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VEGETATION INDICES AS INDICATORS OF DROUGHT, A REMOTE SENSING PERSPECTIVE: A CASE STUDY OF NAROK COUNTY

BY

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Abstract

Vegetation cover is essential in determining the health of ecosystems and critical in planning and management of environmental and land resources. This study aimed at establishing the correlation between vegetation cover and drought indicators in Narok County.

Using the Enhanced Vegetation Index (EVI), the Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), and the Atmospherically Resistant Vegetation Index (ARVI), areas with potential vegetation cover were delineated. Within the same timestamp, the following drought indices were computed; the Temperature Condition Index (TCI), Vegetation Condition Index (VCI), Standardized Precipitation Index (SPI), Land Surface Temperature (LST), Normalized Difference Water Index (NDWI) and Soil Moisture Index (SMI).

A correlation analysis was done to establish the relationship that exists between vegetation cover and drought indicators over a period of 35 years (1987-2022). The findings revealed that SMI, VCI, and NDWI exhibited a correlation with the vegetation indices. However, LST, TCI, and SPI calculated over a period of 1 month (SPI-1) showed no significant correlation with the vegetation indices.

Furthermore, a drought model was developed based on these findings, utilizing regression analysis techniques. The model exhibited strong performance, with an R-squared value of 0.86, indicating a high level of accuracy in predicting drought conditions. The validation of the model using independent data confirmed its reliability and robustness.

The study will benefit a wide range of stakeholders, including farmers, government agencies, environmentalists, and researchers. The advantages will encompass enhanced agricultural output, heightened efficacy in disaster management, refined conservation approaches, and the progression of remote sensing as a discipline.

This study recommends further research and validation studies to strengthen the understanding and applicability of vegetation indices as indicators of drought. Conducting field studies, comparing remote sensing data with ground observations, and evaluating the performance of vegetation indices under different climatic and ecological conditions will enhance the reliability and confidence in their use for drought monitoring and prediction.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

ARVI	Atmospherically Resistant Vegetation Index
ASAL	Arid and Semi-Arid Lands
CDI	Cumulative Drought Index
EVI	Enhanced Vegetation Index
LST	Land Surface Temperature
NDVI	Normalized Difference Vegetation Index
SAVI	Soil-Adjusted Vegetation Index
SMI	Soil Moisture Index
SPI	Standardized Precipitation Index
TCI	Temperature Condition Index

CHAPTER 1: INTRODUCTION

1.1 Background

Drought is a naturally occurring event that is associated with prolonged decrease in the amount of rainfall received, typically lasting for a season or even a whole year. This can lead to inadequate moisture being stored in the soil, exacerbating the effects of dry conditions. There are various kinds of droughts, such as meteorological, agricultural, and hydrological. Meteorological droughts can be classified into different timeframes, while agricultural droughts usually occur over a shorter period of about a month, resulting from insufficient rainfall and soil moisture that can harm crop growth, ultimately leading to yield loss. Surface and subsurface water resources experience a significant reduction during hydrological droughts, which occur over extended periods ranging from three months to a year or even longer (Al-Bakri et al., 2017). The prevalence of drought has noticeably increased with the progression of global warming. Droughts have been experienced in nearly every part of the world, especially in dry regions where the majority of the annual precipitation originates from infrequent, scattered rainfall (Chang et al., 2021).

Climate change has an impact on the vegetation cover, which is a critical component in maintaining the well-being of ecosystems and is a vital consideration in the management and planning of environmental and land resources. Anthropogenic climate change has the potential to induce novel alterations in the geographical and chronological distribution patterns of climate variables, including temperature, sunlight, and precipitation. In order to minimize losses and safeguard the well-being of individuals and property, it is crucial to understand the connection between drought and changes in vegetation (Choubin et al., 2019)

Indirect indicators like vegetation indices, including Normalized Difference Vegetation Index (NDVI), Atmospherically Resistant Vegetation Index (ARVI), Enhanced Vegetation Index (EVI), and Soil-Adjusted Vegetation Index (SAVI), have been utilized to evaluate and map changes in vegetation cover. To highlight specific vegetation characteristics, various satellite imagery channels, such as Red and Near-Infrared (NIR), are utilized to derive these indices. By combining surface reflectance at different wavelengths, each vegetation index can indicate a particular vegetation characteristic (Almalki et al., 2022).

Remote sensing techniques have gained significant importance in the field of environmental studies due to their ability to provide reliable, replicable, and cost-efficient information over vast areas, which can be validated through traditional field data collection methods. A prevalent remote sensing technique used in environmental monitoring is vegetation assessment through vegetation indices that utilize reflectance measurements from the sensor's bands.

