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EVALUATING REMOTE SENSING-BASED DROUGHT INDICES: STRENGTHS, LIMITATIONS, AND APPLICABILITY ACROSS SUB-SAHARAN AFRICA'S AGRO-ECOLOGICAL ZONES: A REVIEW

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ABSTRACT

This study reviews the application and effectiveness of various remote sensing (RS) indices for drought monitoring in Sub-Saharan Africa (SSA). Given the region's diverse climatic zones and frequent drought occurrences, accurate and timely assessment tools are crucial. The study examines indices from different spectral regions, including optical, thermal infrared, and microwave bands, focusing on their spatial and temporal resolutions, data availability, strengths, and limitations. Optical indices such as the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI) are effective in semi-arid and sub-humid zones where vegetation density varies. Thermal infrared indices, including the Temperature Condition Index (TCI), the Vegetation Health Index (VHI), and the Temperature Vegetation Dryness Index (TVDI), provide insights into thermal anomalies and vegetation health, with TCI particularly suited for semi-arid zones and TVDI useful in both semi-arid and sub-humid zones. Microwave indices, such as the Normalized Backscatter Moisture Index (NBMI), Vegetation Optical Depth (VOD), and the Microwave Polarization Difference Index (MPDI), excel in capturing soil moisture and vegetation water content, proving useful in humid forest and semi-arid zones. The integration of these indices with other meteorological and hydrological data enhances drought monitoring and management strategies. Recommendations are made for the optimal use of these indices across different SSA agroecological zones.

Keywords: Drought monitoring, Remote sensing indices, Sub-Saharan Africa (SSA), Vegetation health, Soil moisture

INTRODUCTION

In Sub-Saharan Africa (SSA), majority of the population relies mainly on rainfed agriculture for their sustenance. Because of that, any deficiency in rainfall availability will likely pose a significant threat to food security, social and economic stability of the region. According to studies, SSA is seen as the most susceptible region to the impacts of climate change, and in this region, climate change is projected to increase the frequency and severity of extreme weather events including drought events (Kotir, 2011; Lottering et al., 2021).

Drought defined as a complex natural event marked by an extended period of insufficient rainfall, leading to notable water shortages that impact the environment and various human activities. It can be divided into several types: meteorological drought, which is defined by a lack of precipitation; agricultural drought, where water scarcity hampers crop production; hydrological drought, characterized by lower water levels in rivers, lakes, and groundwater; and socioeconomic drought, where the water shortage affects society and the economy as a whole. (Walia et al., 2024). Drought can pose serious adverse effects on crop yield as well as the ecosystem thus increasing the tendency for food insecurity and poverty across a region. This is why proper strategy is needed to ensure effective monitoring of drought events so as to mitigate their impacts.

In-situ-based drought indices such as the Standardized Precipitation Index (SPI) and Standardized Precipitation Evapo-transpiration Index (SPEI) have been used to monitor drought and is able to provide high accuracy at certain measurement points. However, they are not able to offer coverage over large area (Hazaymeh & Hassan, 2016)

The advent of remote sensing (RS) technologies has facilitated the development of various techniques/indices used for monitoring or evaluating drought as documented in various research articles over the years. These indices are mostly derived from satellite data and allows for the monitoring of large spatial areas over a long temporal period (Bhaga et al., 2020; Frantzova, 2023a; Hazaymeh & Hassan, 2016; Jiao et al., 2021; Lottering et al., 2021; Mishra & Singh, 2011)

According to Hazaymeh & Hassan (2016), RS-based agricultural drought monitoring indices can be categorized as either optical, thermal, microwave or a combination of these categories. Optical remote sensing indices include the Normalized Difference Vegetation Index (NDVI), the Normalized Difference Water Index (NDWI), the Vegetation Condition Index (VCI), the short wave infra-Red Perpendicular Water Stress Index (SWIR-PWSI), the Vegetation Water Stress Index (VWSI) etc. Thermal remote sensing indices includes the Apparent Thermal Inertia (ATI), the Temperature Condition Index (TCI), and the Temperature Vegetation Dryness Index (TVDI), etc. Microwave remote sensing indices include the Microwave Polarization Difference Index (MPDI), the Vegetation Optical Depth (VOD), the Normalized Backscatter Moisture Index (NBMI) etc. Finally, the combined remote sensing methods includes the Normalized Difference Drought Index (NDDI), the Vegetation Health Index (VHI), the Vegetation Temperature Condition Index (VTCI), Temperature-Vegetation Dryness Index (TVDI)etc.

