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Estimating Soil Moisture Content in Nnewi North Local Government Area in Anambra State, Nigeria Using Remote Sensing

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Abstract: The flooding experienced in Nnewi, Anambra State, is significant, leading to the expectation of high soil moisture content in the area. This study focuses on using remotely sensed multispectral electromagnetic data to characterize the soil moisture content of the Nnewi Local Government Area, Anambra State, Nigeria. Landsat-8 Operational Land Imager (OLI) thermal infrared satellite data were used to estimate the soil moisture index (SMI) of the Nnewi Local Government Area for the period from 2016 to 2023. Images were downloaded from the USGS Earth Explorer web application for specific days in the years 2016, 2017, 2019, 2020, 2021, 2022, and 2023, as well as for the wet seasons of 2016, 2022, and 2023. Image processing and SMI estimation were conducted using ArcGIS 10.7.1 software. The results of the study, based on dry season data, revealed that the soil moisture index has been increasing at an approximate annual rate of 7.2% since 2016, rising from a mean value of 0.22 in 2016 to 0.35 in 2023. Similarly, soil moisture content during the rainy season has also increased. The SMI for 2016 was 0.10, while the SMIs for 2022 and 2023 were 0.39 and 0.34, respectively.

Keywords: Operational Land Imager, Soil Moisture Index, Image Processing, Landsat-8, Remote Sensing.

Nomenclature

Abbreviations	Expansion
SMC	Soil Moisture Content
NDVI	Normalized Difference Vegetation Index
LST	Land Surface Temperature
USGS	United State Geological Survey
SMI	Soil Moisture Index
TOA	Top Of Atmospheric
DN	Digital Numbers
ESMP	Environmental and Social Management Plan

1. Introduction

An important application of Remote Sensing is in the determination of SMC. Surface SMC can be estimated based on NDVI and LST. LST/NDVI relationship as a linear relationship with the SMC [1]. The method to retrieve SMC based on the integration of LST and NDVI is called the Triangle method [2]. LST is determined from thermal emission, and NDVI is estimated based on the surface reflectance of red and the near-infrared portions of the electromagnetic spectrum, so these methods sometimes are termed optical, thermal infrared remote sensing [3] [4] [5]. The geology of the study area falls within the Anambra Basin in southeastern Nigeria. Nnewi metropolis lies beneath the Nanka Formation, which is Eocene in age. Generally, the lithology of the area is composed of sandy clays, sandstones, and loose sands. On the other hand, sandstones are porous because of their high permeability potentials, which makes it difficult to obstruct the infiltration of leachates into the aquifer.

Nnewi North lies along the Mamu River basin with an altitude of 105 m to 300 m above sea level. Nnewi metropolis is underlain by unconfined aquifers with an average depth to the water table of approximately 110 m and an average static water level of 120m [16]. The settlements in Nnewi are: Otolo, Uruagu, Umudim, Nnewi-ichi. Nnewi North Local Government Area is situated in Bayelsa state, whose location is within the latitude 4Â°15´ North and latitude 5Â°23´ South. It is also within longitudes 5Â°22´

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West and 6Â°45´ East. The state is bounded by Delta State on the north Rivers Stateon the East and Atlantic Ocean on the western and southern parts [6]. This study aims to characterize SMC using remotely sensed electromagnetic radiation in Nnewi North, Anambra state, Nigeria. SMC is one of the most important factors to consider in agriculture because it affects crop yield and quality and helps farmers manage water resources. High or low SMC can reduce crop yield; thus, a study was done on the Nnewi local government area in Anambra state, Nigeria, to ascertain the reason for the low crop yield in that area [6]. The objectives of this study are to acquire remote sensing data from USGS Landsat-8, process the acquired data (multispectral images) using the ArcGIS 10.7.1 to generate the SMI map, monitor if there is an increase in the SMC of Nnewi North LGA.

