensing can capture soil moisture data over vast areas, making it a critical tool for effective environmental and agricultural management in such regions (Rasheed, 2022).

Building on existing research, several studies have explored the integration of advanced technologies to improve soil moisture mapping accuracy. For example, the combination of OPTRAM (Optical Trapezoid Model) with machine learning techniques, such as random forest algorithms, has shown significant improvements in predicting soil moisture using Landsat 8 imagery (Acharya, Daigh, & Oduor, 2022). Additionally, extensive reviews of various soil moisture measurement methods have highlighted the importance of remote sensing in ecological and agricultural contexts, particularly for understanding the relationship between soil moisture and drought conditions. These studies emphasize the potential of integrating multiple measurement techniques to enhance accuracy and provide a more comprehensive understanding of soil moisture dynamics (Babaeian, Sadeghi, Tuller, & Jones, 2017)

This study seeks to address the current knowledge gap regarding the application of OPTRAM in Sri Lanka, where there has been little research on this topic. By conducting a thorough spatial analysis of soil moisture in the Western Province from 2015 to 2024 using OPTRAM, this research aims to deepen our understanding of soil moisture dynamics in the region. The insights gained from this study are expected to be instrumental in agricultural planning, environmental monitoring, and water resource management. Furthermore, the study highlights how remote sensing technology can effectively address soil moisture measurement challenges across diverse landscapes, offering valuable contributions to the field (Stańczyk, Wołowicz, Szatyłowicz, Gnatowski, & Papierowska, 2023; Sadeghi, Babaeian, Tuller, & Jones, 2017; Sadeghi, 2023).

3. Methodology

Data from the Galle, Gampaha, Kalutara, and Colombo districts will be utilized to conduct the proposed study (Figure 1). These districts were selected because of their diverse soil texture classes, which include sandy loam (SiLo), loam (Lo), sandy clay loam (SaCILo), clay loam (CILo), and sandy clay loam (SaCILo) (Figure 1). The variation in soil types across these districts ensures a comprehensive representation of soil characteristics, enabling a more robust analysis of soil properties and their impact on various environmental and agricultural factors.

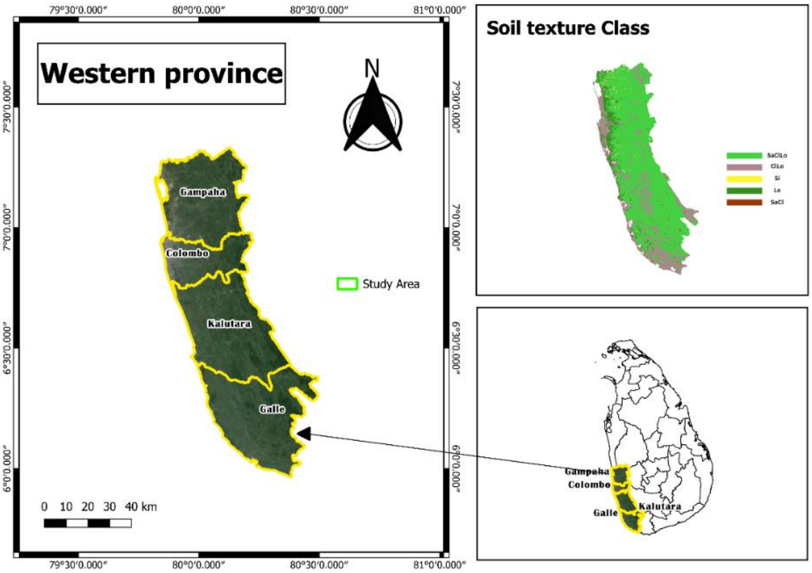

Figure 1: Study Area.

In this study, satellite imagery data were obtained from the Landsat-08 satellite, specifically from the NASA Landsat LC08 C02 T1 L2 dataset, which is accessible through the Google Earth Engine platform (LANDSAT_LC08_C02_T1_L2). This dataset provides high-resolution images that are essential for detailed analysis of soil properties and land cover changes in the selected districts.

Soil moisture was estimated using the OPtical TRApezoid Model (OPTRAM) applied to Landsat-8 imagery. To calculate soil moisture indices, the OPTRAM approach uses the normalized difference between a few bands of Landsat-8 (Sadeghi, Babaeian, Tuller, & Jones, 2017).

