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Spatiotemporal Assessment of Drought under Climate Variability in Dodoma Region, Tanzania

Alex P. Lubida,[*] Joseph M. Mango[**] & Monalisa B. Mahenge

Abstract

While several previous studies have described drought conditions in semiarid areas by incorporating precipitation deficits and poor rainfall distribution, this paper focuses on rainfall, temperature, and vegetation cover to quantify drought phenomena. This study used rainfall and temperature data from the TMA, with additional meteorological data obtained online, and satellite images. A quantitative assessment of drought was conducted using the Mann-Kendall model, NDVI, and Standardised Precipitation Index (SPI). Subsequently, the LANDSAT images were used to calculate NDVI to show vegetation health for a given year, and annual average temperature and rainfall were computed for each year. The rainfall data from meteorological stations were then used to calculate SPI values. The results revealed significant spatial and temporal variations in temperature and rainfall across Dodoma. The time series of climatic changes in rainfall ranged from 740 to 927mm, and temperature ranged from 25°C to 31°C for the years 2000 to 2021. The spatial distribution of vegetation health from 2000 to 2021 ranged from medium to low. Most of the SPI values in the plot are negative, indicating a consistent trend of below-average rainfall over the period. Understanding how climate variability affects future droughts in an area is important for planning appropriate adaptation and mitigation actions to manage drought risks. Further studies are recommended to focus on long-term drought mitigation methods that minimise drought risks, considering a range of drought management strategies.

Keywords: *climate variability, drought, drought trend, GIS, remote sensing*

1. Introduction

Drought is among the most devastating natural hazards affecting ecosystems, water resources, and socioeconomic development across the globe. It is defined as a deficiency of precipitation over an extended period (usually a season or more), resulting in a water shortage (Tabari et al., 2013). Its impacts have intensified in recent decades due to increasing climatic variability driven by global climate change (Shirazi et al., 2024). Climate variability is the extent to which aspects of climate (such as temperature and rainfall) differ from the average. Climate variability results from natural—sometimes periodic—changes in the circulation of the atmosphere and oceans, volcanic eruptions, and other factors.

[*]Department of Transportation and Geotechnical Engineering, University of Dar es Salaam, Tanzania: lubida@udsm.ac.tz/alex.lubida@gmail.com (Corresponding Author)
[**]Department of Transportation and Geotechnical Engineering, University of Dar es Salaam, Tanzania.

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Many people believe that drought is the most complex but least understood natural hazard, affecting more people than any other hazard (Hagman, 1984). Traditional methods of drought monitoring rely heavily on ground-based meteorological observations, such as rainfall and temperature records (Batho et al., 2019; Lukali et al., 2021; Magesa, 2024; Mugabe et al., 2024). However, these datasets are often spatially sparse and inconsistent, especially in developing countries. Climate variations—such as shifts in rainfall onset, rising temperatures, and increased evapotranspiration—have intensified drought episodes, rendering traditional monitoring insufficient (Hamal et al., 2020; Hughes, 2006).

In many parts of the world, particularly in semi-arid regions, the lack of integrated spatial datasets makes it difficult for planners to understand drought patterns, and thereby develop timely mitigation strategies. Existing studies often analyse either climatic variability or vegetation conditions separately, without combining these data to generate a more accurate representation of drought dynamics.

Geographical Information System (GIS) and Remote Sensing (RS) offer robust tools for continuous spatiotemporal assessment of drought conditions. Satellite-derived indices—such as the Normalised Difference Vegetation Index (NDVI), Normalised Difference Water Index (NDWI), Vegetation Condition Index (VCI) and Standardised Precipitation Index (SPI)—provide reliable proxies for detecting vegetation stress, soil moisture deficits, and rainfall anomalies (Kogan, 1997; McKee et al., 1993).

Satellite sensors are more effective at tracking the relationship between changes in vegetation and climate. Such a survey can be completed by satellite within a few days, and repeated in the same area at predetermined intervals. The integration of data from remote sensing technology, in both spatial and non-spatial formats, has a significant promise for drought monitoring and assessment (Price, 1990). Because they provide current data at regional and temporal scales, RS and GIS are crucial for drought identification, assessment, and management (Belal et al., 2012). An area's drought state is evaluated using a variety of drought indices. These comprise soil-, meteorological-, and satellite-based indices, such as soil moisture and the NDVI.

Zhang et al. (2009) investigated spatiotemporal variations in drought and vegetation dynamics within the Three Gorges Reservoir Area of China using NDVI data from Landsat Thematic Mapper (TM). Building on this, Paulo et al. (2012) applied the Mann–Kendall (MK) test, in combination with GIS, to evaluate spatial and temporal patterns of drought occurrence using historical records of the SPI and the Standardised Soil Moisture Index (SMI). The integration of GIS facilitated spatial visualisation, enabling the identification of regions most vulnerable to drought. Their findings revealed a notable increase in drought frequency and severity under projected climate change scenarios. Similarly, Wu et al. (2013) developed a methodological framework for drought risk assessment in the Yellow River Basin, China, producing a comprehensive map of drought vulnerability. This study incorporated GIS with SPI, NDVI, and socioeconomic datasets; and analysed historical rainfall data using SPI and the MK test. The results, consolidated into a drought susceptibility map, highlighted regions experiencing intensifying drought trends, thereby providing critical insights for formulating targeted mitigation strategies.

In many parts of sub-Saharan Africa (SSA), including Tanzania, drought episodes have become more frequent, prolonged, and spatially widespread; and hence have posed severe threats to food security, pastoralism, and livelihood stability (Limbu & Makula, 2023; Mwabumba et al., 2022). In Tanzania, increasing climate variability has intensified the frequency, duration, and severity of drought events, posing significant threats to food security, water resources, and socio-economic development. Recent studies indicate that the country has experienced multiple severe drought episodes in recent decades, affecting millions of people annually, and causing substantial agricultural and economic losses (SADRI, 2019). These trends are closely linked to changes in rainfall patterns, rising temperatures, and increased occurrence of extreme climate events.