Drought indices from remote sensing have been developed and employed on a global scale to detect drought conditions with high accuracy. As vegetation experiences stress due to drought, alterations in the vegetation index can be utilized as a marker to assess the extremity and scope of drought (Chang et al.,2017).

1.2 Problem Statement

Despite the much-anticipated October to December 2022 short rains, which were expected to alleviate the drought situation, 22 out of the 23 ASAL counties in Kenya are still facing critical conditions due to poor performance and the delayed onset of rainfall. National monthly drought updates of January 2023 reported that four consecutive seasons of failed rainfall had compounded this situation. The situation is estimated to extend past November 2023.

There is a need for a solution to the recurrent occurrences of drought, which ultimately impede progress toward achieving a variety of sustainable development goals such as promoting sustainable production and consumption patterns. By establishing the correlation between vegetation cover and drought indicators, authorities will be in a position to develop more accurate drought forecasting models which can help prepare and mitigate the impacts of drought. This will also help in the development of more effective strategies for managing natural resources during drought periods.

Kinoti, 2019 focused on the management of droughts disasters and how different actors coordinate and govern preparedness, response, and recovery activities. She noted that effective governance and coordination are crucial aspects of managing such disasters. According to the study's findings, multiple actors, such as national and county government agencies, non-governmental organizations, financial institutions, and communities, are involved in drought preparedness, response, and recovery.

However, the study indicates that despite their involvement, their efforts are not adequately implemented.

As per the National Drought Early Warning Bulletin released in April 2023, Narok County is still under the alert phase for drought, despite receiving average rainfall in March. To enhance the coordination of drought response activities, the report suggests providing assistance to County Steering Groups (CSGs).

1.3 Objectives

1.3.1 General objective

The general objective was to assess the viability of vegetation indices as indicators of drought using remote sensing

1.3.2 Specific Objectives

The specific objectives were namely to: -

i. Review vegetation indices for mapping vegetation cover
ii. Estimate vegetation cover using vegetation indices
iii. Compute drought indices using remote sensing data
iv. Correlate vegetation cover with drought indicators
v. Develop an Early Drought Warning model based on vegetation indices

1.3.3 Research Questions

1. What are some of the commonly used vegetation indices for vegetation cover mapping?
2. To what extent can vegetation indices accurately estimate vegetation cover?
3. How effectively can remote sensing data be utilized to compute drought indices for assessing and monitoring drought conditions?
4. What is the relationship between vegetation cover and drought indicators?
5. Is it possible to utilize vegetation indices as an early warning system model for drought in Narok County?

1.4 Scope and Limitations of the Study

The study aims to explore the potential of using vegetation indices to detect drought conditions in Narok County, Kenya, through remote sensing.

The scope of the study is to provide insights into the feasibility of using vegetation indices to monitor and assess drought conditions. The study will utilize remote sensing data and vegetation indices to analyze variations in plant cover in response to drought. The findings may provide important information for policymakers, land managers, and other stakeholders in the region to develop appropriate drought management strategies.

However, there are some limitations to the study. First, the study will focus only on Narok County, which may not be representative of other regions with different environmental and climatic conditions. Second, the study will not account for other factors that may affect vegetation cover, such as land use changes and wildfire events. Thirdly, the remote sensing technology used limits the spatial resolution of the study, which may render it unsuitable for certain applications. Finally, the study will not validate the results of the vegetation indices against ground-based data, which could affect the accuracy of the findings.

While the study will provide useful insights into the potential of using vegetation indices to detect drought conditions in Narok County, there is need for additional research to validate the results and generalize them to other regions.

1.5 Justification for the Study

Drought has become a national disaster in Kenya with more than twenty counties experiencing adverse effects according to the report by the task force put in place by the president to access the drought situation in Kenya. According to the task force, the effect could escalate to more parts of the country. They are also estimating that the situation could extend past November 2023.

Currently, the government is pushing for the mass planting of trees countrywide as a remedy for climate change. As a result, this study's main focus is to try and find out if the push for more vegetation cover will ease the drought situation. This will be achieved by studying the correlation between vegetation cover and drought indicators over a period of thirty-five years, from 1987 to 2022. Narok County will be used as a case study due to its diverse ecosystem ranging from wildlife, pastoralism, wheat plantation, small-scale farming, forests, and rivers.

The study will benefit a wide range of stakeholders, including; farmers, government agencies, environmentalists and researchers. The study will provide farmers with early warning indicators of drought, which will help them to make informed decisions on crop selection, planting time, and irrigation management. This will help reduce crop losses and improve overall agricultural productivity. Government agencies responsible for disaster management and agricultural policies will be provided with accurate and timely information on drought conditions in Narok County. This data will serve as the basis for formulating impactful strategies to mitigate the impact of drought on the local population. The study will benefit environmentalists by providing them with valuable information on the impact of drought on vegetation in Narok County. This information will be used to develop conservation strategies to protect the local ecosystem. Lastly, will be provided with new insights into the use of remote sensing techniques to monitor drought conditions in Narok County. This will help advance the field of remote sensing and contribute to the development of new technologies and methodologies for drought monitoring.