The SMC was analyzed using remotely sensed electromagnetic data from the USGS, which was processed in the ArcGIS software using the local government shapefile to clip out the study area. The results show that Nnewi local government area has an increasing SMC both in the wet and dry seasons. Therefore, the reason for the high SMC may have resulted from flooding or poor drainage patterns, but further research to concretize that assertion may be carried out.

2. Literature Review

Estimating Soil Moisture Content (SMC) using remote sensing techniques has been a focal area of research, with various methodologies developed to assess soil moisture across diverse regions. Although specific studies targeting Nnewi North Local Government Area in Anambra State, Nigeria, are sparse, existing literature provides valuable insights into methodologies and findings relevant to soil moisture estimation in similar contexts.

2.1 Remote Sensing for Crop Monitoring and Soil Moisture Estimation

In 2017, Ejikeme [7] utilized Landsat imagery to generate the Normalized Difference Vegetation Index (NDVI) for monitoring crop production in Anambra State. The study demonstrated the efficacy of NDVI, alongside soil moisture, surface temperature, and rainfall estimates, in predicting crop yield and determining cultivated land extent. This underscores the potential of NDVI as a proxy for assessing vegetation health and indirectly inferring soil moisture availability.

Similarly, Aderogbin et al., 2023 explored the integration of remote sensing and Geographic Information System (GIS) techniques for crop production monitoring and yield prediction in Anambra State. The research highlighted the critical role of NDVI in assessing vegetation health, thereby emphasizing its relevance to soil moisture studies. The findings suggest that NDVI-based methodologies can be effectively adapted for soil moisture estimation in agricultural contexts [8].

2.2 Soil Loss and Erosion Studies Using Remote Sensing

While not directly focused on soil moisture, studies such as [9] and [10] provide methodological insights relevant to SMC estimation. Nze et al. estimated soil loss in a regional tropical humid catchment area, including Nnewi North, using remote sensing data. Although primarily addressing soil erosion, the data acquisition and analysis techniques employed in this research could inform soil moisture estimation methodologies. Similarly, [10] applied the Revised Universal Soil Loss Equation (RUSLE) integrated with GIS and remote sensing to detect soil erosion. The approach underscores the utility of remote sensing in assessing soil-related parameters pertinent to soil moisture studies.

2.3 Soil Properties and Spatial Distribution Studies

Nzereogu et al. in 2023 examined soil erodibility factors in Nnewi and Nnobi, Southeastern Nigeria. The research provided insights into the spatial distribution of soil properties, which are crucial for accurate soil moisture estimation. Understanding these factors can aid in refining remote sensing methodologies tailored to the unique soil and climatic conditions of the region [11].

2.4 Implications for Localized Studies in Nnewi North

The reviewed studies collectively underscore the effectiveness of remote sensing and GIS techniques in assessing soil moisture and related parameters. Leveraging satellite imagery and indices such as NDVI enables researchers to monitor vegetation health and infer SMC, thereby contributing to improved agricultural planning and resource management. However, for a comprehensive understanding of soil moisture dynamics in Nnewi North, localized studies are imperative. These studies should account for the specific climatic, soil, and vegetation characteristics of the area, building upon the methodologies outlined in the reviewed literature. Such tailored approaches can enhance the accuracy and applicability of soil moisture assessments in this region.

3. Methodology

In this work, the method used is similar to that employed by [12] and [13] and to estimate the LST, the SMI was then calculated from the LST.

3.1 Data Collection

Necessary bands (bands 4, 5, and 10) of Landsat-8 satellite imagery of Nnewi North were downloaded from the USGS for LST analysis, from which the SMI was calculated. The cloud cover used was 30% for both dry and rainy seasons. The dry season is between November to March while the rainy season is from April to September. Fig 1 shows an example of the Landsat imagery of the study area.