The Dodoma Region, located in central Tanzania, is particularly vulnerable due to its semi-arid climatic conditions characterised by low and highly variable rainfall, typically averaging about 550–610mm annually, and prolonged dry seasons (Shemsanga et al., 2017). Empirical evidence shows that the region has experienced declining rainfall, rising temperatures, and shorter growing seasons over time; all of which contribute to recurrent drought conditions and reduced agricultural productivity (Shemsanga et al., 2017). Furthermore, studies across semi-arid Tanzania highlight that drought frequencies have increased in recent decades, with intensified dry spells and erratic rainfall patterns disrupting traditional farming systems, and exacerbating food insecurity (Matata et al., 2019).

Climate variability and change have also altered the temporal and spatial distribution of rainfall across Tanzania. For instance, recent analyses reveal rising temperatures and unpredictable seasonal rainfall patterns, leading to more frequent extreme events such as droughts and floods (Msomba et al., 2025). These changes are not only affecting agricultural productivity, but are also influencing water availability, ecosystem stability, and rural livelihoods.

Importantly, the impacts are more pronounced at local scales where adaptive capacity is limited, yet such localised assessments remain insufficiently explored in existing literature (ibid.).

Despite the growing body of research on climate variability and drought in Tanzania, several critical gaps remain. First, many studies have focused on general climate trends or localised case studies without integrating both spatial and temporal dimensions of drought dynamics. While tools such as the SPI have been widely applied to assess drought conditions, most applications are limited to single stations or short-time scales, thus failing to capture the full spatiotemporal variability of drought across regions like Dodoma (Hassan et al., 2014). Second, there is limited integration of long-term climatic data with spatial analytical techniques (e.g., GIS-based mapping), which are essential for understanding drought patterns across heterogeneous landscapes. Third, recent literature emphasises that local-scale climate assessments, particularly those linking climate variability to drought occurrence and impacts, remain inadequate, despite being crucial for effective adaptation planning (ibid.).

Moreover, existing studies often overlook the dynamic interaction between climate variability and drought evolution over time, especially under changing climatic conditions. Emerging research suggests that drought processes are inherently spatiotemporal and require advanced analytical frameworks to accurately capture their variability and predict future trends. However, such approaches remain underutilised in the Tanzanian context, particularly in semi-arid regions like Dodoma.

Therefore, this study aims to conduct a comprehensive spatiotemporal assessment of drought under climate variability in Dodoma Region, Tanzania. By integrating long-term climatic data with spatial analysis techniques, the study seeks to bridge existing knowledge gaps and provide a more detailed understanding of drought patterns, trends, and variability. The findings are expected to contribute to improved drought monitoring, early warning systems, and climate-resilient planning strategies in semi-arid environments.

2. Theoretical Framework

This paper is guided by the drought propagation theory that explains meteorological drought as a dynamic, cascading process that evolves through a hydrological cycle over time and space (Mishra & Singh, 2010; Van Loon, 2015a). The theory explains how an initial meteorological drought propagates into agricultural drought, and subsequently into hydrological drought. It stresses that drought signals are altered as they move through environmental systems, resulting in changes in intensity, duration, timing, and spatial extent.

These alterations are driven by both climatic variability and catchment characteristics, making the theory particularly well-suited to spatiotemporal drought analysis.

The drought propagation theory, which originates from advances in hydrology and climatology, specifically studies the relationships between atmospheric processes and terrestrial water systems. The theory was formalised in the work of Van Loon (2015b), who defined drought propagation as the transition of drought signals through the hydrological system.

The drought propagation theory is guided by the following key assumption: the sequential development of drought types, which holds that drought begins as a meteorological anomaly, and then propagates into agricultural and hydrological systems in sequence (ibid.). Time lag indicates a measurable delay between rainfall deficits and impacts on soil moisture, streamflow, and groundwater. This lag varies depending on environmental conditions (Tallaksen & Lanen, 2024). Attenuation and amplification indicate that, as drought propagates, its intensity may weaken or intensify depending on storage processes such as soil water retention and aquifer capacity (Van Loon et al., 2016). Other key assumption includes lengthening of duration, which indicate that hydrological droughts often persist longer than meteorological droughts due to the slow recovery of water storage systems. The influence of catchment characteristics indicate that local factors such as soil type, land use, and topography significantly influence drought propagation pathways and rates. Non-linearity and feedback mechanisms indicate that drought propagation is not strictly linear; feedback such as land degradation and human water use can modify its trajectory.

Based on the drought propagation theory, this study adopts a spatiotemporal conceptual framework that relates climate variability to drought evolution in Dodoma Region. The framework consists of the following components: *climate drivers*, which are the variabilities in rainfall and temperature; *initial drought signal*, which is a meteorological drought assessed using SPI; *propagation pathways*, which are the transmission of drought through soil moisture and hydrological systems; *impacts*, which are agricultural stress and water resource deficits; *modulating factors*, which are soil properties, land use, and groundwater storage; and *outcomes*, which are spatial and temporal drought patterns across Dodoma Region. This framework supports the integration of multi-source data and index analysis, enabling a comprehensive assessment of drought dynamics.

The application of the drought propagation theory is relevant for Dodoma Region due to its semi-arid climate and high rainfall variability. In this context, rainfall deficits frequently trigger meteorological drought, which propagates rapidly into agricultural drought due to limited soil moisture retention.

Hydrological drought may persist due to low groundwater recharge and high evapotranspiration rates. Spatial variability in soils and land use lead to heterogeneous drought impacts across areas.

3. Context and Methods

3.1 Study area

Dodoma Region is located between latitudes 4° and 7° South, and longitudes 35° and 37° East, in the centre of Tanzania (Figure 1). Dodoma is adjacent to four regions: Morogoro to the East, Manyara to the North, Singida to the West, and Iringa to the South. It is the capital of Tanzania, with a population of 765,179 as of the 2022 census. The region is the 12th-largest in the country, covering a total land area of 41,310km². The region is subdivided into seven districts: Mpwapwa, Chemba, Bahi, Dodoma Urban/City, Kondoa, Kongwa, and Chamwino.