1.6 Organization of the report

The report is organized in a systematic and logical manner to ensure clarity and coherence in presenting the research findings. It follows a structured format, commencing with an introduction, this section furnishes a comprehensive outline of the research aims and underscores the significance of the study. This is followed by a comprehensive literature review that establishes the theoretical and conceptual foundation of the research.

The methodology section outlines the research design, data collection methods, and analytical approaches utilized in the study. It highlights the utilization of remote sensing data, computation of both vegetation indices and drought indices, and the development of the drought monitoring model based on vegetation indices.

The results and discussions chapter presents the key findings of the research, including the analysis of vegetation cover, drought indicators, and their correlations. This section also encompasses the creation and validation of the drought monitoring model.

The conclusion chapter summarizes the main findings, reiterates the significance of the research, and provides recommendations for future research and practical applications. The report concludes with a comprehensive list of references cited throughout the study.

CHAPTER 2: LITERATURE REVIEW

2.1 Drought

Drought is a significant issue that affects many Sustainable Development Goals (SDGs) outlined by the United Nations. It has a negative impact on agricultural productivity, water supply, energy production, and human health, among other areas. Drought can lead to hunger, malnutrition, and poverty, which are all major concerns under no poverty and zero hunger goals (Nhemachena et al., 2020).

Under the Clean Water and Sanitation goal, drought exerts a direct effect on the availability of water for both household and industrial purposes. Managing drinking water resources during a drought is challenging due to the reduced availability of water, which can jeopardize the capacity to fulfill fundamental water requirements within communities. that lack a surplus water supply. Water quality is also negatively affected by drought, which can lead to bacterial growth, increased organic load, salinity intrusion, and dissolution of naturally occurring and human-made pollutants into water resources. The extent of these effects on treated drinking water quality may depend on community-based water management strategies and infrastructure conditions. Moreover, drought may further impact treated drinking water quality by damaging pipes, increasing water age in distribution systems, and changing the mix of water sources (Mullin, 2020).

Drought also has implications for SDG 7 (Affordable and Clean Energy) because hydroelectric power generation, which relies on a consistent water supply, can be severely affected. As a result, drought can cause energy shortages and price hikes (Mekonnen et al., 2022).

Finally, under SDG 15 (Life on Land), droughts significantly threaten biodiversity and ecosystem services. Drought can lead to soil degradation, desertification, and the loss of habitats for wildlife. Nearly 80% of the human fatalities and 70% of the economic losses in Sub Saharan Africa are attributed solely to droughts and floods (Ekwezuo et al.,2019).

2.2 Drought situation in Kenya

The Kenyan Arid and Semi-Arid Lands (ASAL) have suffered three consecutive poor rainy seasons, causing families to deplete their resources and leaving over 2.9 million people in dire need of humanitarian aid, as stated in the Flash Appeal launched in September 2021 to urge action in response to drought.

In the final quarter of 2021, the food security situation in the ASAL counties of Kenya significantly worsened due to the inadequate performance of the October-December 2021 short rain season, leaving approximately 3.5 million individuals severely food insecure, with an IPC level of 3 or higher, in 2022. The prolonged drought and several months of insufficient access to food have resulted in more than 650,000 children experiencing acute malnutrition.

As per findings of the National Drought Management Authority (NDMA), the drought situation has left communities without their means of livelihood, with various conflicts emerging across multiple counties. Armed conflicts related to natural resources, such as water and grazing lands, have been prevalent in Mandera, Marsabit, Samburu, Isiolo, Garissa, Kitui, Baringo, Laikipia, and Turkana Counties. Additionally, human-wildlife conflicts have increased significantly in Taita Taveta, Kilifi, Lamu, Meru North, and Marsabit. These conflicts are a result of the desperation caused by the drought, which has resulted in approximately 2.6 million livestock deaths and an estimated value loss of Kshs. 216 billion. Rivers in ASAL areas also have below 40% of normal flows.

2.3 Arid and Semi-Arid Lands (ASALs) in Kenya

The Arid and Semi-Arid Lands (ASALs) encompass a significant portion, approximately 80%, of the country's land area. These regions are inhabited by approximately 36% of the population and are crucial for supporting 70% of the national livestock and 90% of the wildlife. In these areas, the annual rainfall ranges from 150 mm to 550 mm in arid zones and 550 mm to 850 mm in semi-arid zones. Additionally, high temperatures persist throughout the year, leading to substantial rates of evapotranspiration (www.asals.go.ke/, accessed on 28th June 2023).