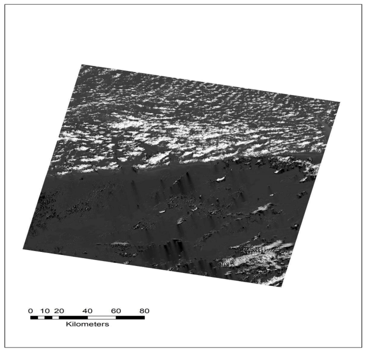

Fig. 1. *Landsat Imagery of the study area*

3.2 Image Processing

For image processing to be done, two tasks needed to be carried out and they are image pre-processing and image analysis.

3.3 Image Pre-Processing

Before image processing, images were loaded into the ArcGIS 10.2.2 software for additional processing. Image pre-processing involves both visual and digital image processing. Bands 4, 5, and 10 of the red, near-infrared, and thermal infrared spectra respectively were chosen for further examination. To subset the area of interest, the Nnewi shapefile was extracted from the entire scene.

Table 1. *Metadata of Landsat images used in the SMI estimation*

Reference year	Sensor_ID	Resolution	WRS: P/R	Date of Acquisition	Season
2016	OLI/TIRS	30m	189/56	2016-03-15	Dry
2016	OLI/TIRS	30m	189/56	2016-08-22	Rainy
2017	OLI/TIRS	30m	189/56	2018-02-01	Dry
2019	OLI/TIRS	30m	189/56	2019-02-04	Dry
2020	OLI/TIRS	30m	189/56	2020-01-06	Dry
2021	OLI/TIRS	30m	189/56	2021-12-10	Dry
2022	OLI/TIRS	30m	189/56	2022-01-03	Dry
2022	OLI/TIRS	30m	189/56	2022-05-03	Rainy
2023	OLI/TIRS	30m	188/56	2023-03-20	Dry
2023	OLI/TIRS	30m	189/56	2023-06-23	Rainy

3.4 Image Analysis

In this study, Bands 4 and 5 of the infrared spectrum were utilized to calculate the NDVI, whereas bands 10 were used to estimate brightness temperature.

The USGS website for extracting TOA spectral radiation was used as the source for the LST retrieval formulas. Following the procedures in Fig. 2. the LST was retrieved.

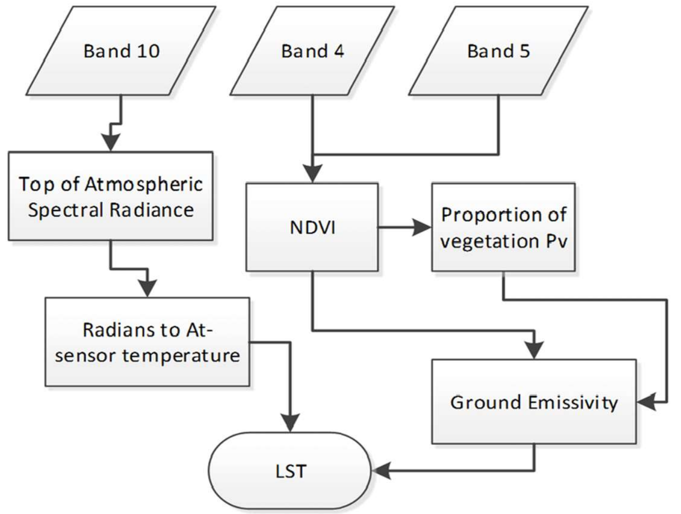

Fig. 2. *Flowchart for LST calculation (Kaplan and Gordana, 2018)*

Using the raster calculator tool of ArcGIS 10.2.2, the following calculations were made in the estimation is SMI.

