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An Assessment of Spatiotemporal Soil Moisture Dynamics in Kumbotso Local Government Area, Kano State, Nigeria

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***Abstract*—Soil moisture is a critical control on vegetation productivity, evapotranspiration and agricultural water availability in the semi-arid Sudano-Sahelian zone of northern Nigeria, yet spatially explicit information on its distribution remains scarce at the local-government scale. This study assessed the spatiotemporal dynamics of soil moisture in Kumbotso Local Government Area (LGA), Kano State, using an integrated remote-sensing and GIS approach. Cloud-filtered Landsat 8 Collection 2 Level-2 surface reflectance and thermal imagery acquired between January and December 2025 were processed in Google Earth Engine and composited to derive the Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI) and Land Surface Temperature (LST). A linear NDVI–LST feature space was used to model the Temperature Vegetation Dryness Index (TVDI), from which a complementary Soil Moisture Index (SMI) was derived. Results revealed pronounced spatial heterogeneity across the LGA: LST ranged from 24.79°C to 45.37°C, NDVI from −0.21 to 0.38 and SAVI from −0.28 to 0.51, with the warmest, least-vegetated conditions concentrated over densely built-up wards such as Danbare, Chiranchi, Dan Maliki and Mariri, and cooler, greener conditions confined to riverine corridors around Panshekara, Kumbotso proper and the Chalawa River basin. TVDI values indicated severe moisture stress (0.70–1.00) across most of the LGA, while the SMI pattern confirmed relatively moist conditions over Chalawa, Gurun Gawa and adjoining northern and central wards, in contrast to drier conditions in the south. The convergence of these five indicators demonstrates that combining thermal, vegetation and moisture information provides a more robust characterization of surface soil-moisture conditions than any single index alone, and identifies specific wards where soil-water conservation, drought-tolerant cropping and vegetation restoration could be prioritized to support sustainable agricultural and land-resource management in Kumbotso LGA.**

Index Terms*—Soil Moisture Index, Google Earth Engine, Drought Assessment, Semi-Arid Environment, Remote Sensing, Land Surface Temperature.

I. NTRODUCTION

Soil moisture is a fundamental component of the land–atmosphere system because it regulates the partitioning of precipitation into infiltration, runoff, evaporation and plant transpiration, in water-limited environments, relatively small changes in soil-water availability can produce substantial ecological and agricultural consequences. The challenge of monitoring soil moisture is particularly pronounced in the Sudano-Sahelian region of West Africa, where climatic variability, recurrent dry conditions, increasing population pressure and changes in land use interact to influence ecosystem functioning and agricultural productivity. The region is characterized by strong seasonal rainfall variability and water limitation, while vegetation dynamics are additionally affected by land-use change and human activities. Recent research in Nigeria demonstrated considerable spatial and temporal variability in soil moisture across different land-use systems, confirming that soil moisture is strongly influenced by land use and environmental conditions [1]. This makes the monitoring of soil moisture particularly important in semi-arid and sub-humid environments where rainfall is highly seasonal and agricultural production depends substantially on the availability and persistence of soil water. Using satellite observations for 2001–2020, [2] demonstrated that vegetation greenness across the Sudano-Sahelian region was influenced by both climatic and non-climatic factors, with rainfall variability playing an important role while land-use change and fire contributed to localized vegetation browning. Such interactions imply that spatially explicit information on soil moisture is essential for understanding vegetation response, identifying moisture-stressed areas and supporting sustainable land and agricultural management in northern Nigeria. Conventional field-based soil-moisture measurements provide valuable and accurate information at individual sampling locations but can be expensive, labour-intensive and spatially limited when applied across large areas. Remote sensing and geographic information systems (GIS) provide an alternative means of assessing moisture-related conditions continuously across extensive areas. Recent research has demonstrated the usefulness of combining land surface temperature (LST), vegetation indices and remotely sensed moisture information to characterize soil-water conditions. For example, Adewole et al. (2024) integrated field observations, GIS and satellite-derived information to investigate soil-moisture dynamics across different land-use systems in Southwestern Nigeria and reported substantial differences in soil moisture among arable, built-up, plantation and riparian environments. Similarly, recent remote-sensing research has demonstrated that the relationship between LST and vegetation indices provides useful information for assessing surface moisture conditions and can be employed for spatial drought monitoring [3].