These RS-Based Drought Monitoring indices mentioned across different categories offer various characteristics (i.e. strength, limitations, as well as applicability across different agroecological zones). Knowledge and understanding of these characteristics are of paramount importance to researchers and policy makers for proper decision making (Hazaymeh & Hassan, 2016; Jiao et al., 2021).

The main objective of this paper is to review various RS-based drought indices to identify their strengths and limitations and recommend their applicability across the different agroecological zones of Sub-Saharan Africa.

This research is justified as it addresses the urgent need for improved drought monitoring in Sub-Saharan Africa (SSA), a region highly vulnerable to droughts due to its diverse climates and ecological zones. Remote sensing (RS) indices are valuable tools for tracking environmental changes, but their effectiveness varies across different agroecological zones. The research provides practical recommendations for enhancing drought monitoring and management, contributing to better decision-making and risk mitigation in SSA.

Overview of RS Techniques

Remote sensing (RS) is the acquisition of information about an object or phenomenon without making physical contact with it. Various remote sensing techniques are employed depending on the application and the type of data required. According to the literature, Optical RS, Thermal Infrared RS, and Microwave RS are some of the techniques extensively used for drought monitoring. These techniques can be used independently or in combination for monitoring drought conditions.

Optical Remote Sensing

Optical remote sensing involves using sensors on satellites or aircraft to collect data about the earth's surface by detecting reflected or emitted light, primarily in the visible (0.38–0.76 µm), near-infrared (NIR) (0.76µm to 1.3µm), and shortwave infrared (SWIR) (1.3µm to 3µm) regions of the electromagnetic spectrum. The above-mentioned spectral range are most frequently used due to their distinct responses to drought, effectively being able to indicate both vegetation greenness and wetness conditions(Hazaymeh& K. Hassan, 2016). Optical remote sensing plays a crucial role in drought monitoring by providing valuable data through vegetation indices like Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Enhanced Vegetation Index (EVI), and Normalized Difference Water Index (NDWI), which help assess vegetation health and drought severity (Ejaz et al., 2023; Frantzova, 2023b; Hazaymeh& K. Hassan, 2016; Saravahidi et al., 2023)

Optical remote sensing offers detailed, high-resolution data essential for monitoring vegetation health and land surface changes, which are critical in assessing drought impacts. The broad availability of satellite data from platforms like Landsat, MODIS, and Sentinel ensures consistent, long-term datasets for comprehensive drought monitoring. This technology supports the calculation of vegetation indices such as NDVI and EVI, which are key indicators of vegetation health and drought conditions. Additionally, optical remote sensing is cost-effective, covering large areas efficiently, thus providing a comprehensive view of drought impacts on both regional and global scales (Hazaymeh & Hassan, 2016; Sharma et al., 2022; Zhao et al., 2022).

Despite its strengths, optical remote sensing is limited by its reliance on reflected sunlight, restricting its use during nighttime and in cloudy conditions. Atmospheric interference from haze and aerosols can degrade data quality, leading to potential inaccuracies. This technology primarily monitors surface-level conditions, making it less effective for assessing deeper soil moisture and groundwater levels, which are also critical for drought monitoring. Again, similarity in spectral signatures among different vegetation types and soil conditions can complicate data interpretation, posing challenges in accurately identifying drought-affected areas(Hazaymeh & Hassan, 2016; Sharma et al., 2022; Zhao et al., 2022).