Conversion of DN to TOA Spectral Radiance: DN, the thermal band data was converted to TOA spectral radiance using the rescaling radiance factors from the metadata file of the satellite image [22]

$$L_\lambda = M_L Q_{cal} + A_L \quad (1)$$

Where

L_λ= TOA spectral radiance (Watt/(m^2*srad*µm))

M_L = Band-specific multiplicative rescaling factor from the metadata

Q_{cal} = Standard product pixel values

A_L=Band-specific additive rescaling factor

Conversion of TOA to Atmospheric Satellite Brightness Temperature: Utilizing the thermal constants in the MTL file, thermal band data can be converted from spectral radiance to TOA brightness temperature [12].

$$BT = \frac{K_2}{In\left(\frac{K_1}{L_\lambda}+1\right)} - 273.15 \quad (2)$$

Where,

BT = Top of atmosphere brightness temperature K

L_λ= TOA spectral radiance (*Watt*/(m^2**srad***µm*)) K_1= Specific band conversion constants from metadata

K_2 = Specific band conversion constants from metadata

Calculating NDVI: The NDVI, is associated with drought conditions. Bands 4 and 5 respectively were used to calculate the NDVI. Since the amount of vegetation present is a crucial element and the NDVI can be used to estimate general vegetation status, calculating the NDVI is crucial [12].

$$NDVI = \frac{NIR(band5) - R(band4)}{NIR(band5) + R(band4)} \quad (3)$$

Where,

NIR (Near Infrared) = Band 5 R (Red) = Band 4

Calculating the Proportion of Vegetation: The percentage of ground covered by vegetation in a vertical projection is referred to as the vegetation fraction (proportion of vegetation) [3] [12]. The NDVI values for vegetation and soil are strongly connected to the percentage of vegetation (Pv).

P_v was calculated in this study using the conventional NDVI approach [12].

$$P_V = \left[\frac{NDVI - NDVI_{\min}}{NDVI_{\max} - NDVI_{\min}}\right]^2 \quad (4)$$

Where

$NDVI_{min}$ is the minimum NDVI.
$NDVI_{max}$ is the maximum NDVI,

Calculating Land Surface Emissivity: The Land Surface Emissivity can be calculated from the Proportion of Vegetation [13] thus:

$$\varepsilon = 0.004P_V + 0.0986 \tag{5}$$

Calculating LST can be computed thus;

$$LST = \frac{BT}{1+\left(\frac{\lambda BT}{\rho}\right)ln(\varepsilon)} \tag{6}$$

Where

BT represents TOA Brightness temperature
λ represents the wavelength of emitted radiance
$\mathscr{E}$ is the emissivity
ρ=hc // σ = 1.438 x 10^{-2} m. K
Where σ is the Boltzmann constant (1.38×10^{-23} J/K), *h* is Planck's constant (6.626×10^{-34} J s), and *c* is the velocity of light (2.998×10^{8} m/s) [12].

Calculating SMI: The Soil Moisture can be calculated from the LST using the formula:

$$SMI = \frac{LST_{max} - LST}{LST_{max} - LST_{\min}} \tag{7}$$

3.5 Clipping of Study Area

After processing the image, it is necessary to clip our area of interest which is Nnewi North in this case. Following the steps below, we can clip the study area;

1. Go to Arc Toolbox and click on Data Management Tools, select Raster, click on Raster Processing, then Clip.
2. Select a grid as the Input Raster in the Clip dialog box.
3. Select the polygon feature class containing the polygons to clip the grid as the output extent.
4. Check the Use input feature for Clipping Geometric option which enables clipping a grid using the polygons in the selected feature class as the clipping extent.
5. Name and location should be specified for the output Raster Dataset.
6. Click Ok so that the clipped grid is added to the map as a new layer.

3.6 Preparation of Smi Map

SMI map was prepared by first changing the layout of the page from data view to layout view. Go to view, then layout view and change the layout page. Go to insert to add a legend, scale bar, and north arrow. To add a grid to the map, click on View > Data Frame Properties > Add new grid. Click on properties > Label to label longitude and latitude.
The map produced can be exported from ArcGIS as a .jpeg image by clicking on File > Export map. Rename the file, choose file format, choose location, and then save.