A number of remotely sensed indicators can therefore be used to characterize different components of the soil–vegetation–atmosphere system. The Normalized Difference Vegetation Index (NDVI) provides information on vegetation greenness and plant condition, whereas the Soil-Adjusted Vegetation Index (SAVI) minimizes the influence of exposed soil, making it particularly useful in sparsely vegetated environments. LST provides information about the thermal state of the land surface and is closely related to evapotranspiration and surface water availability. These variables can subsequently be combined into indicators such as the Soil Moisture Index (SMI) and Temperature Vegetation Dryness Index (TVDI) to characterize relative moisture and dryness conditions. Recent studies have confirmed the value of temperature–vegetation relationships for soil-moisture and drought assessment, although TVDI performance depends on the quality of the LST–vegetation feature space and appropriate characterization of wet and dry edges [4]; [5].

Despite the importance of soil moisture to agriculture, ecosystem functioning and environmental management in northern Nigeria, spatially explicit information on its distribution and dynamics at the local-government scale remains limited. Consequently, there is the need for an integrated remote-sensing and GIS assessment capable of examining the spatial relationships among soil moisture, vegetation and surface temperature. This study, therefore, assesses the spatiotemporal dynamics of soil moisture in Kumbotso LGA using remotely sensed LST, NDVI, SAVI, SMI and TVDI, with the aim of identifying spatial variations in moisture conditions and providing information useful for agricultural planning, drought-risk assessment, soil-water conservation and sustainable land-resource management. The integrated approach is consistent with recent research demonstrating that combining thermal and vegetation information can provide a more comprehensive representation of surface moisture conditions than relying on a single remotely sensed indicator [4];[1]

II. MATERIALS AND METHODS

A. Description of the study Area

Kumbotso Local Government Area (LGA) is one of the eight metropolitan local government areas comprising the Kano urban agglomeration in Kano State, North-Western Nigeria. It is geographically situated between latitudes 11°50N and 11°58N and longitudes 8°25E and 8°35E. The LGA covers a total land area of approximately 158 km² to 186 km² with its administrative headquarters located in Kumbotso town (Figure 1). It is strategically positioned on the southern peri-urban fringe of Kano metropolis, bordered by Kano Municipal and Gwale LGAs to the north, Tarauni LGA to the northeast, Dawakin Kudu LGA to the east and south, Madobi LGA to the southwest, and Rimin Gado LGA to the west. Its geographic proximity to the central urban core makes Kumbotso a vital transition zone linking rural hinterlands with the densely built-up metropolitan area.

Topographically, Kumbotso LGA lies within the semi-arid High Plains of Hausaland, featuring a generally undulating terrain with average elevations ranging around 450 m to 480 m above sea level. The underlying geology predominantly consists of Precambrian basement complex rocks, overlain by sandy-loam and alluvial soils along river valleys. Hydrologically, the area forms part of the larger Kano River and Challawa River basin system, which provides essential drainage and surface water resources for urban, industrial, and agricultural utilization. The region experiences a Tropical Wet-and-Dry climate (Köppen classification Aw), characterized by two distinct contrasting seasons: a dry season lasting from October to April and a rainy season spanning May to September. Mean annual rainfall ranges between 700 mm and 900 mm, while ambient temperatures typically fluctuate from a low of 13°C during the cold harmattan period (December–January) to daytime maximums exceeding 38°C during the hot pre-monsoon months of March to May. Kumbotso is one of the most rapidly urbanizing and densely populated local government areas in Kano State, with a projected population exceeding 450,000 inhabitants driven by steady suburban expansion and rural-urban migration. The area features a complex mosaic of land use and land cover (LULC) types, transitioning from high- density residential developments and vibrant commercial hubs such as the prominent Yan Lemo fruit market to peri-urban agricultural lands devoted to rainfed and irrigated farming of crops like rice, maize, sorghum, and vegetables. Significantly, Kumbotso hosts key industrial estates, including parts of the Challawa and Sharada industrial corridors, making it a major hub for manufacturing, leather tanning, and commercial processing within the the State.

The study area was defined using the administrative boundary of Kumbotso Local Government Area (LGA), Kano State, Nigeria. A polygon shapefile containing the official LGA boundary was uploaded as an Earth Engine asset and imported as a FeatureCollection into the Google Earth Engine (GEE) environment. The study area was then visualized and centered within the GEE map interface to facilitate data inspection and processing. The use of an administrative boundary was essential for ensuring that all remotely sensed products were spatially constrained to the study area. Clipping the satellite imagery to the Kumbotso boundary reduced unnecessary computational requirements and prevented adjacent land-cover characteristics from influencing the analysis. This approach also ensured consistency in calculating vegetation, temperature, and soil moisture indices by limiting all pixel-based computations to the same geographic extent.