Thermal Infrared Remote Sensing (TIR)

Thermal infrared remote sensing is a technique used to measure radiation emitted from ground objects. This radiation is captured using a thermal band sensor, which operates based on fundamental laws of thermal radiation (Payra et al., 2023). This type of remote sensing typically focuses on the infrared portion of the electromagnetic spectrum, particularly within the 3-5 µm and 8-14 µm wavelength ranges. Unlike optical remote sensing, which relies on reflected sunlight, thermal infrared remote sensing detects the naturally emitted thermal radiation from objects, making it effective for capturing temperature variations and thermal properties of the Earth's surface and atmosphere.

Thermal remote sensing offers several advantages for drought monitoring. It measures land surface temperature (LST), directly linked to evapotranspiration and soil moisture levels, making it effective for early drought detection (Anderson et al., 2016; Hazaymeh & Hassan, 2016). Unlike optical methods limited to daytime operations, thermal sensors can operate both day and night, providing continuous data collection unaffected by the diurnal solar cycle. This capability is crucial for comprehensive drought monitoring, allowing for timely and frequent updates (Schott et al., 2012). However, a significant challenge in thermal infrared remote sensing is atmospheric interference, particularly from water vapor and clouds, which can affect the accuracy of LST measurements and drought assessments (Li et al., 2013). In addition, thermal sensors often have lower spatial resolution compared to optical sensors, limiting the precision of data in heterogeneous landscapes (Ali et al., 2023). Interpreting thermal data can be complex, requiring advanced algorithms and models to accurately relate thermal signals to soil moisture and vegetation health (Alahacoon & Edirisinghe, 2022; Anderson et al., 2016). Surface characteristics, such as vegetation cover, soil type, and land use, also influence the accuracy of thermal remote sensing, complicating data interpretation (Wan et al., 2002).

Microwave Remote Sensing

Microwave remote sensing exploits the longer wavelengths of microwaves, which range from 1 millimeter to 1 meter, enabling the penetration of clouds, rain, and even the surface of the Earth to some extent. These techniques utilize both active and passive sensors. Active microwave sensors, such as Synthetic Aperture Radar (SAR), emit microwave signals towards the Earth's surface and analyse the reflected signals. This method allows for detailed mapping of surface properties, including soil moisture, which is a direct indicator of drought conditions. The information obtained can be used to assess drought severity, duration, and spatial extent by measuring changes in soil moisture over time(Vreugdenhil et al., 2022).Passive microwave sensors detect natural microwave emissions from the Earth’s surface. These emissions vary with soil moisture content and vegetation water content, making passive microwave remote sensing an effective tool for monitoring drought. For instance, the SMOS (Soil Moisture and Ocean Salinity) satellite provides soil moisture data that can be correlated with drought indices such as the Standardized Precipitation Index (SPI) to identify drought patterns (Cheng et al., 2021).

The primary strength of microwave remote sensing is its all-weather capability, allowing for continuous monitoring without interference from cloud cover or darkness. This is particularly valuable in drought monitoring where consistent data collection is critical(Cheng et al., 2021). Microwave sensors can also provide high-resolution data (especially temporal), which is essential for continuous real-time drought assessment. For example, the study by Lin et al., (2024)demonstrated the effective use of Sentinel-1 and Sentinel-2 satellites with a 12- and 10-day temporal resolution respectively, to retrieve surface soil moisture data., in another example, the CPC Morphing Technique (CMORPH) which uses (low orbiter satellite microwave observations),produces global precipitation analyses at very high temporal resolution (30 minutes) over a 20-year period of record from January 1998 to present (NCEI-NOAA, 2024). This significantly improves the precision of drought monitoring and demonstrates the ability of microwave sensors to capture data at short intervals (daily or even multiple times per day) allowing for real-time drought monitoring and early warning systems. Again, Satellite-based microwave sensors offer extensive global coverage, making it possible to monitor drought conditions on a global scale. For example, the CMORPH product has a near total coverage of the globe covering between (60°N–60°S). This is particularly beneficial for regions with limited ground-based observation networks (Zhu et al., 2019). Another important strength of microwave remote sensing is its penetration ability. The L-band (1.4 GHz) microwave sensors found on the SMOS and SMAP missions is ideal for measuring soil moisture because of its unique ability to penetrate deeper into the soil (as deep as ~5 cm). This allows for the assessment of subsurface soil moisture, which is critical for understanding root-zone moisture and long-term drought impacts (Cheng et al., 2021)