One of the primary aspects of the OPTRAM method is choosing the right spectral bands from the Landsat-8 dataset.

Table 1: Details of 7 Bands of Landsat 8.

Band	Description
SR_B1	Records aerosol and coastal data, which is helpful for studies on water bodies and atmospheric correction.

SR_B2	Captures blue light, which helps assess vegetation and water quality
SR_B3	Captures green light, which is crucial for classifying land cover and analyzing the health of the vegetation.
SR_B4	Captures red light, which is important for analyzing the land cover and vegetation.
SR_B5	Captures near-infrared light, which is critical for evaluating the condition of water bodies and vegetation.
SR_B6	Captures shortwave infrared light, which is beneficial for analyzing the moisture content of vegetation and soil.
SR_B7	Captures shortwave infrared light at longer wavelengths, crucial for studying soil and vegetation moisture.

Several important computations were part of the method.

The SR_B5 and SR_B4 bands were used to calculate the Normalized Difference Vegetation Index (NDVI). NDVI helps in differentiating vegetation from soil. This is essential for estimating soil moisture content precisely. The NDVI is calculated with this formula:

$$NDVI = \frac{SR_{B5} - SR_{B4}}{SR_{B5} - SR_{B4}}$$

To better understand soil properties, the Shortwave Infrared 1 (SR_B6) and Shortwave Infrared 2 (SR_B7) bands were used to calculate the Soil Tillage Ratio (STR). Utilizes shortwave infrared wavelengths to analyze the properties of soil. By comparing reflectance in several SWIR bands, STR facilitates the identification of soil parameters such as moisture content. The STR is given by

$$STR = \frac{\left(1 - \frac{SR_{B6}}{SR_{B7}}\right)^2}{2}$$

Two bands were used to determine the Soil Moisture Index (SMI). The Green (SR_B3) and Near Infrared (SR_B5). The SMI is calculated with this formula:

$$SoilMoisture_{Optram} = \left(\frac{SR_{B5} - SR_{B3}}{SR_{B5} + SR_{B3}}\right)$$

Water bodies were taken out of the study to increase the accuracy of the soil moisture estimation. This method guaranteed that water bodies wouldn't affect the soil moisture indices. The unique reflectance properties of water bodies can cause computations of soil moisture to be misinterpreted. We used a water index to mask off certain areas to prevent this. Water is generally indicated by Normalized Difference Water Index(NDWI) values greater than 0 (McFeeters & K, 2013).

OPTRAM technique efficiently estimates soil moisture while considering vegetation and soil features by combining these indices and approaches, leading to more precise and trustworthy soil moisture evaluations.

4. Results/Analysis and Discussion

The results of this study highlight the significant role of the OPtical TRApezoid Model (OPTRAM) in tracking and analyzing soil moisture dynamics over a long period, specifically from 2015 to 2024, in the Western Province of Sri Lanka. The processed soil moisture images, exported as GeoTIFF files and analyzed using QGIS, reveal a range of soil moisture values from 0 to 1, with 0 indicating completely dry soil and 1 representing fully saturated soil. These values provide a nuanced view of soil moisture distribution across the study area, allowing for the identification of spatial and temporal variations. The use of OPTRAM in this context underscores its utility in capturing detailed soil moisture fluctuations, essential for understanding environmental changes and guiding agricultural and water resource management.

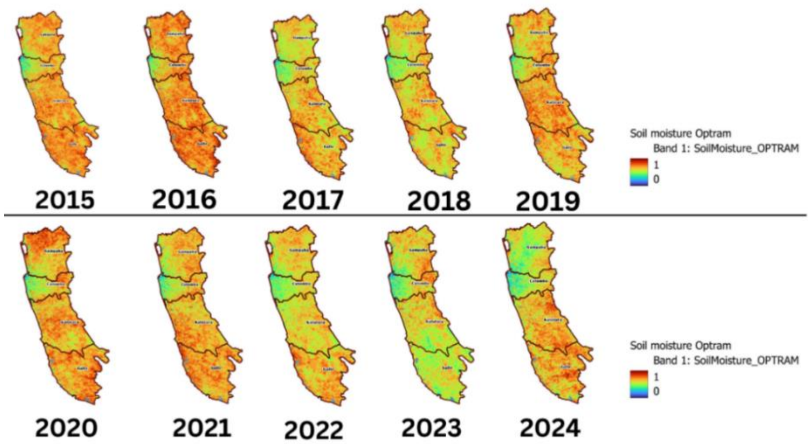

Figure 2: Yearly Changes in Soil Moisture (2015-2024).