The arid and semi-arid lands (ASALs) in Kenya are distributed among 29 counties, each characterized by different levels of aridity.

Drought has significantly impacted 23 counties located in Kenya's arid and semi-arid lands (ASALs), leading to severe consequences for food security within these regions. The Infographic highlights the challenges faced by communities in pastoral areas, where individuals are compelled to undertake extensive journeys in search of water for themselves and forage for their livestock. Distressingly, the drought has resulted in the loss of over 1.4 million livestock, primarily due to prolonged treks and the depletion of pastures.

Within the agro-pastoralist regions, the decline in agricultural activities has led to a reduction in casual labor opportunities, ultimately depleting household reserves and purchasing power. Additionally, the scarcity of water resources has affected approximately 2.8 million individuals residing in ASAL counties like Turkana and Marsabit, resulting in the drying up of crucial water pans, boreholes, wells, and dams (McCormack et al., 2022).

2.4 Vegetation indices

2.4.1 Normalized Difference Vegetation Index (NDVI)

NDVI (the Normalized Difference Vegetation Index) has become a popular tool for monitoring and assessing vegetation. NDVI has proven to be an invaluable tool for monitoring health and growth of vegetation, and for making informed decisions about agricultural practices and land management. (Lillesand & Kiefer, 1994)

The NDVI approach relies on the observation that green vegetation reflects less visible light in the electromagnetic spectrum, primarily due to the absorption of light by chlorophyll and other pigments. At the same time, healthy vegetation reflects more light in the near-infrared segment of the spectrum, mostly because of internal reflectance by the spongy mesophyll tissue of green leaves (Bajgirana et al., 2008)

$$NDVI = \frac{NIR - RED}{NIR + RED} \tag{2.1}$$

NDVI values typically fall within the range of -1 to +1, with higher values indicating better vegetation condition. Index values close to zero reflect low presence of green vegetation or the absence of vegetation cover (Munawar et al., 2013).

2.4.2 Enhanced vegetation index (EVI)

The Enhanced Vegetation Index (EVI) was created to improve the performance of the commonly-used Normalized Difference Vegetation Index (NDVI) in high leaf area index (LAI) areas. The index corrects background soil signals and reduces atmospheric effects, including aerosol scattering, by utilizing the blue reflection region. It is especially helpful in high LAI regions where NDVI may become saturated. Vegetation pixels analyzed with EVI produce values ranging from 0 to 1. However, it is important to note that anomalous pixel values may arise due to the presence of highly illuminated features such as clouds or white buildings, as well as lowly illuminated features like water. Nevertheless, the EVI is a valuable tool for evaluating crop development variability in areas with both dense and sparse vegetation cover.

$$EVI = 2.5 * \frac{(NIR - R)}{(NIR + C1 * R - C2 * Blue + L)} \tag{2.2}$$

Where;

- C1 and C2 are correlations to correct for the aerosol scattering in the atmosphere
- L is a coefficient to compensate for soil and canopy background.

2.4.3 Atmospherically Resistant Vegetation Index (ARVI)

The Atmospherically Resistant Vegetation Index (ARVI) is a vegetation based index that effectively minimizes the impact of atmospheric scattering caused by aerosols. (Esri, 2020).

$$ARVI = \frac{(NIR - RED - y * (RED - BLUE))}{(NIR + RED - y * (RED - BLUE))} \tag{2.3}$$

ARVI ranges from values between -1 and 1, with values ranging from 0.20 to 0.80 typically indicating the presence of green vegetation.

2.4.4 Soil-Adjusted Vegetation Index (SAVI)

It accounts for the presence of soil in areas with limited vegetation cover (Lillesand & Kiefer, 1994).

$$SAVI = \frac{(NIR - RED)(1 + L)}{(NIR + RED + L)} \tag{2.4}$$

The parameter L is a scale factor that varies between 0 and 1, where L=0 indicates very dense vegetation, and L=1 indicates sparse vegetation cover with high soil reflection.

2.5 Drought indicators

Drought indicators are parameters or variables that are used to characterize and measure drought conditions. Drought indices are generally calculated as numerical representations of the severity of drought conditions, which are evaluated using climatic or hydro-meteorological inputs, such as the indicators mentioned earlier. The aim of these indices is to quantify the qualitative drought conditions on the land during a particular time frame.