While passive microwave sensors provide valuable data, their spatial resolution is generally lower compared to optical sensors. This limitation can affect the ability to perform detailed local drought assessments and identify small-scale drought conditions(Lin et al., 2024). Also, interpreting microwave remote sensing data requires complex algorithms and models. The accuracy of drought monitoring depends heavily on the calibration and validation of these models, which can introduce uncertainties (Zhu et al., 2019). Another limitation pertains to the development, and maintenance costs of microwave remote sensing satellites and ground stations. This financial barrier can limit the widespread adoption and continuous operation of these systems in some regions (Cheng et al., 2021)

Recent advancements in microwave remote sensing involve integrating data from multiple sources to enhance drought monitoring accuracy. A good example is the improved Temperature-Vegetation-Soil Moisture Dryness Index (iTVMDI) which combines passive microwave data with optical and infrared data to monitor drought more effectively. This index has shown strong correlations with meteorological data, providing a reliable measure of drought conditions (Z. Wang et al., 2020). Despite these Advancements, challenges still remain in integrating microwave data with other datasets due to differences in spatial and temporal resolutions. Research continues to address these issues by developing new algorithms and models that can better harmonize data from various sources to improve drought monitoring capabilities (Wei et al., 2021)

Evaluation of various Remote Sensing Techniques used for Drought Monitoring in SSA

Sub-Saharan Africa (SSA) encompasses the regions of Africa located south of the Sahara Desert, spanning an area characterized by diverse climates and landscapes. The region includes 46 countries, exhibiting a range of Agro-ecological zones (AEZs) that are critical for agricultural activities and food security.

According to Winrock (1992) SSA can be divided into five (5) primary agroecological zones (AEZs). These are; the Humid Forest Zone characterized by high annual rainfall exceeding 1,500 mm and dense tropical rainforests, supporting crops such as cocoa, rubber, and oil palm; the Sub-Humid Zone which has moderate rainfall between 1,000-1,500 mm with mixed woodlands and savannas, suitable for cereals like maize and root crops such as cassava; the Semi-Arid Zone which experiences lower rainfall of 500-1,000 mm, featuring open savannas and grasslands, and is suitable for drought-resistant crops like millet and sorghum; the Arid Zone which has very low rainfall under 500 mm with sparse vegetation, limited to nomadic pastoralism and sparse cropping; and the Highland Zone which varies climatically with cooler temperatures due to altitude, supporting high-value crops like coffee and tea.

Optical-Based RS Indices in SSA

Optical remote sensing is a pivotal technology for drought monitoring, utilizing various indices to assess vegetation health, soil moisture, and overall drought conditions. Key indices include the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and the Normalized Difference Water Index (NDWI). NDVI, which measures vegetation greenness by comparing red and near-infrared reflectance, is widely used due to its simplicity and effectiveness in indicating vegetation health and stress levels (Pettorelli, 2013). EVI improves upon NDVI by reducing atmospheric and soil background noise, providing a more accurate assessment of vegetation vigor in areas with dense canopies (Huete et al., 2002). NDWI, on the other hand, is effective for assessing water content in vegetation and soil, making it a crucial index for drought monitoring (Gao, 1996).