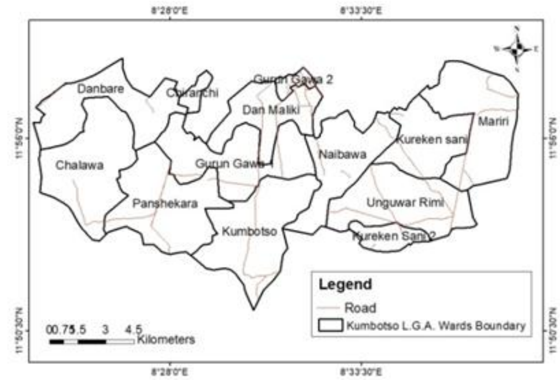

Figure 1. The Study Area

B. Satellite Data Acquisition and Image Pre-processing

Landsat 8 Collection 2 Tier 1 Level-2 Surface Reflectance imagery was used as the primary remote sensing dataset for this study. Images acquired between 1 January 2025 and 31 December 2025 were retrieved directly from the Google Earth Engine data catalogue. The Landsat Collection 2 Level-2 product provides atmospherically corrected surface reflectance and surface temperature datasets, making it suitable for vegetation, thermal, and soil moisture analyses. Only images intersecting the Kumbotso boundary were considered for further processing.

To improve image quality, cloud-contaminated observations were removed using the QA_PIXEL quality assurance band. Bitwise operations were applied to identify cloud and cloud-shadow pixels, which were subsequently masked from each image. Furthermore, scenes with more than 20% cloud cover were excluded to minimize atmospheric contamination and improve the reliability of the derived indices. Cloud masking is an essential preprocessing step because clouds significantly alter surface reflectance and thermal measurements, leading to inaccuracies in vegetation and temperature estimates.

Following quality filtering, all cloud-free Landsat scenes were composited using the median reducer to generate a single representative image for the study period. Median compositing effectively minimizes residual atmospheric noise and eliminates outlier pixel values that may remain after cloud masking. The resulting composite image was subsequently clipped to the Kumbotso boundary and served as the primary dataset for deriving vegetation indices, land surface temperature, drought indices, and soil moisture estimates.

C. Derivation of Vegetation and Thermal Parameters

Three primary environmental variables were generated from the processed Landsat composite, namely the Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), and Land Surface Temperature (LST). These parameters represent the vegetation condition, soil-adjusted vegetation response, and thermal characteristics of the land surface, respectively, and constitute the primary inputs for subsequent drought and soil moisture analyses. The NDVI was calculated using the normalized difference between the near-infrared (Band 5) and red (Band 4) reflectance bands according to:

$NDVI=NIR+REDNIR-RED$

where NIR represents surface reflectance in Landsat Band 5 and RED represents reflectance in Band 4. NDVI values range theoretically between −1 and +1, with higher positive values indicating healthier vegetation and greater photosynthetic activity. Because vegetation responds directly to water availability, NDVI serves as an important indicator of vegetation condition and indirectly reflects variations in soil moisture.

To reduce the influence of exposed soil commonly encountered within semi-arid environments, the Soil-Adjusted Vegetation Index (SAVI) was computed using:

$SAVI=(NIR+RED+L)\ (NIR-RED)\ (1+L)$

where L = 0.5 represents the soil adjustment factor suitable for intermediate vegetation cover. Surface reflectance values were first scaled using the Landsat Collection 2 calibration coefficients before computing SAVI. Land Surface Temperature (LST) was subsequently derived from the thermal infrared Band 10 using the Landsat scaling parameters provided by the United States Geological Survey (USGS):

$LST=(STB10\times 0.00341802+149)-273.15$

where STB10 denotes the thermal band digital values and the resulting temperature is expressed in degrees Celsius. LST provides valuable information regarding surface energy balance and evaporative processes and serves as the principal thermal variable for estimating surface dryness and soil moisture.

D. Estimation of Temperature Vegetation Dryness Index (TVDI)

The Temperature Vegetation Dryness Index (TVDI) was employed to quantify surface moisture conditions by integrating land surface temperature and vegetation information. TVDI is based on the conceptual relationship between vegetation density and land surface temperature, where surfaces with similar vegetation cover exhibit varying temperatures depending on their moisture status. Areas experiencing moisture stress generally exhibit higher land surface temperatures than well-watered surfaces with comparable vegetation density. Consequently, TVDI provides a relative measure of surface dryness and has been widely applied in agricultural drought and soil moisture assessments.

To establish the TVDI model, a linear regression was performed between NDVI and LST using the linearFit () reducer available in Google Earth Engine. In the regression model, NDVI was assigned as the independent variable (X) and LST as the dependent variable (Y). The regression produced the slope and intercept describing the dry edge of the NDVI–LST feature space. The minimum land surface temperature (LSTmin), representing the wet edge, was independently extracted from the study area using the minimum reducer.