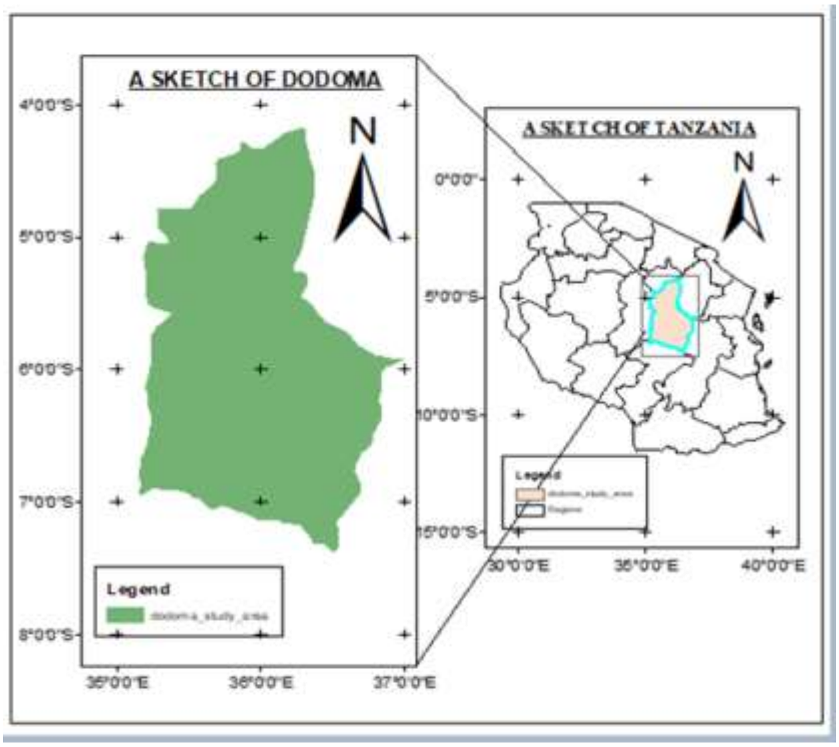

Figure 1: Location of the Study Area

Dodoma Region features a semi-arid climate, with warm to hot temperatures year-round. While average highs are somewhat consistent throughout the year, average lows dip to 13°C in July. Dodoma averages 610mm of rainfall per year, the vast majority of which occurs during its wet season between December and April. The remainder of the year comprises the region's dry season.

The two main data sets used in this study were satellite images and meteorological dataset, which were used to show the different spatial and temporal distributions and, later, to study the drought trend in the area.

3.2 Data Collection Methods

This study employed both primary and secondary data collection methods to assess the spatiotemporal characteristics of drought under climate variability in Dodoma Region, Tanzania. The data collection methods focus on acquiring climatic, hydrological, remote sensing, and geospatial datasets necessary for drought monitoring and spatial analysis.

3.2.1 Secondary Data

Secondary data refers to existing data collected by institutions or previous studies, and used by a researcher for analysis. Secondary datasets form the core of spatiotemporal drought assessment because drought analysis requires long-term climatic and environmental records.

Historical rainfall records were required to assess meteorological drought and rainfall variability. The rainfall data were acquired from the Tanzania Meteorological Authority (TMA) in .xls format; and contained monthly data for each year from 2000 to 2021 (see Table 1). The TMA maintains several rainfall and meteorological observation stations in Dodoma Region. The main rain-gauge/rainfall stations include the Dodoma Meteorological Station, Dodoma Airport, Mpwapwa, Kongwa, Kondoa, Bahi, Chamwino, Chemba, and the Hombolo Agro-meteorological Station.

Table 1: Key Datasets Used in the Study

Data Type	Name	Spatial Resolution	Temporal Resolution	Path	Acquisition Dates	Source
Satellite Imagery	-LANDSAT 8 -LANDSAT 7 -LANDSAT 5	30m x 30m	16 days	168/63 168/64 168/65 169/63 169/64 169/65	2000, 2005, 2010, 2015 and 2021	USGS https://earthexplorer.usgs.gov/
Climatic data	-Temperature -Rainfall	~4-km			2000 to 2021	https://climate.northwestknowledge.net/TERRACLIMATE/index_ directDownloads.php

Additional meteorological data, consisting of temperature and rainfall, were acquired from the Climatic Research Unit (CRU), CHIRPS climate data, and the NASA Power Access: these data were used to supplement station observations and improve spatial coverage across the region. It was difficult to acquire enough additional data—such as humidity, sunshine, and soil moisture—for the study site. Such data were acquired in the Network Common Data Format (NetCDF) for each year. Both datasets have the spatial resolution of 0.5˚ × 0.5˚ latitude-longitude, which is roughly equivalent to 55 kilometres at the equator. The rainfall data were primarily used to compute the SPI, while the temperature data were used to support climate variability analysis, and the interpretation of drought dynamics.

A Landsat image is a satellite-captured image of the Earth's surface, provided by a joint NASA/USGS program that has operated since 1972. These medium-resolution (30-meter) images provide a continuous, reliable, and free records of land use, environmental changes, and natural disasters. LANDSAT images were obtained in the GeoTIFF data format. When acquiring data for each year, cloud cover between 0% and 5% was considered.

3.2.2 Primary Data

The primary data included ground verification surveys that were conducted in selected areas of Dodoma Region using QGIS base maps, and the Google Earth application. The verification of vegetation was performed by visualising and comparing satellite-derived vegetation indices (NDVI) with actual vegetation conditions observed in the field using online images. Key informant interviews (KIIs) were conducted to gather additional information and elaboration from officers at the TMA. Moreover, field observations, using alternative online platforms, supported validation of remotely sensed drought indicators.

3.3 Data Processing

The climatic datasets were screened and processed before analysis. The procedures included data cleaning, removal of missing and inconsistent records, homogeneity testing, and temporal aggregation into monthly and annual datasets. Rainfall time series were organised into continuous datasets suitable for SPI computation and trend analysis. The rainfall and temperature data acquired as NetCDF files were then imported into QGIS for preprocessing. This conversion was done to enable spatial analysis within a GIS environment. NetCDF is primarily used to store multidimensional climate variables across time and space. Multidimensional tools were used to convert the data into raster format and a shapefile covering Dodoma Region.