Table 1: Characteristics of Optical-Based Indices and their Applicability in SSA

Index	Spatial Resolution	Temporal Resolution	Data Availability for Sub-Saharan Africa	Strengths	Limitations	References	Recommendation for use in SSA
NDVI (Normalized Difference Vegetation Index)	>Landsat satellites provide 30-meter spatial resolution >MODIS at a range of 250 meters to 1 KM and >AVHRR at 1–8-KM spatial resolution	>MODIS and AVHRR provide daily NDVI data >Landsat, data is retrieved after every 16 days.	>MODIS is Freely available since 2000. >Landsat Data is available from 1972 to present. >AVHRR Data is available since 1981.	>Extensive spatial coverage >Long-term datasets from MODIS and AVHRR >Frequent data collection	> Can be affected by cloud cover, > May not differentiate well between different types of vegetation, >Variations in soil colour and moisture can influence NDVI values,	(Hazaymeh& K. Hassan, 2016) (Peng et al., 2020) (DEAfrica, 2021) (Safiétou et al., 2022)	>NDVI will be more suited to Monitoring Drought in the Semi-Arid Zonesof SSA
NDWI (Normalized Difference Water Index)	> Sentinel-2 provides 10 m spatial resolution, > Landsat-8 offers 30 m spatial resolution,. > MODIS and VIIRS data at 250 m to 1 km resolution	>MODIS and VIIRS provide daily observations. >Sentinel-2 and Landsat-8 have revisit periods of 5-16 days, >> Older Landsat missions and similar sensors have 16-day revisit times	Data from Sentinel-2, Landsat-8, and MODIS are readily available and extensively used for monitoring environmental conditions, including drought in Sub-Saharan Africa	>High sapatial resolution >Facilitates near-real-time monitoring, crucial for timely drought response and management. >Effective in regions with dense vegetation.	>Optical sensors like Sentinel-2 and Landsat-8 can be hindered by cloud cover, affecting data quality. >Lower revisit times can lead to gaps in continuous monitoring, especially in older missions of Landsat	(Moser et al., 2014) (Bhaga et al., 2020) (Bhaga et al., 2021) (IyinoluwaOjumu, 2023)	>Highly recommended for use in Sub-Humid Zone of SSA >Could also be effective in Humid Forest Zones and the Semi-Arid Zones of SSA
SWIR-PWSI (Short wave infra-Red Perpendicular Water Stress Index)	>Sentinel-2 provides a spatial resolution of 10 meters. >Landsat offers 30 meters resolution for its SWIR bands >MODIS provides a coarser spatial resolution of 500 meters for SWIR bands	>MODIS offers 1-2 days revisit times >Sentinel-2 has a revisit time of 5 days at the equator, and > Landsat has a revisit time of 16 days, offering lower temporal resolution	Data availability for Sub-Saharan Africa is supported by several satellite missions like MODIS, Sentinel-2 and Landsat.	> Highly sensitive to vegetation water content > The index can be derived from various satellite platforms, > SWIR bands can penetrate through thin clouds,	>Dense cloud cover can still create data gaps. > Variations in sensor calibration across different platforms can affect the consistency of SWIR-PWSI data. >Accurate computation of SWIR-PWSI relies on multispectral data, which may not always be available or may come at higher costs	(Fensholt & Sandholt, 2003) (Feng et al., 2013) (Bhaga et al., 2020) (Wu & Li, 2021) (Bhushan et al., 2024) (Komi et al., 2024)	>Highly recommended for use in the Humid Forest Zone with dense vegetation >it could also be effective for use in the Highland zone and Subhumid zones of SSA

Thermal Infrared-Based RS Indices in SSA

Thermal infrared remote sensing-based drought-monitoring indices are crucial tools for assessing and managing drought conditions by capturing surface temperature variations and evapotranspiration rates. These indices, such as the Temperature Condition Index (TCI), Vegetation Health Index (VHI), and the Temperature Vegetation Dryness Index (TVDI), utilize thermal infrared data to monitor the thermal state of the surface and its vegetation. TCI, for instance, reflects the thermal state of the vegetation and is derived from the land surface temperature (LST) measurements, providing an insight into the severity of drought by comparing current LST to historical values (Karnieli et al., 2010). Similarly, VHI combines TCI with the Normalized Difference Vegetation Index (NDVI) to detect drought stress on vegetation (Rojas et al., 2011). TVDI, on the other hand, utilizes the relationship between LST and NDVI to estimate soil moisture content and drought severity (A. Chen et al., 2023; J. Chen et al., 2011)

These indices have been validated and applied in various regions worldwide, demonstrating their effectiveness in early drought detection and mitigation strategies. For instance, a study on the application of these indices in the African Sahel region showed a strong correlation between TVDI and ground-based drought measurements, highlighting the utility of thermal infrared remote sensing in areas with limited in-situ data (Sandholt et al., 2002). By integrating these indices with other meteorological and hydrological data, a more comprehensive and timely assessment of drought conditions can be achieved, aiding in better decision-making for drought management.