The TVDI was subsequently calculated using:

$TVDI=(a+b\times NDVI)-LSTmin\ LST-LSTmin$

where a is the regression intercept, b is the regression slope, and LSTmin represents the minimum land surface temperature within the study area. The resulting values were constrained between 0 and 1 using the *clamp ()* function to maintain the conventional interpretation of TVDI, whereby values approaching 0 indicate relatively wet conditions and values approaching 1 represent increasingly dry conditions.

E. Estimation of Soil Moisture Index (SMI)

Following the computation of TVDI, the Soil Moisture Index (SMI) was estimated to characterize the spatial distribution of relative surface soil moisture across Kumbotso LGA. The SMI is based on the inverse relationship between moisture availability and surface dryness, whereby increasing dryness corresponds to decreasing soil moisture. Since TVDI quantifies relative drought conditions, soil moisture was estimated by inverting the TVDI values.

The Soil Moisture Index was computed as:

$SMI=1-TVDI$

This transformation produces normalized values ranging between 0 and 1, where values approaching 1 represent relatively wet soil conditions, while values approaching 0 indicate relatively dry conditions. The normalized range facilitates comparison with previous soil moisture studies and allows the results to be interpreted consistently across different environmental conditions.

The derived SMI raster represents a relative estimate of near-surface soil moisture rather than direct volumetric soil water content. Nevertheless, previous studies have demonstrated that remotely sensed SMI exhibits strong spatial correspondence with observed surface moisture patterns, particularly in semi-arid agricultural environments where vegetation and temperature are closely coupled. Consequently, SMI provides an effective means of identifying moisture-stressed areas and evaluating spatial variability in soil water availability.

III. RESULTS AND DISCUSSION

The results provide complementary evidence for assessing the spatial dynamics of soil-moisture conditions in Kumbotso Local Government Area (LGA), Kano State. Land surface temperature (LST) reflects the thermal state of the land surface, Normalized Difference Vegitation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI) represent vegetation response, while Soil Moisture Index (SMI) and Temperature Vegetation Dryness Index (TVDI) provide indirect estimates of surface moisture and dryness. Recent studies similarly demonstrate that combining thermal and vegetation information gives a more robust interpretation of agricultural drought and soil-moisture conditions than relying on one index alone [6]; [1]; [7].

1. Land Surface Temperature (LST)

The spatial distribution of Land Surface Temperature (LST) across Kumbotso LGA demonstrates significant thermal heterogeneity, with values ranging from a minimum of 24.79°C to a maximum of 45.37°C. High thermal pockets are heavily concentrated in heavily built-up and bare surface wards, such as Danbare, Chiranchi, Dan Maliki, Gurun Gawa 2, Kureken Sani, Unguwar Rimi, and Mariri. Conversely, lower surface temperatures (24.79°C–32.00°C) are distinctly confined to riverine boundaries, low-lying wetlands, and vegetative corridors located along Panshekara, Kumbotso proper, and the Chalawa River basin.

Surface temperature provides an important indirect indication of the surface energy and water balance. Where adequate soil water is available, a greater fraction of available energy can be dissipated through evapotranspiration, whereas water-limited surfaces tend to partition more energy into sensible heating. Consequently, LST is widely used alongside vegetation indices for agricultural-drought and soil-moisture assessment. [1] working in southwestern Nigeria, found clear differences in LST among land-cover types, with built-up and arable areas generally warmer than vegetation-rich areas; they also found an inverse relationship between LST and NDVI and a positive relationship between vegetation and SMI. Similarly, [8] found that vegetation–temperature relationships vary across Africa but that vegetation-induced cooling can be particularly important in semi-arid environments.

The relatively large LST range observed in Kumbotso therefore suggests strong contrasts in surface conditions and potentially different levels of evaporative cooling. Areas with comparatively high thermal values may represent locations where vegetation cover is sparse, soil is relatively exposed, or water availability is limited. Conversely, cooler locations may reflect greater vegetation cover, moisture availability, shaded surfaces or other local surface characteristics. This interpretation is consistent with [9] who demonstrated that LST and vegetation characteristics are useful for identifying degradation and land-surface conditions in semi-arid environments. [10] further demonstrated that the combined NDVI–LST space can distinguish drought and non-drought conditions in semi-arid environments, although they cautioned that the relationship between LST and vegetation is not universally identical across landscapes.

From a management perspective, the LST pattern is important for identifying locations that may require closer investigation for agricultural water stress, land degradation and urban thermal effects. In Kumbotso, areas where high LST coincides with low NDVI/SAVI and low SMI would provide particularly strong evidence of moisture stress, whereas high LST accompanied by healthy vegetation would require a different interpretation. This distinction is important because LST alone is not equivalent to soil moisture. Recent work has shown that soil moisture is influenced simultaneously by vegetation, topography, soil characteristics, precipitation and land use [11]. Therefore, the LST result should be regarded as one component of the soil-moisture assessment rather than an independent measure of volumetric soil-water content.