The NetCDF data was converted to raster format, and then the raster was exported to the projected data frame for UTM zone 36 South, into which the region belongs. The projection process was important to ensure that all datasets were set in a common coordinate reference system. The cell statistic was used to calculate the average temperature and rainfall for each of the years 2000, 2005, 2010, 2015, and 2021.

Thereafter, the map was converted to points, and Inverse Distance Weighted (IDW) interpolation was performed. The IDW method operates using point-based input data. Each point carried climatic attribute values corresponding to its spatial location. The IDW operates on the principle that points closer together are more similar than those farther apart; in this way, it preserves observed data values without generating unrealistic extremes. The processing produced smooth and continuous spatial distribution maps of temperature and rainfall for the study area.

The images acquired, especially the Landsat 7 images, had many strips; so corrections were applied to obtain clear images and visualise the changes after the NDVI calculations. The software used here was QGIS, version 3.40; in which we had to correct the specific bands we would use for the calculation to remove scan-line errors. The bands we corrected were bands 4 and 3 for each row and path image. The Landsat 5 and 8 images were suitable for performing the calculations. Figure 2 summarises the methodology flow chart.

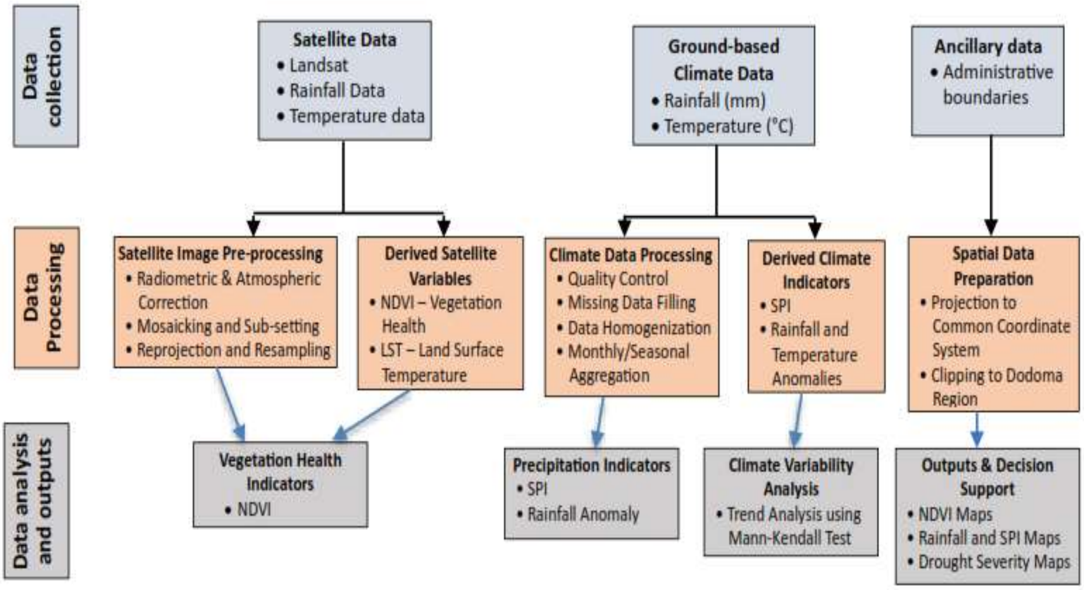

Figure 2: A Flow Chart Showing the Sequential Procedure

3.4 Data Analysis

The study employed both statistical and geospatial data analysis techniques to assess the spatiotemporal characteristics of drought under climate variability in Dodoma Region. The climatic data, including rainfall and temperature records obtained from the meteorological stations, were analysed to determine temporal trends and variability in climate conditions across the region. The NDVI derived from satellite imagery was analysed to assess vegetation health. Figure 2 shows the flowchart of the stages of data collection, processing, and analysis.

The rainfall data that were acquired from the TMA as an Excel file were used to calculate the SPI for each particular year. In the calculation of SPI, the 12-time series of calculating SPI was used, as shown by the formula:

$$SPI = \frac{X_i - X_m}{SD}$$

Where: SPI is a Standardised Precipitation Index; X_i is annual, seasonal, or monthly rainfall; X_m is a long-term mean; and SD is the standard deviation.

The computed SPI values were used to plot the intensity and frequency of drought for each year, and were spatially integrated in QGIS to generate drought severity maps for different periods.

The SPI values were used to show the trend of how it was significant in certain years, and when it was not significant in other years; and for this, the Mann-Kendall (MK) test was used. Temporal drought trends and climate variability were analysed using the MK trend test, a non-parametric statistical method widely used in hydro-climatic studies.

The Mann–Kendall statistic is expressed as:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(x_j - x_k)$$

The standardised test statistic is:

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{S+1}{\sqrt{Var(S)}} & S < 0 \end{cases}$$

The MK test was used to detect increasing or decreasing rainfall trends, identify temporal drought patterns, and assess climate variability over time. Trend outputs were integrated into GIS to spatially represent climatic changes across districts. Therefore, the sequential Mann-Kendall test was performed in RStudio, where SPI values were imported alongside the years, and the Sequential Mann-Kendall package was used to generate a graph showing the drought trend.

Moreover, GIS and remote sensing techniques were integrated with SPI and Mann–Kendall analyses to enhance spatial drought assessment. Integration procedures included overlaying SPI drought maps with NDVI maps, and spatial comparisons of vegetation stress and precipitation anomalies.

3.4.1 NDVI Analysis

The NDVI was used to assess vegetation conditions and drought stress across the region. The NDVI is a widely used remote sensing indicator that measures vegetation greenness and photosynthetic activity using satellite imagery. A healthy vegetation strongly reflects near-infrared radiation and absorbs red light, while a stressed vegetation shows reduced reflectance differences.