Microwave-Based RS Indices in SSA

Microwave remote sensing has emerged as a crucial tool for drought monitoring, leveraging its sensitivity to soil moisture and vegetation conditions. The Soil Moisture Active and Passive (SMAP) satellite, for example, provides critical data for assessing soil moisture, which is essential for understanding agricultural drought. In a study focusing on Henan Province, China, a random forest model using SMAP data achieved high accuracy in detecting drought conditions, illustrating the potential of microwave remote sensing for agricultural applications (Tian & Zhu, 2024). Similarly, in northeastern China, the Soil Moisture and Ocean Salinity (SMOS) satellite demonstrated effectiveness in capturing drought patterns, showing high correlation with traditional meteorological indices like the Standardized Precipitation Index (SPI) (Cheng et al., 2021).

Moreover, the development of the Standardized Vegetation Optical Depth Index (SVODI) combines data from multiple passive microwave sensors to monitor vegetation conditions, providing a reliable indicator of drought impacts on plant health (Moesinger et al., 2020). These indices are particularly advantageous due to their ability to operate under cloud cover and low light conditions, offering consistent data collection compared to optical sensors. However, challenges remain in integrating these data with other hydro-meteorological variables to refine drought monitoring models further (Vreugdenhil et al., 2022).

Table 2: Characteristics of Thermal Infrared-Based Indices and their Applicability in SSA

Index	Spatial Resolution	Temporal Resolution	Data Availability for Sub-Saharan Africa	Strengths	Limitations	References	Recommendation for use in SSA
TCI (Temperature Condition Index)	> Advanced Very High-Resolution Radiometer (AVHRR) can offer 1 km spatial resolution. > MODIS can provide data at 250 m to 1 km	MODIS data offers an 8-day temporal resolution,	TCI data is accessible through platforms such as NASA's Earth Observing System Data and Information System (EOSDIS) and NOAA's National Environmental Satellite, Data, and Information Service (NESDIS).	>sensitive to surface temperature changes, and effective in detecting thermal anomalies associated with drought. > Can be combined with vegetation indices like NDVI, and VCI to enhances the accuracy of drought assessments > Frequent updates provided by satellites like MODIS enable near-real-time monitoring.	> Can be affected by dense cloud cover, > Accurate calibration and validation of TCI require extensive historical temperature data. > While high spatial resolution data is beneficial, it also requires significant computational resources and storage, which can be challenging for large-scale applications.	(Kogan, 1995) (Patel et al., 2012) (Drought Management Info, 2016) (Mullapudi et al., 2023)	> Highly recommended for use in Semi-Arid Zone of SSA > Could also be effective in subhumid and arid Zones of SSA
VHI (Vegetation Condition Index)	> MODIS data offers a spatial resolution of 250 meters to 1 km. > Advanced Very High-Resolution Radiometer (AVHRR) offers a resolution of 4 km to 16 km,	> VHI benefits from the high temporal resolution of AVHRR data, which is available on a daily basis	VHI data can be accessible for SSA through platforms like AVHRR, NOAA STAR and the MODIS Terra/Aqu satellite products.	>VHI combines information from both the Vegetation Condition Index (VCI) and the Temperature Condition Index (TCI) > Provides high temporal. >Has long-term data availability and established methodology	> Accuracy of can be affected by cloud cover, > Coarser resolutions may miss finer-scale drought impacts. > Variations in data quality due to sensor differences and atmospheric conditions can affect the consistency of VHI data over time and space.	(Rojas et al., 2011) (Sheffield et al., 2014) (TerwayetBayouli et al., 2023) (Gbaguidi et al., 2024) (Bento et al., 2018)	> Highly recommended for use in the Semiarid and Sub-Humid Zones.
TVDI (Temperature Vegetation Dryness Index)	> MODIS provides data at 250m to 1km resolution. > Landsat and Sentinel can offer higher spatial resolutions of 30m to 10m respectively	> MODIS provides daily and 8-day composites. > Landsat and Sentinel provide data with a temporal resolution of 16 days and 5-10 days respectively.	Data for TVDI calculation are readily available for Sub-Saharan Africa through satellite platforms such as MODIS, Landsat, and Sentinel.	> Integrates LST and vegetation indices providing a robust measure of soil moisture and drought conditions. > TVDI does not depend on ancillary data like soil properties or precipitation > The use of vegetation indices allows TVDI to be sensitive to changes in vegetation health.	> Accurate simulation of dry and wet edges in the LST-NDVI space can be challenging, affecting the precision of the TVDI, especially in areas with sparse vegetation. > NDVI can saturate in areas with dense vegetation. EVI can mitigate this issue to some extent but introduces its own set of challenges. >The presence of bare soil can affect the NDVI values, affecting the accuracy of the TVDI in areas with sparse vegetation	(Du et al., 2017) (A. Chen et al., 2023) (Guo et al., 2023) (Przeździecki et al., 2023)	> Highly recommended for use in the Semiarid and Sub-Humid Zones. > Could also be effective in the Arid Zone