4. Results and Discussion

The SMI maps show the soil moisture distribution of Nnewi North for the 2016 rainy season, 2022 rainy season, 2023 rainy season and 2016 dry season, 2018 dry season, 2019 dry season, 2020 dry season, 2021 dry season, 2022 dry season, 2023 dry season are given in fig. 3,4,5,6,7,8,9,10,11, and 12 respectively.

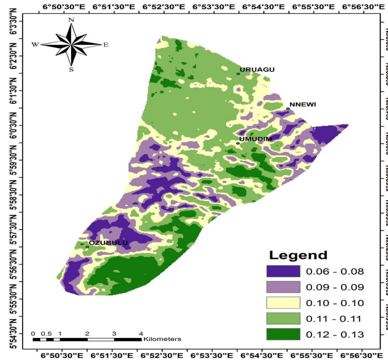

Fig. 3. *SMI map for 2016 rainy season*

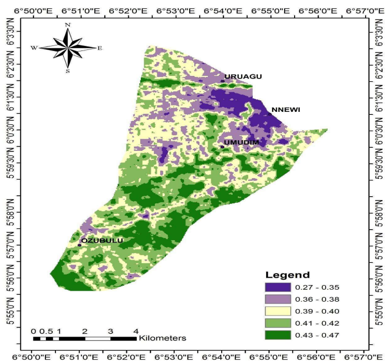

Fig. 4. *SMI map for the 2022 rainy season.*

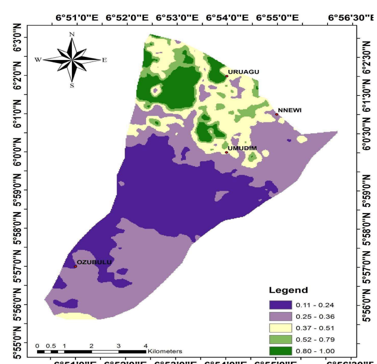

Fig. 5. *SMI map for the 2023 rainy season.*

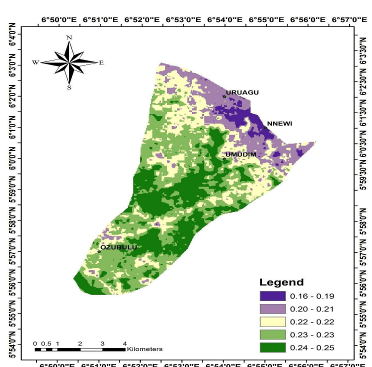

Fig 6. *SMI map for the 2016 dry season.*

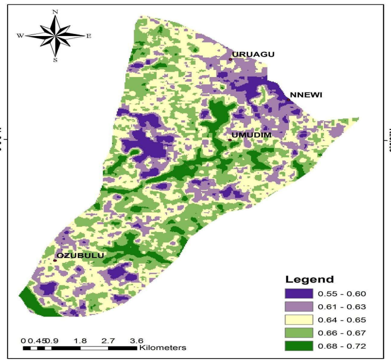

Fig. 7. *SMI map for the 2017 dry season.*

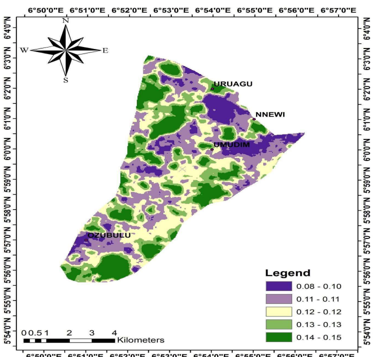

Fig 8. *SMI map for the 2019 dry season.*

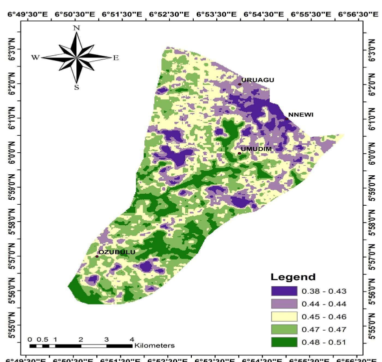

Fig. 9. *SMI map for the 2020 dry season.*

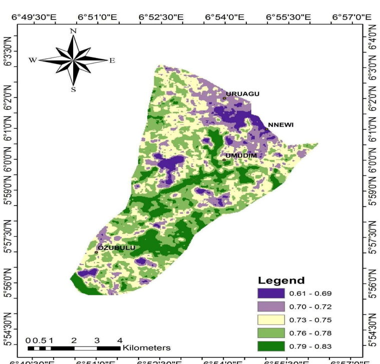

Fig. 10. *SMI map for 2021 dry season.*

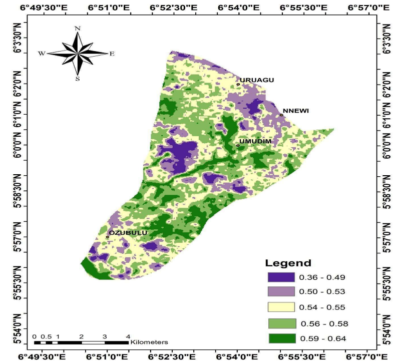

Fig. 11. *SMI map for the 2022 dry season.*

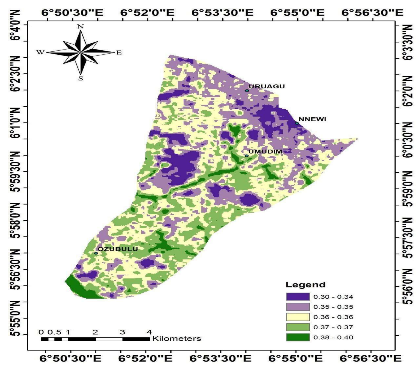

Fig. 12. *SMI map for 2023 dry season*

5. Discussion of Results

The analysis of Soil Moisture Index (SMI) values across Nnewi North Local Government Area from 2016 to 2023 reveals critical trends and insights into soil moisture dynamics and their implications for water management and flood control.

5.1 Temporal Trends in SMI