2.5.1 Standardized precipitation Index (SPI)

The SPI utilizes past precipitation data across different locations to calculate the likelihood of precipitation occurring during different time frames. The SPI scale has a range of values that includes positive and negative values. Positive values suggest an abundance of precipitation while negative values suggest a scarcity of precipitation. The intensity scale of SPI is thus used to identify both surplus and deficit events (Yihdego et al., 2019).

When the SPI values for a particular timescale remain continuously negative and drop to a level of -1, it is an indication of a drought event. The drought is deemed ongoing until the SPI values rise back up to 0.

2.5.2 Land Surface Temperature (LST)

Land Surface Temperature (LST) is the temperature of the earth's surface, which is determined by utilizing remote sensing instruments., typically using thermal infrared sensors on satellites. Air temperature, solar radiation, and surface characteristics affect the Land Surface Temperature.

2.5.3 Temperature Condition Index (TCI)

The Temperature Condition Index (TCI) is used to monitor the effect of temperature on the status of vegetation. It is commonly combined with the Vegetation Condition Index (VCI) to offer a more complete evaluation of the overall health and condition of vegetation cover. The TCI is designed to capture the effects of temperature on vegetation growth and development, with higher TCI values indicating more favorable temperature conditions for plant growth, and lower TCI values indicating less favorable temperature conditions.

$$\mathrm{TCI}=\frac{LST\max - LST}{LST\max - LST\min} \qquad (2.5)$$

2.5.4 Vegetation Condition Index (VCI)

While NDVI has proven to be effective in identifying both healthy and stressed crops, difficulties in interpretation can originate from variations in environmental factors such as soil conditions, climate, and vegetation characteristics, and vegetation levels within a particular region. These factors can affect the accuracy of NDVI-based analysis, making it challenging to draw definitive conclusions without considering additional contextual information (Alahacoon et al., 2021). The VCI was developed to facilitate the identification of the effects of weather conditions on crops

$$VCI = \frac{(\mathrm{NDVI\ -\ NDVI\ min})}{(\mathrm{NDVI\ max\ -\ NDVI\ min})} \qquad (2.6)$$

VCI index spans from value 0 to 100. A VCI value near 100 implies favorable crop conditions, while a VCI value near 0 indicates poor crop conditions.

2.5.5 Soil Moisture Index (SMI).

The Soil Moisture Index is calculated using an approach that involves parameterizing the relationship between two key environmental factors: The Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST). By analyzing the correlation between these two variables, researchers can estimate soil moisture levels, which are valuable indicators of environmental conditions (Saha et al., 2018).

$$SMI= (LST_{max}-LST) / (LST_{max}-LST_{min}) \tag{2.7}$$

Where,

$$LST_{max}= a_1 * NDVI + b_1 \tag{2.8}$$

$$LST_{min}= a_2 * NDVI + b_2 \tag{2.9}$$

Where $a1$, $a2$, $b1$, and $b2$ define the slope and intercept of the linear relationship between the input features and the output feature.

2.5.6 Normalized Difference Water Index (NDWI)

The Normalized Difference Water Index (NDWI) is an indicator employed in remote sensing to identify fluctuations in leaf water content. Calculated from the Near-Infrared (NIR) and Short Wave Infrared (SWIR) channels, the SWIR reflectance encapsulates alterations in both vegetation water content and the inner spongy mesophyll arrangement within vegetation canopies. In contrast, the NIR reflectance is influenced by leaf internal structure and dry matter content, remaining unaffected by water content. (Bade, 2020).

$$NDWI = \frac{NIR - SWIR}{NIR + SWIR} \tag{2.10}$$

The NDWI ranges from -1 to +1, and its value is influenced by leaf water content as well as the type and extent of vegetation cover. In this index, high NDWI values (displayed in blue) indicate high levels of vegetation water content and a greater fraction of vegetation cover. Conversely, low NDWI values (shown in red) indicate lower levels of vegetation water content and a reduced fraction of vegetation cover.

2.6 Remote Sensing for Drought Mapping

Prior to satellite technology, low orbiting aircraft were used to capture aerial photographs to create maps of vegetation classes. Remote sensing has been widely utilized to observe and track any alterations or updates on the earth surface and offer precise information to various professionals since the launch of Landsat satellite in 1972 (Bhaga et al., 2020).

Currently, a range of satellites orbit the Earth, collecting data at varying resolutions, which can be utilized to evaluate droughts and climate variability. Drought can be identified by utilizing a drought index that evaluates the impact, strength, length, severity, and geographical scope of drought. The indices rely on meteorological data, such as soil moisture, temperature, and precipitation data, to evaluate drought conditions.

