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Estimation of Soil Moisture Content in Oredo Local Government Area of Edo-State using Remote Sensing Technique: 2018 Study

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Abstract

Accurate estimation of soil moisture is crucial for effective water and soil resource management. Surface soil moisture, a key variable in the natural water cycle, significantly influences hydrological, ecological, and meteorological processes, thereby impacting global water and energy equilibrium. Understanding the spatiotemporal variability of soil moisture is essential due to its direct influence on vegetation distribution. Insufficient moisture leads to yield loss and plant mortality, while excessive moisture can cause root diseases and water wastage. Soil moisture measurements can be conducted through in situ methods or indirectly through transfer functions or remote sensing. However, in situ measurements are often too expensive and time-consuming for large areas, making remote sensing an attractive alternative for soil moisture estimation on larger scales. This study aims to estimate soil moisture using land surface temperature as a proxy. To achieve this, ground temperature was derived from Landsat-8 thermal infrared band for the Oredo Local Government Area. ArcGIS (ArcMap 10.2.2) was employed to estimate soil moisture based on the calculated ground temperature. The study identified areas with low, moderate, and high moisture contents, with the moderate moisture index being predominant during both seasons. These findings establish a valuable database that can support farmers in implementing precision farming practices within the investigated local government area.

1.0. Introduction

Soil moisture plays a crucial role in the hydrological cycles and biophysical processes influenced by global climate changes. It represents the water content in the upper 10cm of soil, residing in soil pores and excluding water bodies and groundwater. Soil moisture levels are influenced by various factors, including weather conditions, soil type, and vegetation cover. To assess soil moisture, airborne microwave radiometers have commonly been used to measure water retention between soil particles. This assessment is vital due to its impact on microorganism activity, soil temperature regulation, nutrient transport, and other important functions. In cold desert soils, soil moisture manifests as small ice crystals, vapor, or minute liquid water particles.

Soil moisture is a very important component in hydrology, climate and soil vegetation interaction. Hence, soil moisture estimation helps in many natural resource applications such as hydrological modeling, stream flow and flood and drought mapping and monitoring. Drought mapping was done by [1]. The moisture content in the surface layers of the soil is an important parameter for many applications in agriculture and meteorology. Soil moisture is one of the few directly observable hydrological variables that play an important role in the water and energy budgets necessary for climate studies. In agriculture point of view, soil moisture information is essential for many applications like irrigation scheduling, plant stress and improving crop yield, weather, climate and crop yield forecasts, water resource management, drought forecasts, and ecosystem mapping to the ecosystem health [2].

Precise soil moisture is very vital in these studies. Remote sensing techniques for soil moisture estimation include the use of visible, thermal infrared and active/passive microwave data. However, optical remote sensing is an effective technique for estimating soil moisture. This method requires the estimation of land surface temperature and vegetation index for soil moisture calculation.

[3] carried out a research titled “Evaluation of the extent of land-use cover changes in Benin-City using Landsat8 satellite data and ENVI 5.2 software and ArcGIS. The result showed that 284.56 km2 of forest lands were lost over 32 years and built-up areas increased by 153.96 km3 over the same period. The present study aimed to provide soil moisture estimation model using NDVI and LST indices for Oredo Local Government Area, Edo-State.

2. Methodology

2.1. Study Area

The study was carried out in the Oredo local government area of Edo-state of Nigeria.

Oredo has an area of 237.4 square km, which lies between longitude 5°2'00" E and 5°18'30" E and latitude 6°18'30" N and 6°31'00" N. Oredo is bounded in the north by Egor LGA; west by Ovia North-East LGA; south and east by Ikpob -Okha LGA.

The Oredo area has a tropical savanna climate and has a population of over 1,125,058 people.

Figure 1. Map of Edo State with Oredo Local Government Area indicated in red rectangle. [4].

2.2. Data Collection

The work on Oredo Local Government Area was carried out using Landsat-8 satellite data from the United States Geological Survey (USGS) and downloaded using the google earth engine and analyzed using ArcGIS software 10.2.2. The LST of the study area for all the seasons was gotten using a java-script within the google earth engine from which the SMI was calculated.