In 2016, the SMI values exhibited notable spatial variability, with Nnewichi recording the lowest rainy season SMI of 0.09, while other areas peaked at a maximum of 0.11. Umudim displayed an average SMI value of 0.10 during the rainy season. During the dry season, the SMI ranged from a minimum of 0.20 to a maximum of 0.23, with a mean value of 0.22. These values highlight a baseline of relatively low soil moisture levels in 2016.

Over subsequent years, SMI values demonstrated fluctuations across seasons and locations, reflecting both natural variability and anthropogenic impacts. For instance, in 2017, Nnewichi experienced a very low SMI value of 0.55 during the dry season, while Ozubulu and Umudim recorded higher SMI values of 0.64 and 0.66, respectively. These differences underline localized factors such as drainage infrastructure and land use practices influencing soil moisture retention.

By 2019, contrasting patterns emerged, with Uruagu, Nnewichi, and Ozubulu showing high, average, and very low dry season SMI values of 0.14, 0.12, and 0.08, respectively. This variation suggests ongoing challenges in managing soil moisture effectively across the area. Similarly, in 2020, while Nnewichi and Uruagu recorded very low and low SMI values of 0.38, Umudim and Ozubulu experienced higher values of 0.47, indicating uneven impacts of local drainage conditions.

The upward trend in SMI was more pronounced by 2021 and 2022, with dry season values showing incremental increases. For instance, Nnewichi recorded an SMI of 0.61 in 2021, a slight improvement from 2020. In 2023, Umudim recorded average SMI values of 0.36 and 0.37 during the dry and rainy seasons, respectively, illustrating a stabilization in soil moisture levels.