Table 3: Characteristics of Microwave-Based Indices and their Applicability in SSA

Index	Spatial Resolution	Temporal Resolution	Data Availability for Sub-Saharan Africa	Strengths	Limitations	References	Recommendation for use in SSA
NBMI (Normalized Backscatter Moisture Index)	> Sentinel-1 offers data at 10 meters spatial resolution >SMAP offers data at 36 km	>Sentinel-1 revisits every 12 days >SMAP revisitsevery 2-3 days,	Sentinel-1 and SMAP data are freely available on platforms such as the European Space Agency (ESA) and NASA.	>NBMI derived from Sentinel-1 provides detailed spatial information on soil moisture changes. > It is highly sensitive to changes in soil moisture. >Radar backscatter is not affected by cloud cover.	>Radar data requires complex processing and calibration. >Variability in surface roughness can affect backscatter readings >Radar signals primarily capture moisture content only in the top few centimetres of the soil.	(Shoshany et al., 2000) (Q. Gao et al., 2017) (Bormudoi et al., 2023) (Tao et al., 2023) (Komi et al., 2024)	> Highly recommended for use in the Semiarid Zones. > Could also be effective in the Arid and Sub-Humid Zones.
VOD (Vegetation Optical Depth)	>AMSR-E and AMSR-2 have coarse spatial resolutions of about 25 km. >Sentinel-1 can achieve spatial resolutions as high as 1 km.	>AMSR-E and ASCAT provide data ranging from daily to every few days. > Sentinel-1 data, has a repeat cycle of approximately 12 days,	>VOD data is widely available on various satellite missions such as AMSR-E, AMSR-2, SMOS, SMAP, and Sentinel-1. >Also available on VODCA (Vegetation Optical Depth Climate Archive),	>VOD is directly sensitive to the water content in vegetation >Microwave-based VOD measurements can penetrate clouds >VOD products utilize multiple microwave frequencies, which captures different vegetation characteristics from leaf moisture to stem biomass.	>VOD data, from older sensors, have coarse spatial resolutions >Combining data from multiple sensors with different frequencies and spatial resolutions can be challenging >High spatial resolution data like those from Sentinel-1 have limited temporal resolution	(Moesinger et al., 2020) (Vreugdenhil et al., 2020) (Zhou et al., 2022) (Zotta et al., 2024)	> Highly recommended for use in the Humid Forest and Sub-Humid Zones. > Moderately effective in the Semi-Arid and Highland Zones.
MPDI (Microwave Polarization Difference Index)	AMSR-E has a spatial resolution of about 25 km. >SSMI (Special Sensor Microwave/Imager) data are available at >>25 km resolution for lower frequencies (19, 22, 37 GHz) >>and 12.5 km for higher frequencies (85 GHz).	>AMSR-E has typically 1-2 days temporal resolutions. >SSMI has about 1-2 days as well.	Data availability is generally good for SSA	>MPDI is highly sensitive to soil moisture and vegetation water content. > Generally, has frequent revisit time ensuring near real-time monitoring. >It can penetrate clouds and provide reliable data under various weather conditions.	> It relativelyhas coarse spatial resolution compared to optical based indices. >Calibration and validation of MPDI data can be complex. >Different frequency channels provide different resolutions, which can complicate data integration and interpretation	(Becker & Choudhury, 1988) (Teng et al., 1995) (Felde, 1998) (S. Wang et al., 2010) (Meier et al., 2021)	> Highly recommended for use in the Humid Forest, Sub-Humid, and Semi-Arid Zones