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 top of atmospheric (TOA) spectral radiation was used as the source for the LST retrieval formulas. Following the procedures in Figure 2, the LST was retrieved.

Figure 2 presents the flowchart of this research. It illustrates different processing steps to achieve the soil moisture map.

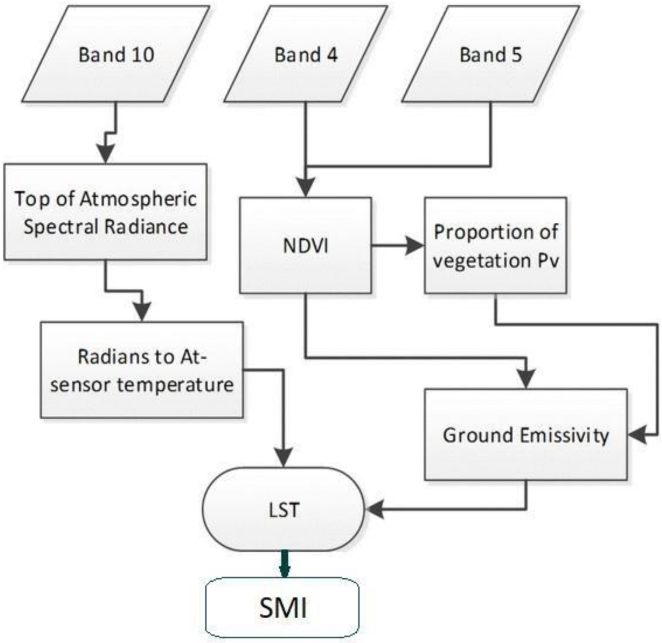

Fig. 2. Flowchart for SMI calculation (modified after Kaplan and Gordana, 2018)

2.3. Conversion of Digital Numbers (DN) to Top of Atmospheric 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. [5]

$L_\lambda = M_L Q_{cal} + A_L$ 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

2.4. 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 top of atmospheric brightness temperature. [5]

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

Where;

BT = Top of atmosphere brightness temperature K

L_λ= TOA spectral radiance ($Watt/(m^2 * srad * \mu m)$)

K_1 = Specific band conversion constants from metadata

K_2 = Specific band conversion constants from metadata

2.5. Calculating NDVI: The Normalized Difference Vegetation Index (NDVI), 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. [6]

$$\mathrm{NDVI} = \frac{\mathrm{NIR(band\ 5)} - \mathrm{R(band\ 4)}}{\mathrm{NIR(band\ 5)} + \mathrm{R(band\ 4)}} \qquad 3$$

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

2.6. 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). The NDVI values for vegetation and soil are strongly connected to the percentage of vegetation (P_v). P_v was calculated in this study using the conventional NDVI approach. [6]

$$P_v = \left[\frac{\mathrm{NDVI} - \mathrm{NDVI}_{min}}{\mathrm{NDVI}_{max} - \mathrm{NDVI}_{min}}\right]^2 \qquad 4$$

Where, NDVI_{min} is the minimum
NDVI_{max} is the maximum

2.7. Calculating Land Surface Emissivity: The Land Surface Emissivity can be calculated from the Proportion of Vegetation thus. [7]

$$\mathcal{E} = 0.004 P_v + 0.986 \qquad 5$$

Calculating Land Surface Temperature: LST can be computed thus;

$$\mathrm{LST} = \frac{BT}{1 + \left[\left(\frac{\lambda BT}{\rho}\right)\right] \ln \mathcal{E}} \qquad 6$$

Where;
BT represents Top of Atmosphere Brightness temperature
λ represents the wavelength of emitted radiance
$\mathcal{E}$ is the emissivity
$\rho = hc \quad \sigma = 1.438 \times 10^{-2}$ mK
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).

2.8. Calculating Soil Moisture Index: The Soil Moisture can be calculated from the LST using the formula;

$$\mathrm{SMI} = \frac{\mathrm{LST}_{max} - \mathrm{LST}}{\mathrm{LST}_{max} - \mathrm{LST}_{min}} \qquad 7$$

Table 1. Metadata for the year, 2018.