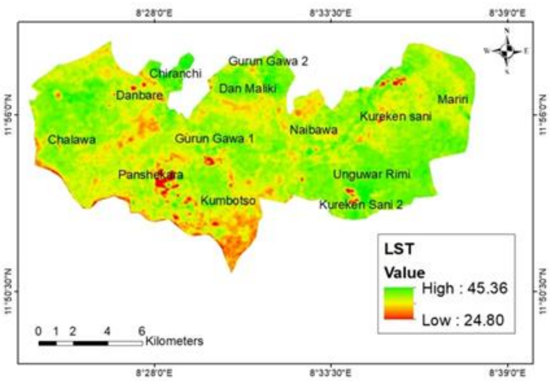

Figure 2. Land Surface Temperature (LST)

2. Normalized Difference Vegetation Index (NDVI)

The NDVI map records values between −0.21 and 0.38, indicating considerable spatial variation in vegetation greenness within Kumbotso LGA. Positive values approaching 0.38 occur mainly in greener parts of the study area, while the lowest values, including negative values, occur in localized patches. Relatively greener conditions are evident across portions of Chalawa, Gurun Gawa 1, parts of Kumbotso and other scattered areas, whereas lower NDVI concentrations occur around portions of Panshekara, Mariri, Danbare, Chiranchi, Naibawa and built-up or disturbed locations. The generally modest maximum NDVI value is consistent with the semi-arid character of the Kano environment, where vegetation is often spatially discontinuous and strongly dependent on rainfall, soil water availability and land management.

The NDVI pattern is important because vegetation provides an ecological response to the availability of water in the soil. In water-limited environments, insufficient soil moisture can restrict plant growth and reduce chlorophyll activity, resulting in lower NDVI values. Conversely, adequate water availability promotes vegetation growth and higher greenness. This relationship has been demonstrated across the Sudano-Sahelian region, where NDVI has been used successfully as a proxy for vegetation condition and where rainfall variability, land-use change and other factors jointly influence vegetation greenness (12). [6] similarly incorporated NDVI and LST into a composite drought index for the West African Sahel and found that NDVI contributed substantially to the identification of agricultural drought conditions.

The spatial concentration of lower NDVI around densely settled or disturbed locations has important implications for soil-moisture dynamics. Reduced vegetation means less shading of the soil surface and potentially greater exposure to solar radiation, while vegetation loss can also alter infiltration, runoff and evapotranspiration. In contrast, areas retaining greater vegetation cover may have improved microclimatic conditions and greater capacity to retain surface moisture. Evidence from southern Niger is particularly relevant: [13] found that remotely sensed NDVI responded strongly to land-management interventions, with substantial increases in vegetation greenness following water-conservation interventions. This demonstrates that NDVI is not merely a descriptive vegetation variable; it can respond to changes in land and water management in semi-arid West African environments.

The NDVI result consequently provides an important ecological dimension to the soil-moisture assessment in Kumbotso LGA. Areas of higher NDVI should not automatically be classified as wet because vegetation may also reflect irrigation, crop type, seasonal phenology or groundwater access. Similarly, low NDVI does not necessarily prove severe soil dryness because built-up surfaces, bare soil and recently harvested agricultural fields can produce low values. This limitation is recognized in recent remote-sensing research, which emphasizes the value of combining NDVI with thermal and moisture indicators. For example, [1] found that NDVI increased with SMI and decreased with LST in southwestern Nigeria, while Bichi [7] concluded that combining different remotely sensed indices improves drought assessment across Sub-Saharan Africa.

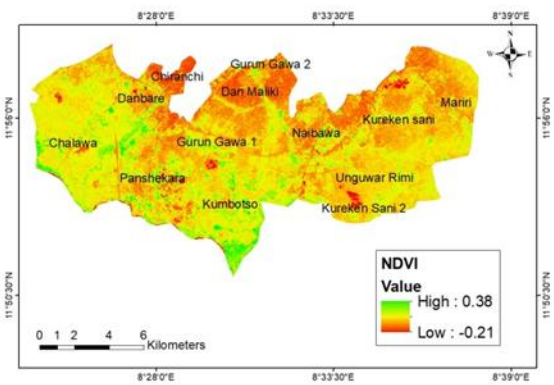

Figure 3 Normalized Difference Vegetation Index (NDVI)

3. Soil-Adjusted Vegetation Index (SAVI)

The SAVI map ranges from approximately −0.28 to 0.51 and reveals a highly heterogeneous vegetation pattern. Unlike NDVI, SAVI is specifically designed to reduce the influence of exposed soil on vegetation estimates, making it particularly relevant to semi-arid environments such as Kumbotso where bare soil and sparse vegetation are common. The map shows relatively high SAVI across substantial portions of Chalawa, Gurun Gawa 1, parts of Kumbotso, Dan Maliki and sections of Mariri, while low values occur in scattered patches, particularly around Panshekara, southern Kumbotso, Danbare, Chiranchi and localized areas around Kureken Sani and Mariri.