5.2 Long-term Changes in Mean SMI

The broader trend in mean SMI values highlights significant increases over the years. Rainy season SMI values rose from 0.10 in 2016 to 0.39 in 2022 before slightly declining to 0.34 in 2023. Similarly, dry season SMI values showed a consistent increase, rising from 0.22 in 2016 to 0.35 in 2023. These trends indicate a general rise in soil moisture levels over time, likely exacerbated by persistent flooding and inadequate drainage infrastructure.

5.3 Flooding and Water Management in Nnewi: Findings and Implications

Plate1: Flood in Nnewi North (Ikenna Obianeri. Punch News online, 20th July 2024)

The mean Soil Moisture Content (SMC) during the dry season of 2016 was 0.22, while in the dry season of 2023, it increased to 0.35. This rise in SMC within the observed period may be attributed to inadequate drainage systems and the increasing frequency of flooding in the area. These findings correlate strongly with documented issues of flooding and poor drainage in the study area. According to the Environmental and Social Management Plan (Abiodun, 2017), the Nnewi erosion site has been significantly impacted by improperly connected culvert outlets, inadequately constructed drainage trunks, and terminated drainage systems in surrounding areas. These structural deficiencies have likely contributed to the observed increases in soil moisture levels, particularly during the dry season, when natural drainage and evaporation are expected to lower SMI values.

Despite the significance of these findings, drawing meaningful inferences from rainy season data was challenging due to cloud cover interference. However, based on the values obtained from the Soil Moisture Index (SMI) maps, it can be concluded that Nnewi North exhibits high SMC levels. The persistent increase in SMC across the area over the years suggests that no significant remedial measures have been implemented to mitigate flooding. This lack of impactful intervention has likely amplified soil moisture retention, leading to further environmental degradation and adverse impacts on agriculture.

5.4 Role of Remote Sensing in SMI Monitoring

The use of remote sensing techniques in this study has proven invaluable for tracking soil moisture dynamics over time and across different spatial locations. The ability to visualize and quantify SMI variations through temporal mapping provides critical insights into how soil moisture responds to climatic and anthropogenic factors. Despite its efficacy, the methodology is limited by cloud cover during the rainy season, which can obscure accurate SMI readings. Future studies should address this limitation by integrating additional satellite datasets and ground-based measurements to enhance data accuracy.

5.5 Recommendations

Given the observed trends, it is imperative to adopt comprehensive water management strategies to address the underlying causes of increased soil moisture levels. These strategies should include:

1. **Improving Drainage Infrastructure**: Upgrading and properly connecting culvert outlets and drainage trunks to prevent water stagnation and soil saturation [14].
2. **Flood Mitigation Measures**: Implementing flood control systems, such as retention basins and reinforced drainage channels, to manage excess water [15][16].
3. **Sustainable Land Use Practices**: Promoting practices that enhance soil permeability and reduce waterlogging, such as reforestation and controlled urban expansion[17].
4. **Enhanced Monitoring Systems**: Utilizing advanced remote sensing technologies and integrating them with ground-truth data to improve the accuracy and reliability of SMI assessments [18, 19].

6. Conclusion

This study effectively characterized the Soil Moisture Content (SMC) of Nnewi North Local Government Area, Anambra State, Nigeria, using remote sensing techniques. The findings demonstrated a consistent rise in soil moisture levels during both dry and wet seasons over the observed years, correlating with the area's prevalent flooding challenges and inadequate drainage systems. This trend underscores the urgent need for enhanced water management strategies to minimize potential agricultural losses and mitigate environmental degradation.

The results validate the utility of remote sensing as a reliable tool for SMC monitoring and emphasize its value in supporting localized decision-making for flood management and agricultural planning. To further enhance soil moisture assessments, future research should consider integrating additional satellite datasets and ground-based measurements, addressing limitations such as cloud interference during the rainy season.

Compliance with Ethical Standards

Conflicts of Interest: Authors declared that they have no conflict of interest.

Human Participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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