YEAR(2018)	SENSOR ID	RESOLUTION(m)	SENSING TIME/DATE	CLOUD COVER	LOCATION
JAN-MAR.	OLI&TIRS	30	2018/03/28 T09:50:06.3140510Z	25	OREDO
APR-SEPT.	OLI&TIRS	30	2018/09/20 T09:56:47.8501740Z	35	OREDO
OCT-DEC.	OLI&TIRS	30	2018/12/25 T09:57:02.1228809Z	25	OREDO

3. Results and Discussion

The soil moisture index (SMI) which is a measure of the soil moisture is an index ranging between 0 and 1 with 0 indicating very dry conditions with extremely low moisture content and 1, wet conditions with high moisture content. In the maps, the results are presented in three different colors. The yellow color has 0 - 0.3 moisture index value indicating low moisture content, the blue color has 0.3 - 0.6 moisture index value indicating moderate moisture content and the green color has 0.6 – 1 representing high moisture content.

From Figure 6, it is observed that the mean soil moisture index increased between the year 2017 and 2018 and this can be attributed to the seasonal climate variations such as rainfall and flooding between both years.

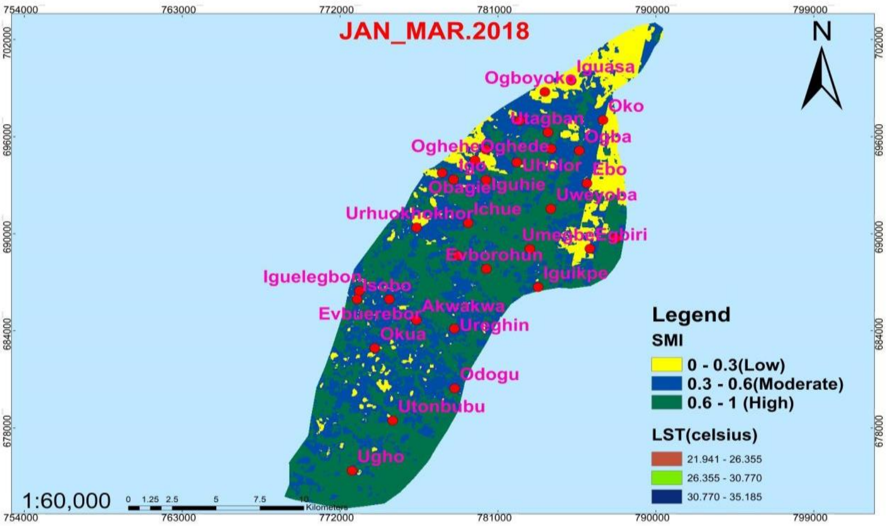

Figure 3: Soil moisture index map for 2018 dry season

The moisture index for Jan. to Mar.2018, showed that a low moisture index class was observed in the northern region of the study area especially places like Iguasa, Ogboyoko, and Oko. The moderate moisture index class occurs all over the study area such as Ogba, Utagban, Oghehe, Oghede, Isobo fall within this class. The high moisture index occurs within the southern and eastern parts of the study area. Areas such as Ugho, Odogu, Ureghin, Uholor, Utonbubu, and Okua fall in this class. The low moisture index covers 10.4%, the moderate moisture index covers 38.2%, the high moisture index covers 10.8%. The high moisture index class is the most dominant. The mean moisture index is 0.61, the standard deviation is 0.14.