Recommendations of RS-Based Indices in SSA

NDVI will be more suited to Monitoring Drought in the Semi-Arid Zone as it generally experiences less cloud cover compared to the Humid Forest Zone. Also, NDVI performs better in areas where vegetation is not overly dense and the semi-Arid Zone has a sparse vegetation compared to the lush vegetation of the Humid Forest Zone.

For NDWI, which is most effective in areas with significant vegetation, the Sub-Humid Zone appears to be its best match as it has moderate vegetation cover with mixed woodlands and savannas where it can detect changes in water content and early stages of drought. However, it could also be effective in the Humid Forest and Semi-Arid Zones of SSA, though it may be affected by challenges related to cloud cover.

The Short-Wave-Infra-Red of SWIR-PWSI has the ability to penetrate thin clouds which makes it suitable for assessment of the Humid Forest Zone with dense vegetation, and frequent cloud conditions. It could also be effective for use in the Highland zone and Subhumid zones of SSA.

TCI which is Thermal infrared based will be highly suited for use in Semi-Arid Zone of SSA which has minimal cloud cover and is vulnerable to drought occurrence. TCI could also be effective in Sub-Humid and Arid Zones of SSA. However, challenges such as dense cloud conditions may result in data gap especially in Sub-Humid Zones.

VHI is an effective tool for monitoring drought impacts on vegetation health and temperature stress. Hence, it will be well suited to monitoring the Semi-Arid and Sub-Humid Zones having sufficient vegetation cover to monitor any changes in vegetation health as well as temperature stress.

TVDI is highly recommended for use in the Semiarid and Sub-Humid zones. The semi-arid zone is prone to drought and features moderate vegetation cover while the Sub-Humid zone experiences moderate rainfall and periods of drought. TVDI's sensitivity to vegetation health changes makes it valuable for monitoring and managing drought conditions these regions. TVDI could also be effective in the Arid zone.

NBMI has high sensitivity to soil moisture changes which makes it an ideal tool for drought monitoring in the Semi-Arid zone of SSA which is highly susceptible to drought due to its lower rainfall. It could also be effective for use in Arid and Sub-Humid zones. However, radar signals which captures moisture content in only the top few centimeters of the soil may not fully reflect deeper soil moisture conditions during prolonged droughts common to the arid zones.

For VOD, its ability to penetrate clouds ensures consistent data acquisition, making it highly suitable for monitoring vegetation health in Humid Forest and Sub-Humid zones having frequent cloud cover which can obstruct optical remote sensing methods. VOD may also be moderately suitable to the Semi-Arid and Highland Zones.

Finally, MPDI also having the ability to penetrate clouds is highly suitable for monitoring soil moisture and vegetation water content in dense forest as well sparsely vegetated regions. Thus, it will be suited for monitoring the Humid Forest, Sub-Humid and the Semi-Arid zones of SSA.

CONCLUSION

In conclusion, remote sensing indices are essential tools for effective drought monitoring and management in Sub-Saharan Africa, a region characterized by diverse climatic zones and varying levels of vegetation cover. Optical indices like NDVI and NDWI excel in areas with moderate to sparse vegetation but are challenged by cloud cover and dense vegetation. Thermal infrared indices, such as TCI and VHI, provide valuable information on temperature stress and vegetation health, with TCI being particularly suited for semi-arid zones and VHI for semi-arid and sub-humid regions. Microwave-based indices, including NBMI, VOD, and MPDI, offer robust solutions for assessing soil moisture and vegetation water content, especially in regions with frequent cloud cover. The integration of these indices into a comprehensive drought monitoring framework can enhance early detection and response strategies. Future research should focus on improving data integration techniques and validating these indices with ground-based observations to refine drought management practices in SSA.

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