The analysis of soil moisture trends over the study period shows significant annual fluctuations, with different regions experiencing varying levels of moisture content. The initial years (2015-2016) recorded high soil moisture levels in the Kalutara and Galle areas, marked by red and yellow shades, indicating high to medium moisture levels. In contrast, Colombo and Gampaha showed lower moisture levels, highlighted by blue spots, likely due to insufficient rainfall (Jin & Menglin , 2014). However, by 2017-2018, there was a noticeable reduction in high moisture areas, with more regions showing average moisture levels. This decline in soil moisture could be attributed to increasing urbanization and changes in land use, which disrupt natural water flow and affect soil moisture (Ratnayake & Ranaweera, 2017). These findings are critical for understanding how urban expansion and land use changes impact local hydrology and soil conditions, offering valuable insights for urban planning and environmental management.

The study also observed a partial recovery or stabilization in soil moisture levels between 2019 and 2020, with blue spots in Colombo and Gampaha slightly decreasing. This improvement could be linked to seasonal variations, enhanced water management practices, or land use changes that mitigated earlier declines in moisture levels (Eriyagama, Smakhtin, Chandrapala, & Fernando, 2010; Ying Yao, 2023). However, by 2021-2022, there was a noticeable decline in high soil moisture areas, indicating a progressive decrease in moisture levels leading up to 2023. The expansion of low soil moisture areas beyond Colombo and Gampaha, including Kalutara and Galle, by 2023 suggests a broader geographic impact of these changes. The observed decline may result from a combination of factors, including seasonal variations, altered rainfall patterns, land use changes, and potentially inefficient water management practices during this period (Qin, 2023). These findings are vital for developing adaptive strategies to mitigate the adverse effects of declining soil moisture on agriculture and urban environments.

The results of this study, while illuminating, also highlight several limitations and challenges. One of the primary challenges is the reliance on remote sensing data, which, despite offering extensive spatial coverage, may not always capture the fine-scale variations in soil moisture. Additionally, the accuracy of OPTRAM could be influenced by the quality of input data, such as satellite imagery, and the model's ability to integrate ground-based observations effectively. Furthermore, the study acknowledges the potential impacts of urbanization and land use changes on soil moisture, but further research is needed to quantify these effects more precisely. Despite these challenges, the study provides valuable insights into the dynamics of soil moisture in the Western Province, offering a foundation for future research and the development of more effective water management strategies. These insights are crucial for optimizing agricultural practices, improving urban planning, and mitigating the impacts of climate change on soil moisture levels.

5. Conclusion

This research has successfully assessed the long-term fluctuations of soil moisture in the Western Province of Sri Lanka from 2015 to 2024 using the Optical Trapezoid Model (OPTRAM). The data shows large differences in soil moisture levels, strongly related to the region's urbanization and land use changes. Notably, the study discovered a significant drop in soil moisture during increasing urbanization, emphasizing the critical necessity for good water resource management measures.

The use of OPTRAM alongside Landsat 8 satellite data has proven to be an efficient way of recording soil optical properties and giving accurate moisture content estimates across a wide range of soil types. This strategy not only improves our understanding of soil moisture dynamics but also provides a practical alternative to existing measuring techniques, which are sometimes labor-intensive and have limited spatial coverage. This study's findings have important implications for agricultural planning and environmental management. The study provides insights into the relationship between soil moisture and land use, enabling policymakers, farmers, and environmental managers to develop sustainable practices that can reduce the negative effects of urbanization on soil health.

Furthermore, the findings emphasize the need to incorporate remote sensing technology into soil moisture assessments, which can help make timely and educated decisions in response to changing climatic circumstances. Future research should investigate the long-term effects of urbanization on soil moisture retention, as well as the efficacy of various agricultural strategies in increasing soil moisture levels.

In summary, this study contributes valuable knowledge to the field of soil moisture assessment, emphasizing the critical role of sustainable management practices in ensuring the resilience of agricultural systems and the health of the environment in Sri Lanka.

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