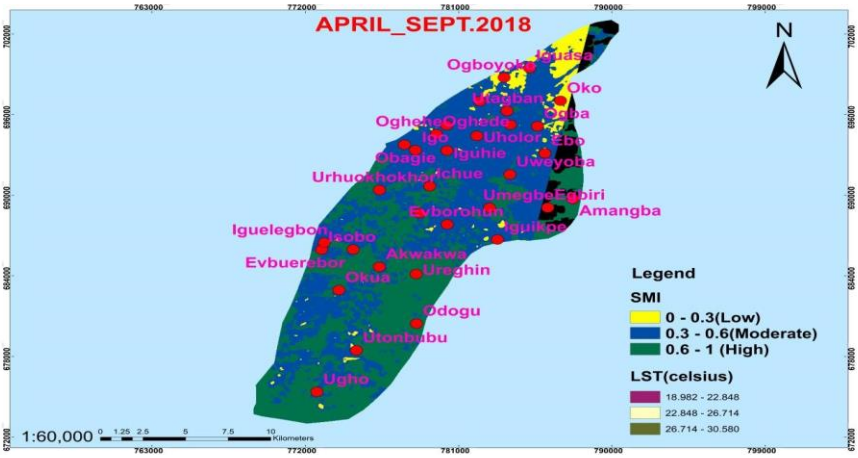

Figure 4: Soil moisture index map for 2018 wet season

The moisture index for April. to Sept.2018, showed that a low moisture index class was observed in the northern region of the study area especially places like Iguasa, Ogboyoko, and Oko. The moderate moisture index class occurs all over the study area such as Ogba, Utagban, Oghede, Oghehe, Igo, and Uweyoba fall within this class. The high moisture index Occurs within the southern and eastern parts of the study area. Areas such as Ugho, Odogu, Ureghin, Uholor, Utonbubu, and Okua fall in this class. The low moisture index covers 4.9%, the moderate moisture index covers 49.7%, the high moisture index covers 41.1% and while 4.2% of the area was distorted by cloud cover. The moderate moisture index class is the most dominant. The mean moisture index is 0.55, the standard deviation is 0.19.

The moisture index for Oct. to Dec.2018, showed that a low moisture index class was observed in the northern region of the study area especially places like Iguasa, Ogboyoko, and Oko. The moderate moisture index class occurs all over the study area such as Ogba, Egbiri, Urhuokhokhor and fall within this class. The high moisture index occurs within the southern and eastern parts of the study area. Areas such as Ugho, Odogu, Ureghin, Uholor, Utonbubu, and Okua fall in this class. The low moisture index covers 24%, the moderate moisture index covers 25.8%, and the high moisture index covers 22%. The high moisture index class is the most dominant. The mean moisture index is 0.35, the standard deviation is 0.09.