After preprocessing the data, the images for each year were processed to calculate NDVI, which was calculated for the infrared and near-infrared bands using the formula:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

Where: NIR = Near Infrared band reflectance, and Red = Red band reflectance.

Here, band 4 (NIR) and band 3 (Red) were used for Landsat 7 and 5, and band 5 (NIR) and 4 (Red) were used for Landsat 8.

The raster calculations were done as:

$$NDVI = \frac{BAND\ 5 - BAND\ 4}{BAND5 + BAND4} \qquad \text{Landsat 8 images}$$

$$NDVI = \frac{BAND\ 4 - BAND\ 3}{BAND\ 4 + BAND\ 3} \qquad \text{Landsat 7 and 5 images}$$

The generated NDVI values were classified into vegetation condition categories to indicate vegetation health and drought severity (Table 1).

Table 1: NDVI Values Classified Into Vegetation Categories

NDVI Range	Vegetation Condition	Drought Interpretation
< 0.0	Water/Bare surfaces	Extremely degraded
0.0–0.2	Very sparse vegetation	Severe drought stress
0.2–0.4	Sparse vegetation	Moderate drought stress
0.4–0.6	Moderate vegetation	Mild drought stress
0.6–0.8	Dense healthy vegetation	Normal condition
> 0.8	Very dense vegetation	Very healthy vegetation

The calculation was done per each band and row, meaning one after the other; and then after all the paths were done, the mosaic to combine all images was performed to form a single image. Later we added the shape file while the image was clipped, and the Dodoma Region—which showed the spatial distribution of vegetation health—was able to be formed. This was done for all the years 2000, 2005, 2015, and 2021. However, we were unable to acquire the Landsat images for the year 2010. Validations were performed on certain parts using online platforms such as Google Earth and GIS base maps.

The NDVI images from different years and seasons were overlaid in QGIS to assess vegetation changes over time. The overlay analysis enabled the visualisation of drought propagation across time and space. The NDVI anomaly analysis was conducted to determine deviations from normal vegetation conditions using the equation:

$$NDVI_{anomaly} = NDVI_i - \bar{NDVI}$$

Where: $NDVI_i$= NDVI for a given year or season, and $\bar{NDVI}$ = long-term mean NDVI.

4. Results and Discussion

4.1 Spatial and Temporal Distribution of Rainfall and Temperature

The rainfall and temperature were analysed to the level that yielded the output shown in Figure 3, which illustrates the visualised maps for average rainfall for 2000–2021. The time series of climatic changes shows rainfall ranging from 740 to 927mm, and temperature ranging from 25°C to 31°C for the same period.

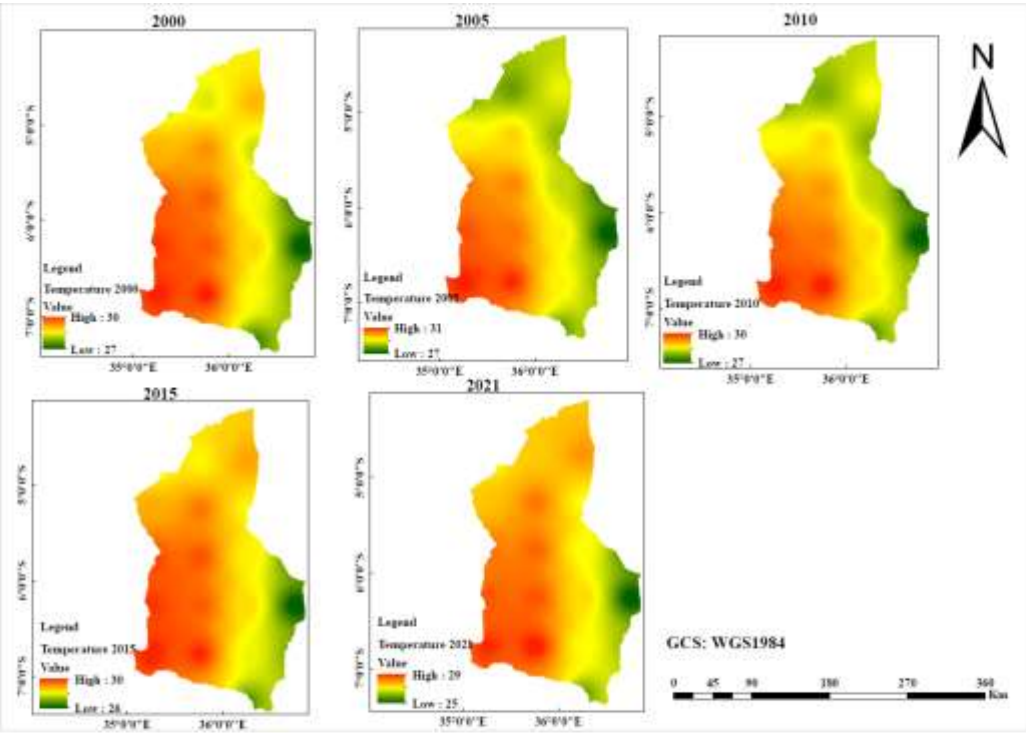

Figure 3: Visualised Maps for Average Rainfall for 2000–2021.

Rainfall distribution in the region revealed strong spatial and temporal variability throughout the study period. The eastern, north-eastern and southern-eastern sections—that is, Mpwapwa, Kongwa, Kondoa, some parts of

Chemba, and some parts of Chamwino districts—consistently received relatively higher rainfall amounts; whereas the western and central-western areas—that is, parts of Chemba, parts of Chamwino, and some parts of Bahi districts—remained comparatively dry. The rainfall maps showed no consistent increase or decrease in rainfall trend, significant year-to-year fluctuations and expansion and contraction of wetter zones over time. Moderately wetter conditions were observed around 2010, while drier conditions dominated in 2000 and 2015. Despite occasional improvements, the western part of Dodoma remained persistently dry throughout the study period, indicating chronic susceptibility to drought and water stress.