Earth observation technologies have made significant progress, leading to the development and evaluation of various remote-sensing-based drought indices for monitoring drought. They include the Temperature Condition Index (TCI), the Normalized Difference Vegetation Index (NDVI), the Vegetation Condition Index (VCI), and the Vegetation Health Index (VHI). VHI, VCI, and TCI are classified as vegetation indices since they assess the condition of vegetation in a distinct region, categorize it into drought categories, and are widely used to monitor drought (Ejaz et al., 2023).

Remote sensing technology has been utilized in numerous studies to evaluate and track drought conditions. Krishna et al., (2009) investigated the severity of agricultural drought in the Palar Basin, located in Tamil Nadu, India, using IRS ((Indian Remote Sensing Satellites) by employing NDVI-based assessment methods. Das et al., (2021) used optical and thermal remote sensing and SPI to assess drought stress in tea plantations. The results showed a decrease in crop yield during drought periods. The results demonstrate that remote sensing can be employed in drought mapping.

An investigation was undertaken in South Africa to assess the effect of drought on forest estates using climate data and MODIS time series analysis. The study revealed that the normalized difference moisture index (NDMI) is a dependable parameter for understanding the correlations between water content, precipitation, and soil moisture in the plant cover. Consequently, this study underscores the importance of NDMI in monitoring drought (Xulu et al., 2018).

CHAPTER 3: MATERIALS AND METHODS

3.1 Study Area

Narok County is located in the southern region of the Great Rift Valley. Geographically, Narok stretches between latitude ranging from 0° 50´ to 1° 50´ South and longitude ranging from 35° 28′ to 36° 25´ East. The county neighbors are Nakuru, Kisii, Bomet, Migori, Nyamira, and Kajiado counties, as well as the Republic of Tanzania as shown in figure 3.1. In the county, the predominant economic activities comprise of small-scale pastoralism, crop farming, tourism, and trade, among other minor activities.