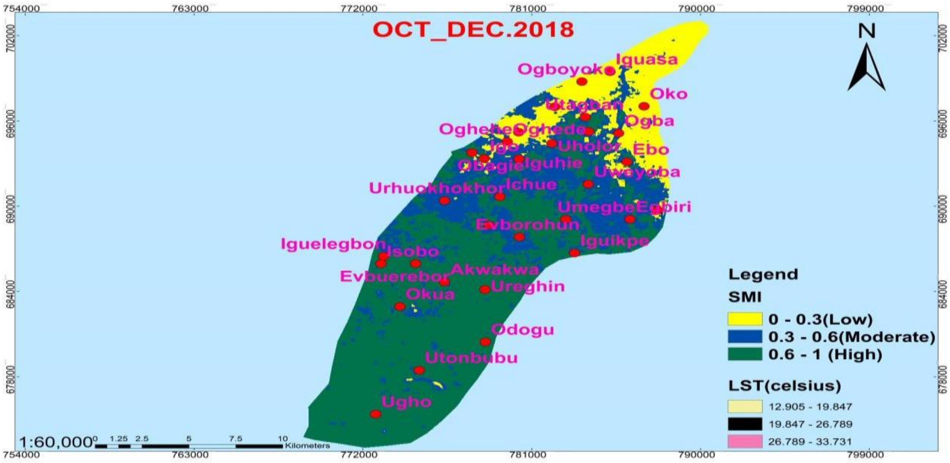

Figure 5: Soil moisture index map for 2018 dry season

Table 2. The mean soil moisture index, 2018

MEAN SOIL MOISTURE INDEX, 2018	
WET SEASON	**DRY SEASON**
0.55	**0.48**

Table 3. The mean soil moisture index, 2017

MEAN SOIL MOISTURE INDEX, 2017	
WET SEASON	**DRY SEASON**
0.47	**0.41**

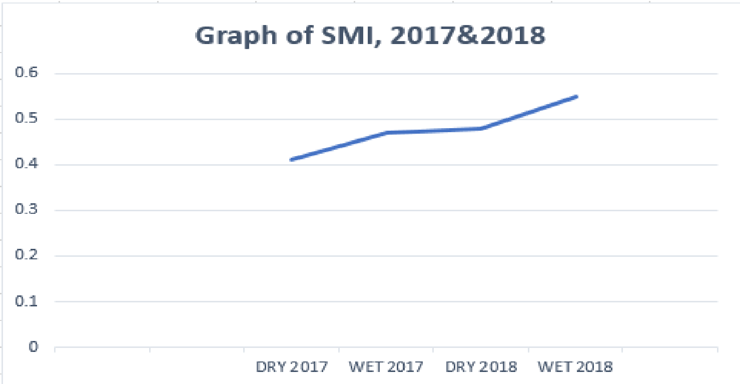

Figure 6: Soil moisture index against time (from 2017 to 2018)

Table 4. Percentage of soil moisture index 2018, distribution in Oredo LGA Benin City.

	DRY SEASON			WET SEASON		
YEAR	**HIGH(%)**	**MODERATE(%)**	**LOW(%)**	**HIGH(%)**	**MODERATE(%)**	**LOW(%)**
2018	**33.6**	**32.0**	**34.4**	**41.1**	**49.7**	**4.9**

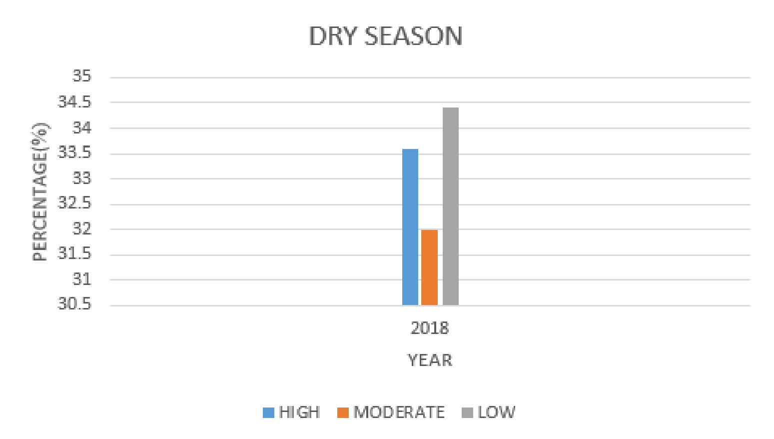

Figure 7: Bar Chart showing the percentage of soil moisture index

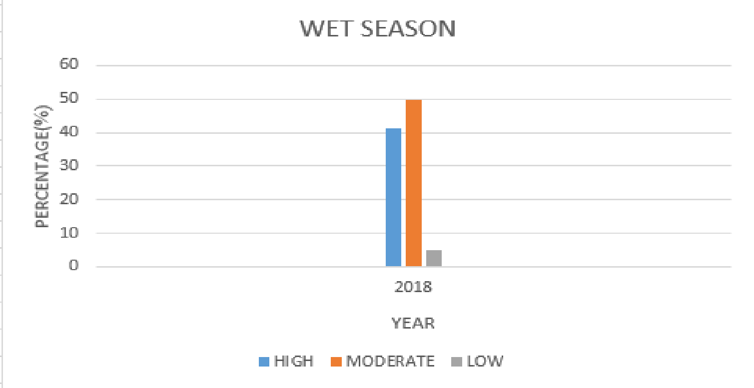

Figure 8: Bar Chart showing the percentage of soil moisture index

4. Conclusion

In this research, a prediction soil moisture model has been applied to Oredo Local Government Area which demonstrates the power of remotely sensed data. This model can be applied without the need to move to the area of interest to predict soil moisture in an environmentally sustainable way with minimum economical costs to easily analyze large areas. The soil moisture map obtained by this model is able to show good soil moisture variation within the studied area.

Conflict of Interest

There is no conflict of interest associated with this work.

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