Figure 4 shows the visualised maps of average temperature for 2000–2021. The temperature maps show a general warming trend across Dodoma between 2000 and 2021. Higher temperatures were consistently observed in the western and south-western parts of the region, including parts of Chemba, Chamwino, and Bahi districts; while relatively calm conditions persisted in the eastern and north-eastern areas. Over time, warm zones expanded spatially, cooler areas gradually reduced, and temperature intensity increased, especially by 2021. The year 2021 saw the highest prevalence of high temperatures, indicating intensified heat. The persistent warming trend suggests increasing climatic stress, enhanced evapotranspiration, and rising drought vulnerability across the region.

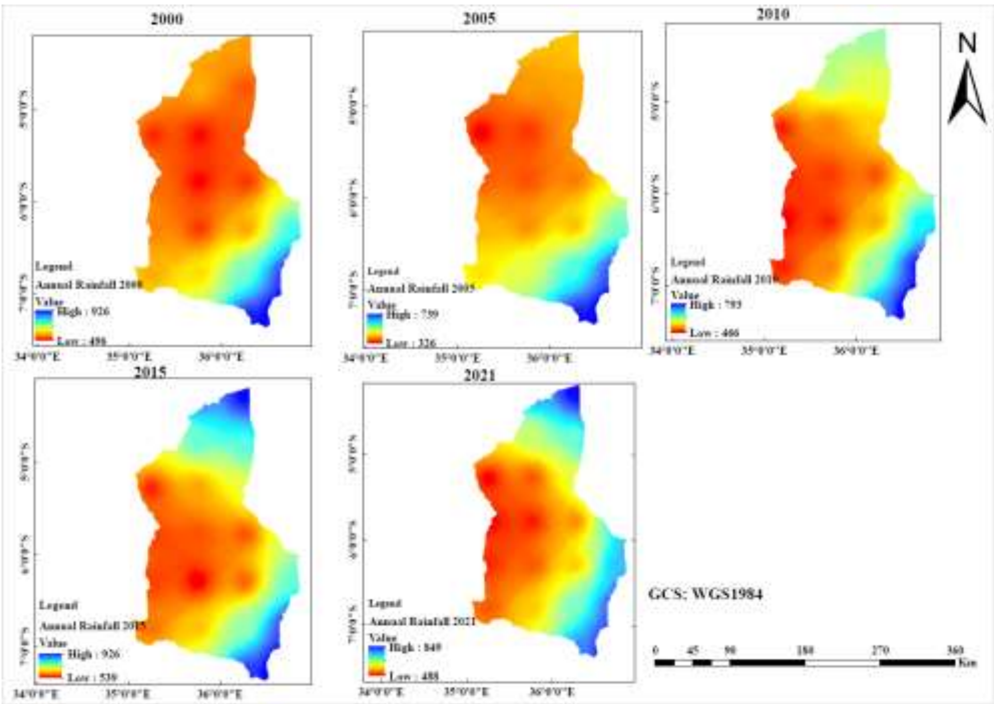

Figure 4: Visualised maps of Average Temperature for 2000–2021.

Rainfall and temperature are the major factors that influence the well-being of communities in Tanzania (Mrema, 2012; Ripkey et al., 2021). The results show greater variability in total annual rainfall over the last 20 years in Dodoma Region. According to Myeya (2021), rainfall variability in the study area is influenced by local, regional, and global variations. The observation raises concern that rising temperatures and declining rainfall will continue to exacerbate water stress; thereby affecting surface water availability for human uses (Myeya, 2021; Ripkey et al., 2021).

4.2 Vegetation Health Spatially and Temporally

Figure 5 shows visualised maps of NDVI for the period 2000–2021, using remote sensing data (Landsat 8, Landsat 5, and Landsat 7) from the years 2000, 2005, 2015, and 2020 with a spatial resolution of 30m.

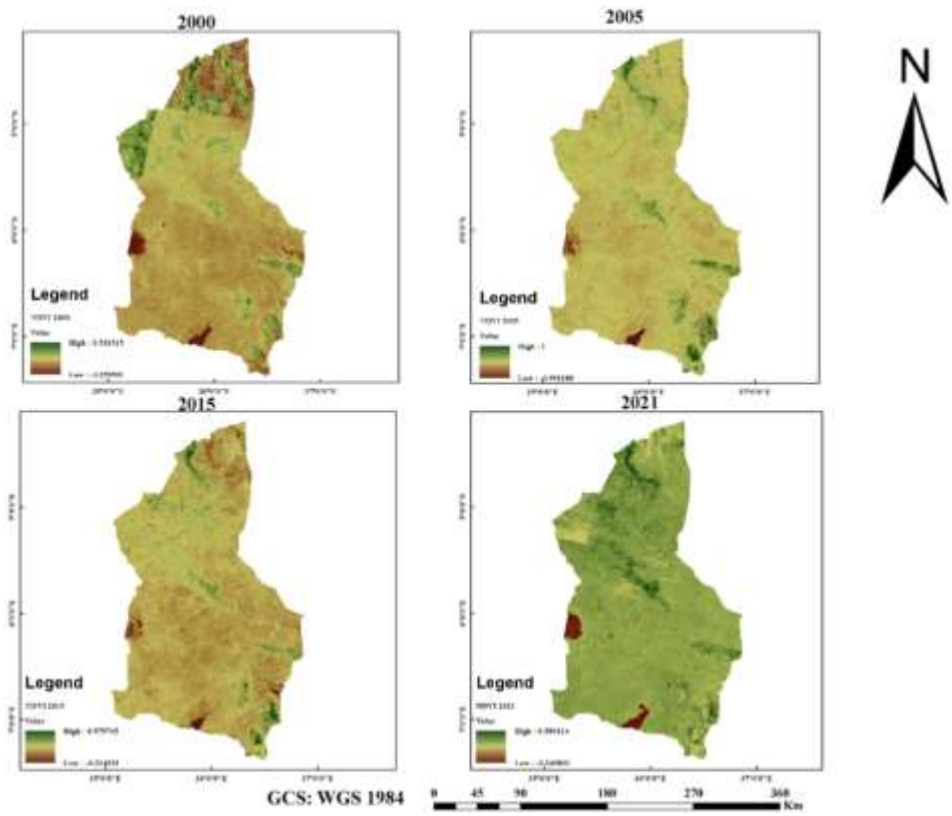

Figure 5: Visualised Maps of NDVI for 2000 to 2021

The NDVI maps in Figure 5 exhibit considerable changes in vegetation cover and health across the region from 2000 to 2021. Higher NDVI values were primarily concentrated in the eastern and northern parts of the region, indicating healthier vegetation and improved moisture conditions. Lower NDVI values consistently occurred in the western and south-western areas, indicating sparse vegetation and environmental stress. The results also showed a gradual decline in vegetation from 2000 to 2015, increased vegetation stress during dry periods, and significant vegetation recovery by 2021.