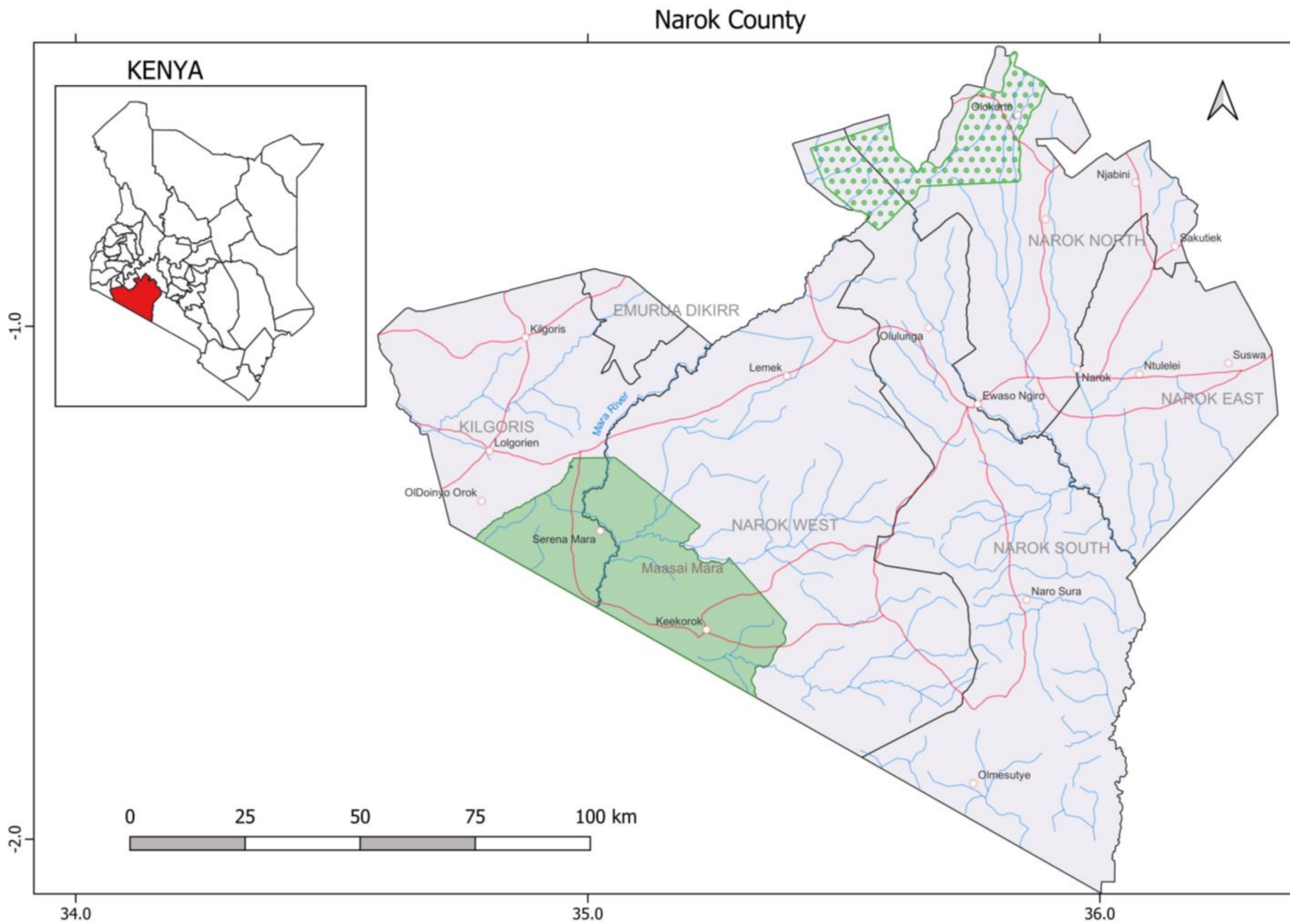

FIGURE 3.1: STUDY AREA-NAROK COUNTY

3.2 Data Sources and Tools

3.2.1 Data Sources

Landsat 8 OLI, Landsat 7 ETM+, and Landsat 5 TM images representing the data for 35 years from 1987 through 2022 were used. The time series images were obtained from the United States Geological Survey (USGS) website (https://glovis.usgs.gov/). Images were captured between the months of January and March of each of 35 years.

The meteorological data (Rainfall data) was obtained from Google Earth Engine.

Vegetation indices were calculated from the satellite imagery.

3.2.2 Tools

Google Earth Engine, a web-based computing platform that allows users to access a wide range of satellite imagery and other geospatial datasets for scientific analysis and visualization, was used to derive the Landsat images.

QGIS was employed for the computation of vegetation indices and the creation of the drought monitoring model.

ArcGIS was used for regression analysis of both vegetation indices and drought indices.

3.3 Methodology

The methodology employed in this study encompasses a comprehensive approach to effectively address the research objectives. It encompasses several key stages, each contributing to a robust and holistic understanding of the subject matter. The methodology (see figure 3.2) begins with data acquisition, involving the collection of pertinent information, followed by pre-processing to ensure data quality and consistency. Subsequently, the calculation of essential indices facilitates the assessment of vegetation and drought indicators. Correlation analysis sheds light on the interrelationships between variables, while the development of a drought warning model serves as a proactive tool for anticipatory measures. Finally, model validation ensures the reliability and accuracy of the developed model.

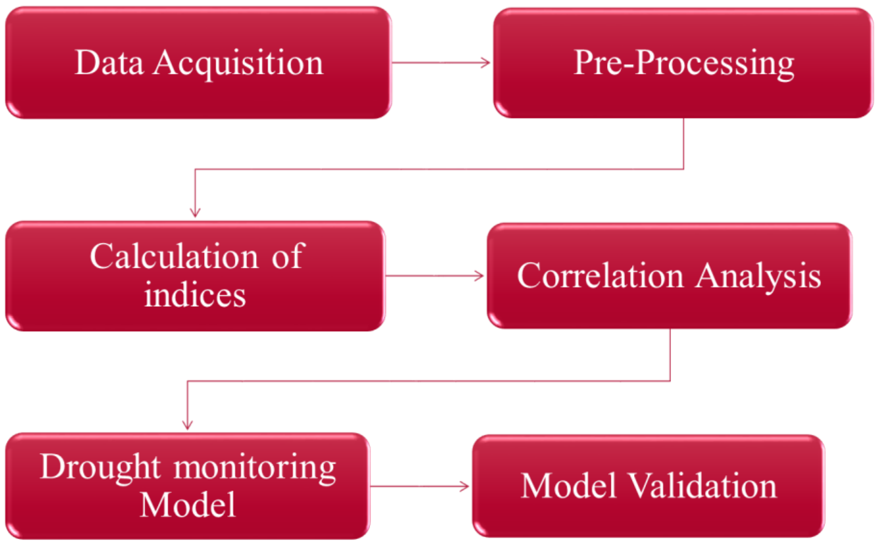

FIGURE 3.2: METHODOLOGY FLOWCHART

3.4 Data Acquisition

Landsat Images were downloaded from Google Earth Engine platform.

Meteorological data (Rainfall data) was downloaded from Google Earth Engine.

3.5 Pre-Processing of Data

The Landsat images were mosaicked using the Google Earth Engine platform. Subsequently, the study area was clipped from the mosaic. The rainfall data in raster format was extracted and saved into an Excel file.