The significance of SAVI in this study is that it provides a complementary assessment of vegetation condition where soil-background effects could influence NDVI. In sparsely vegetated landscapes, the spectral response of exposed soil can substantially influence conventional vegetation indices. This is especially important in Kumbotso because the landscape contains a mixture of built-up surfaces, agricultural areas, bare soil and vegetation. Recent research has continued to demonstrate the value of soil-adjusted vegetation indices for semi-arid environments. [14], for example, found that Landsat-derived SAVI showed a moderate positive relationship with measured soil moisture, with the Landsat 9 SAVI–soil-moisture correlation reaching $r = 0.62$ in their study.

The SAVI distribution also strengthens the interpretation of the NDVI result. Where high SAVI corresponds spatially with relatively high NDVI, there is stronger evidence that the observed greenness represents genuine vegetation rather than merely differences in soil reflectance. Conversely, areas with low SAVI and low NDVI are more likely to represent sparse vegetation, exposed soil, built-up surfaces or stressed vegetation. This complementary use of NDVI and SAVI is supported by recent research in semi-arid environments, where vegetation indices are increasingly used together to overcome the limitations of individual indices. [15], for example, used LST, SAVI, NDVI and SPI jointly to investigate agricultural drought over a long Landsat time series in South Africa.

For Kumbotso, the SAVI result therefore has direct implications for agricultural land management and soil-moisture conservation. Locations with relatively high SAVI may represent areas with better vegetation establishment and potentially more favourable moisture conditions, whereas low-SAVI zones may be vulnerable to soil exposure, rapid surface heating and moisture loss. However, SAVI should still be interpreted as a vegetation-response indicator rather than a direct measurement of soil-water content. [14] demonstrated that SAVI can be related to measured soil moisture, but the relationship was only moderate, illustrating that vegetation response is influenced by factors other than moisture alone. Consequently, the strongest conclusions arise when SAVI is interpreted jointly with SMI, TVDI, LST and field observations.

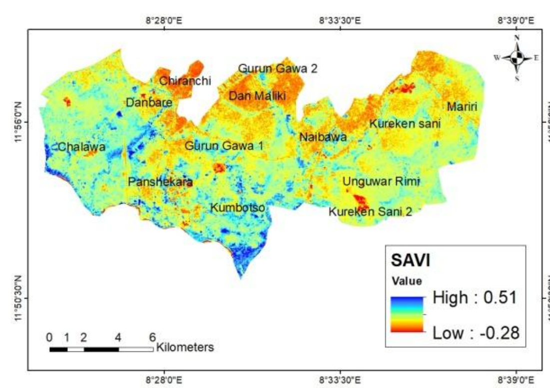

Figure 4. Soil-Adjusted Vegetation Index (SAVI)

4. Temperature Vegetation Dryness Index (TVDI)

The Temperature Vegetation Dryness Index (TVDI) map exhibits a range from 0.00 (wet/unstressed) to 1.00 (extremely dry/severely stressed). Severe dryness (TVDI values from 0.70 to 1.00, covers nearly the entire spatial extent of Kumbotso LGA, including

Danbare, Chiranchi, Dan Maliki, Gurun Gawa 2, Naibawa, Kureken Sani, Unguwar Rimi, and Mariri. Low TVDI values (0.00 to 0.30 are exclusively localized along the moist alluvial floodplains and watercourses of Panshekara, Kumbotso, and Chalawa. The significance of TVDI is that it integrates land surface temperature and vegetation information rather than considering either variable independently. Conventional TVDI is constructed from the LST–vegetation-index feature space and is intended to represent the degree of surface dryness. Recent literature generally defines conventional TVDI on a 0–1 scale, where values close to 0 represent wetter conditions and values close to 1 represent increasing dryness. For example, [11] used TVDI to examine soil-moisture dynamics in a semi-arid region and explicitly described its 0–1 range, while [16] showed that modified TVDI can have a strong association with observed soil moisture at different soil depths.