The NDVI patterns closely corresponded with rainfall and temperature variations. Areas experiencing higher rainfall and lower temperatures generally exhibited healthier vegetations, while areas with lower rainfall and higher temperatures showed reduced vegetation cover. This NDVI data provided valuable information about temporal and spatial changes in vegetation distribution, productivity, and dynamics; allowing the monitoring and assessment of the ecological effects of climate change. NDVI values ranged from -1 to +1. This shows the area is a semi-arid region with little vegetation. The results obtained are in line with other studies, such as Kilemo (2023) and Kisamba and Li (2023), which studied and mapped land use and land cover in Dodoma Region, and concluded that there is a decline in vegetation in some parts, and an increase in others due to urban expansion.

4.3 Trend of Drought

The drought trend was determined and evaluated using the SPI, a monthly indicator of meteorological drought. The SPI is now one of the most widely used drought indicators (Guttman, 1998; Vicente-Serrano et al., 2010) as it enables the tracking of drought intensity, frequency, and duration in a particular region across time. Figure 6 shows the monthly rainfall data of the Dodoma stations from 2000 to 2021.

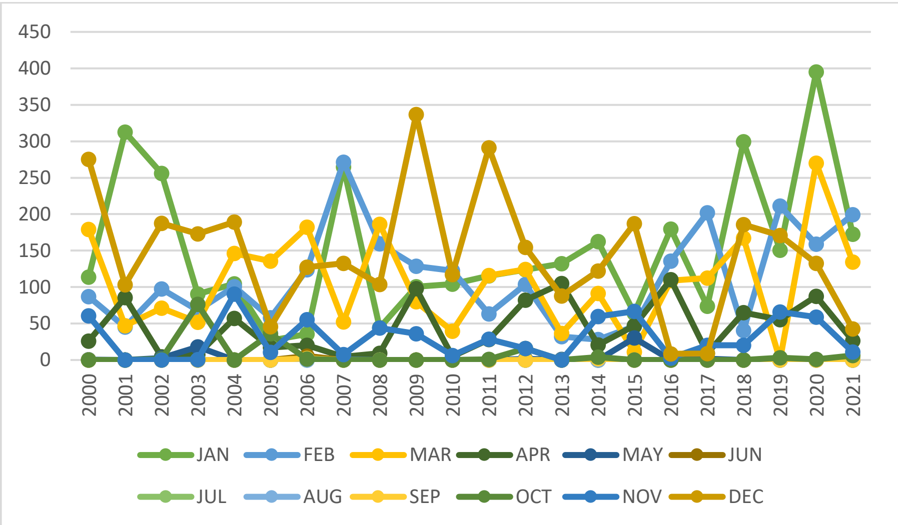

Figure 6: Monthly Rainfall Data of Dodoma Stations from 2000 to 2021

The graph shows that rainfall is clustered mainly in a few months, particularly between January and April, which represents the main rainy season in Dodoma. Among these months, January, February, and March often record the highest rainfall amounts; with some years experiencing exceptionally high peaks, such as around 2001, 2007, 2018, and 2020. In contrast, many months during the dry season receive little or no rainfall, with several observations near zero. The graph also shows irregular extreme rainfall events, in which monthly totals rise sharply above average. Examples include unusually high rainfall in June 2009 and January 2020. These incidents suggest intense seasonal storms or unusually wet years.

Table 3 shows the time series SPI values obtained from 2000 to 2021. After acquiring the SPI value for each year, the graph of SPI value (Figure 7) was plotted against the year as shown in the figure.

Table 3: Time Series SPI Values Obtained from 2000 to 2021

Year	SPI Values	Year	SPI Values
2000	-0.6076	2011	-0.7459
2001	-3.0292	2012	-1.2444
2002	-2.4520	2013	-2.1499
2003	-0.9683	2014	-2.2699
2004	-0.7285	2015	-0.5140
2005	0.0205	2016	-2.0785
2006	0.1791	2017	-0.6303
2007	-2.0431	2018	-2.4742
2008	0.0169	2019	-1.1852
2009	-0.3784	2020	-2.4651
2010	-1.4659	2021	-1.7312

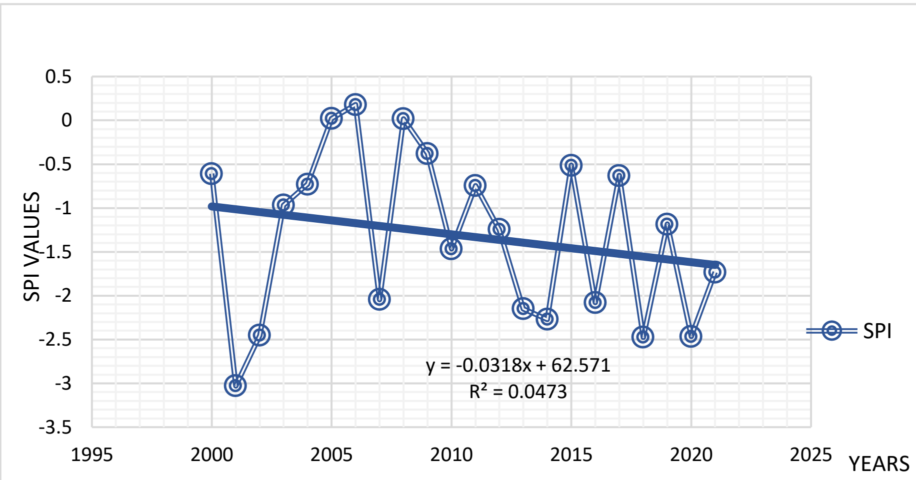

Figure 7: SPI Graph of 12-time Series of Dodoma Station (2000 to 2021)