[17] demonstrated that TVDI can successfully capture soil-moisture variability and found a negative relationship between TVDI and soil moisture at several soil depths. More recent work by [16] further shows that improved treatment of the wet and dry edges can strengthen the relationship between TVDI and actual soil moisture. The TVDI result is highly valuable because it provides an independent thermal–vegetation perspective on the SMI distribution. The most convincing evidence of soil-moisture stress would occur where low SMI, low NDVI/SAVI and high conventional TVDI spatially coincide, while areas showing high vegetation, high SMI and low TVDI would represent relatively favourable moisture conditions. This multi-index approach is supported by recent studies showing that TVDI, NDVI, LST and other remotely sensed variables jointly improve soil-moisture and drought assessment [18]; [16])

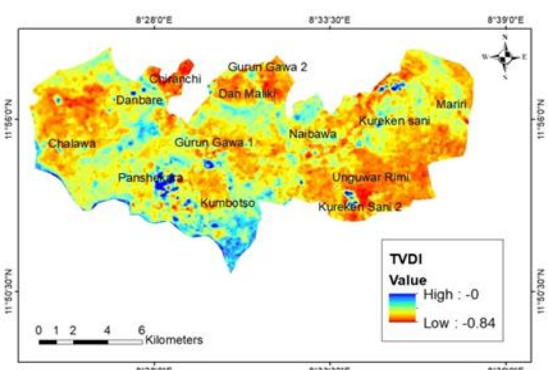

Figure 5. Soil-Adjusted Vegetation Index (SAVI)

5. Soil Moisture Index (SMI)

The result shows ranges from 1.00 to 1.84, with relatively moist conditions dominating large parts of Chalawa, Gurun Gawa 1, Gurun Gawa 2, Dan Maliki, Naibawa, Unguwar Rimi and portions of Mariri, while relatively low-moisture conditions are particularly conspicuous around Kumbotso, Panshekara and portions of southern and eastern parts of the LGA. The resulting pattern demonstrates that soil moisture is spatially heterogeneous rather than uniformly distributed across Kumbotso.

The significance of this pattern is substantial because soil moisture represents the link between rainfall, vegetation productivity, evapotranspiration and agricultural water availability. In semi-arid environments, even relatively small spatial differences in water availability can produce substantial differences in vegetation performance and surface temperature. [1], working elsewhere in Nigeria, found strong spatial and temporal variability in soil moisture across different land-use types and demonstrated that satellite-derived SMI, NDVI and LST can reveal these differences. Their results showed higher SMI in vegetation-rich environments and lower SMI in built-up and some agricultural areas. This provides a strong comparison for the heterogeneous SMI pattern observed in Kumbotso.

The areas of comparatively low SMI identified in the southern portion of Kumbotso, particularly around Panshekara and Kumbotso, are therefore potentially important soil-moisture stress zones. These areas could experience greater evaporative demand, lower water retention or stronger human disturbance, although the map alone cannot determine which mechanism dominates. Similarly, the relatively high SMI areas around the northern and central parts of the LGA may reflect differences in vegetation, soil texture, drainage, land use, rainfall redistribution or local infiltration conditions.

Recent research emphasizes that soil moisture is controlled by multiple interacting factors rather than a single environmental variable. [11], for example, found that vegetation, precipitation, elevation, slope and soil properties jointly influenced soil-moisture spatial variability, with interactions among factors being stronger than many individual effects.

Soil-moisture conditions in Kumbotso LGA are spatially heterogeneous and closely associated with vegetation and thermal characteristics. The NDVI and SAVI maps demonstrate spatial differences in vegetation condition, while the LST map demonstrates substantial thermal variability. The SMI and TVDI maps then translate these vegetation–temperature differences into relative moisture/dryness patterns. This integrated interpretation agrees with recent research showing that soil moisture is influenced by the interaction of vegetation, temperature, rainfall, soil characteristics, terrain and land use rather than by a single controlling factor [1]; [11].

A particularly important finding is the apparent concentration of less favourable moisture/vegetation conditions around Panshekara and Kumbotso and parts of the southern LGA, whereas more favourable vegetation and moisture conditions occur across portions of the northern and central areas such as Chalawa, Gurun Gawa and parts of Naibawa and Mariri.

Such spatial contrasts are highly relevant to agricultural planning because they suggest that water availability and vegetation response are not uniform even within the same LGA. In the wider West African Sahel, [6] demonstrated that combining NDVI and LST with precipitation substantially improves agricultural-drought characterization, while [13] showed that improved land and water management can produce measurable increases in NDVI in semi-arid Niger.

The findings also have implications for climate adaptation and land management in Kumbotso. Areas characterized by low vegetation indices and relatively unfavourable moisture conditions could be prioritized for soil-water conservation, improved rainwater infiltration, drought-tolerant cropping, supplementary irrigation where feasible, and vegetation restoration. Vegetation restoration is particularly relevant because recent continental-scale evidence indicates that increasing vegetation cover can influence local land-surface temperature through evapotranspiration and other biophysical processes, with strong cooling effects possible in semi-arid African environments [8]. Consequently, the results of this study can contribute not only to drought assessment but also to spatial prioritization of land and water management interventions.