From Figure 7, the more negative the SPI value, the more severe the drought; while positive values indicate above-average precipitation. This aligns with the standard interpretation of SPI graphs (McKee et al., 1993). Most SPI values in the plot are negative, indicating a consistent trend of below-average precipitation over the period. This confirms the fact that Dodoma is generally experiencing a drought. The graph clearly shows notable negative spikes in 2001, 2002, 2013, 2014, 2018, and 2020: all with levels well below -2. The SPI readings below -2 typically denote severe or extreme drought conditions. These times likely correspond to Dodoma's most significant droughts over the previous 20 years. There are intervals that show near-average precipitation, or even less severe drought conditions relative to the overall trend, although they remain negative. The linear trend line has a negative slope, indicating a steady decline in SPI over time. This suggests an increasing tendency towards drier conditions in Dodoma during the period 2000–2021. However, the coefficient of determination (R2) is very low, indicating that the downward trend is weak and explains only a small proportion of the variability in SPI. Therefore, rainfall variability is highly variable and influenced more by interannual climate variations than by a strong and consistent trend.

The Mann-Kendall test was used to assess whether the drought trend is increasing or decreasing, and to determine its significance. The graph in Figure 8 was generated by extracting data from the RStudio application, and exporting it to Excel to produce the graph.

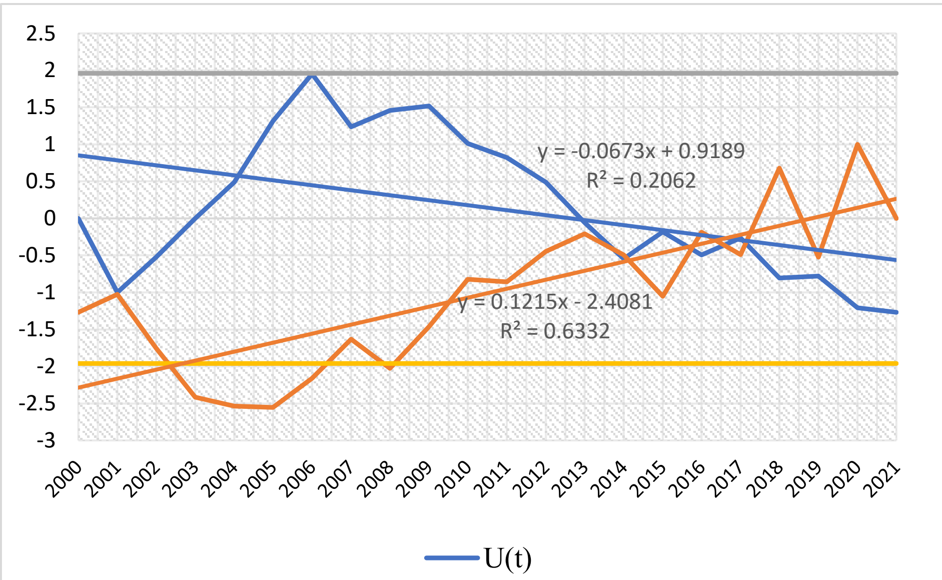

Figure 8: Sequential Mann-Kendall Plot Showing the Trend of Drought at Dodoma Station (2000 to 2021)

The prograde line U(t)) rises from about 2000 to 2008, suggesting a gradual increase from negative values to a peak close to +2; suggesting that drought conditions had an increasing trend during the early years of the study period. However, because the U(t) values did not exceed the upper critical limit (+2), the increasing trend was not statistically significant at the 95% confidence level.

After 2008, the prograde line starts to show a declining trend, indicating a weakening of the increasing drought tendency. The decline suggests fluctuations in drought intensity, and a possible transition towards less severe drought conditions during this intermediate period. The retrograde line U'(t)) shows a similar behaviour: first decreasing and then increasing around 2008; indicating the same trends but in the reverse order. The areas within the 95%cl bounds indicate where the trend is not statistically significant. After 2013, the forward statistics fell below zero, and remained predominantly negative up to 2021. This pattern indicates a downward trend in drought occurrence or severity in the later years of the study period. Nevertheless, the values remain within the confidence boundaries, implying that the decreasing trend is also statistically insignificant.

The backward series U′(t) shows an opposite behaviour. It begins with strongly negative values between 2002 and 2008, reaching values below -2 around 2003 to 2005. This suggests that the earlier period experienced notable drought variability and possible abrupt changes. The crossing points between U(t) and U′(t), particularly around 2013–2015, may indicate a probable turning point or change point in drought dynamics at the Dodoma Station. Such intersections are commonly interpreted as the approximate time when the trend shifts direction (Mann, 1945).

5. Conclusion and Recommendations

This study has revealed that climate variability has significantly influenced the occurrence, distribution, and intensity of drought across Dodoma Region between 2000 and 2021. There are notable spatial and temporal variations in rainfall and temperature, with areas experiencing persistently low rainfall and high temperatures being more vulnerable to drought. These variations highlight the importance of understanding regional climate dynamics for effective drought assessment and management.

The analysis of vegetation health using indicators, such as the NDVI, showed notable fluctuations over the study period. The trend analysis indicated a decreasing frequency and intensity of drought events in the region. The study findings demonstrated that prolonged periods of low rainfall and high temperatures are key drivers of drought. The SPI was utilised to show the severity and intensity of drought in the region across different years. The region appears more accustomed to drought, possibly due to its semi-arid nature.

It is recommended that further research focus on long-term drought mitigation methods to reduce drought risk. Important analyses—such as monitoring, early warning and prediction, and vulnerability assessment—should be conducted to mitigate drought conditions in Dodoma Region.

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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