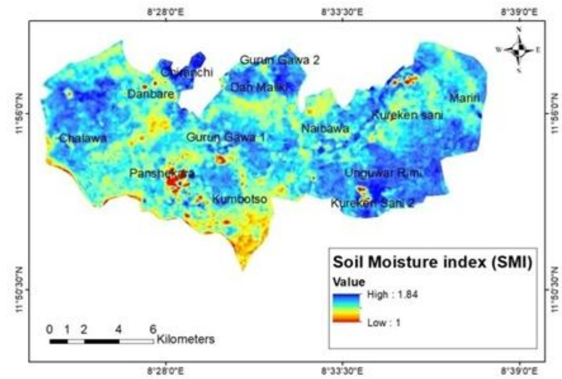

Figure 6. Soil Moisture Index (SMI)

IV. CONCLUSION

This study set out to assess the spatiotemporal dynamics of soil moisture in Kumbotso Local Government Area, Kano State, through an integrated remote-sensing and GIS framework combining land surface temperature, vegetation indices and derived dryness/moisture indicators. By processing cloud-filtered Landsat 8 Collection 2 Level-2 imagery within Google Earth Engine and deriving NDVI, SAVI, LST, TVDI and SMI for the 2025 study period, the work has produced a spatially explicit, surface moisture conditions across the LGA rather than relying on any single remotely sensed variable in isolation.

The results reveal pronounced spatial heterogeneity in surface conditions across Kumbotso. LST ranged from 24.79°C to 45.37°C, with the warmest surfaces concentrated over densely built-up and bare wards such as Danbare, Chiranchi, Dan Maliki, Gurun Gawa 2, Kureken Sani, Unguwar Rimi and Mariri, while cooler surfaces were confined to riverine and vegetated corridors along Panshekara, Kumbotso proper and the Chalawa River basin. NDVI (−0.21 to 0.38) and SAVI (−0.28 to 0.51) traced a broadly consistent vegetation pattern, with greener, better-vegetated conditions over Chalawa, Gurun Gawa 1 and parts of Kumbotso, and sparser cover over the same disturbed and built-up wards that recorded elevated LST. TVDI values approaching the severely stressed end of the scale (0.70–1.00) dominated most of the LGA, with low-stress conditions restricted to alluvial floodplains and watercourses, while the corresponding SMI pattern confirmed that relatively moist conditions prevailed over Chalawa, Gurun Gawa and adjoining northern and central wards, in contrast to comparatively drier conditions around Panshekara, Kumbotso and parts of the southern and eastern LGA. Taken together, the five indicators converge on a consistent spatial narrative: moisture-favourable, vegetated conditions in the north and centre of the LGA, and moisture-stressed, thermally elevated conditions concentrated in the south and in densely settled areas. These findings carry direct practical relevance for agricultural planning, drought-risk assessment and soil-water conservation in Kumbotso LGA. The consistent coincidence of low NDVI/SAVI, low SMI and high TVDI in wards such as Panshekara, Danbare, Chiranchi and southern Kumbotso identifies these areas as priority zones for intervention, where measures such as rainwater harvesting, improved infiltration, drought-tolerant cropping, supplementary irrigation and targeted vegetation restoration could help offset moisture deficits and reduce surface heating. By contrast, the comparatively favourable conditions observed around Chalawa, Gurun Gawa and parts of Naibawa and Mariri suggest zones where existing land and water management practices are sustaining more resilient vegetation and moisture regimes and could serve as reference conditions for wider land-use planning. More broadly, the study demonstrates that an integrated, multi-indicator remote-sensing approach can generate the kind of local-government-scale, spatially explicit evidence on soil-moisture and vegetation stress that is presently lacking for much of northern Nigeria, and that is essential for evidence-based land- and water-resource management in a rapidly urbanizing, semi-arid setting. Nevertheless, the SMI and TVDI values derived here are relative, image-based estimates rather than direct measurements of volumetric soil-water content, and the single-year, median-composite approach cannot capture intra-seasonal or inter-annual variability in rainfall and land management that are known to influence soil moisture in the Sudano-Sahelian zone. Future work should therefore incorporate multi-year and multi-seasonal Landsat or Sentinel-2 time series, validate the derived indices against in-situ soil-moisture and meteorological observations, and examine the influence of soil texture, topography and land-use change more explicitly. Extending the analytical framework applied in Kumbotso to other local government areas in Kano State and the wider Sudano-Sahelian region would further strengthen its value as a low-cost, replicable tool for drought monitoring and land- and water-resource planning across northern Nigeria.

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