3.6 Mapping Drought using Vegetation Indices

3.6.1 Extraction of Vegetation indices

The raster calculator in Qgis was utilized to compute vegetation indices by making use of corresponding spectral bands from satellite imagery. Given the moderately sparse vegetation in Narok County, the soil-brightness correction factor for the Soil-Adjusted Vegetation Index (SAVI) was fixed at 0.5 during the calculation process. Table 3.1 below summarizes the formulas used for the calculation of the vegetation indices.

TABLE 3.1: VEGETATION INDICES

Index	**Equation**
Normalized Difference Vegetation Index	$NDVI = \frac{NIR - RED}{NIR + RED}$
Enhanced Vegetation Index	$EVI = 2.5 * \frac{(NIR - R)}{(NIR + C1 * R - C2 * Blue + L)}$
Soil-Adjusted Vegetation Index	$SAVI = \frac{(NIR - RED)(1 + L)}{(NIR + RED + L)}$
Atmospherically Resistant Vegetation Index	$ARVI = \frac{(NIR - RED - y * (RED - BLUE))}{(NIR + RED - y * (RED - BLUE))}$

3.6.2 Extraction of Drought Indices

Rainfall data was used for calculation of SPI. SPI was calculated by fitting a probability distribution function (PDF) to a time series of precipitation data for a given location. The PDF was then used to calculate the probability of different precipitation values occurring in the future, based on the historical record. The SPI was computed mathematically. The results were initially generated in CSV format and later transformed into a tabular format for utilization in ArcGIS for SPI mapping.

The calculation of Land Surface Temperature (LST) involved utilizing the thermal bands present in the satellite imagery.

The Temperature Condition Index (TCI) was computed using the Land Surface Temperature estimated from the thermal infrared bands of the satellite imagery.

The Normalized Difference Water Index (NDWI) was calculated from the NIR and Short Wave Infra-Red (SWIR) bands of the satellite imagery.

The VCI was obtained from the NDVI.

The Soil Moisture Index (SMI) was computed from both the NDVI and LST derived from the satellite imagery

3.6.3 Vegetation indices and Drought Indicators Correlation Analysis

A critical step in developing a reliable drought warning model is correlation analysis. It is beneficial to examine the statistical significance and direction of the link between the variables. Correlation analysis yields these two measurements in the form of a numerical coefficient, the sign of which indicates the direction of influence. When two variables exhibit a similar movement, they are considered to have a positive correlation; when they show an inverse movement, they are regarded as having a negative correlation

ArcMap was utilized to perform exploratory regression analysis. The objective was to systematically test various combinations of explanatory variables (drought indices) in order to identify models that successfully met all the essential diagnostic criteria of Ordinary Least Squares (OLS) regression. The output of this process depicted the percentage influence of each independent variable (drought indices) on the dependent variable (vegetation indices).

Cumulative Drought index, a metric that combines various indicators of drought severity over a specific period, providing a comprehensive measure of the cumulative effects of drought, was then calculated by aggregating the drought indices identified from the exploratory regression.

Regression analysis was done using ArcMap with the objective of modeling, examining, and exploring spatial relationships. The primary aim was to explain the factors contributing to observed spatial patterns between vegetation indices and drought indices. Ordinary Least Squares (OLS) regression was used to estimate the parameters of the model, with the Cumulative Drought Index as our dependent variable and the vegetation indices as our explanatory variables.

3.7 Developing a Drought warning model

A drought warning model is a system that can predict and issue warnings about potential drought conditions in a particular area. The model utilizes vegetation indices in its implementation. OLS regression outputs coefficients of each vegetation index. These coefficients are used to define a mathematical expression in QGis graphical model builder which takes vegetation indices as input data and outputs drought index after applying the expression defined. It can help stakeholders such as farmers, water managers, and policymakers to prepare for and mitigate drought effects.

Drought Warning Model Validation

Model validation is a process of evaluating the performance of a predictive model using a dataset that was not used to develop the model. This is very important because it ensures that the model is reliable when used with a new dataset. This study uses a historical dataset to test the model for its reliability and performance. The model was developed using data spanning from 1987 to 2018. To validate the model's performance, data from the year 2022 was utilized.

CHAPTER 4: RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents a comprehensive analysis of the study's findings. The chapter encompasses various aspects, including the assessment of vegetation cover using vegetation indices, the correlation between vegetation cover and drought indicators, and the development of an early drought warning model based on vegetation indices. The findings shed light on the dynamics of drought conditions and provide valuable insights for effective drought management and mitigation strategies.

4.2 Vegetation Cover based on Indices

Vegetation cover was mapped using the vegetation indices. The ranges of values obtained demonstrate the heterogeneity of vegetation conditions across Narok County. Higher values signify denser and healthier vegetation cover, while lower values indicate sparser or stressed vegetation

The analysis of vegetation cover trends over the years reveals notable changes in Narok County. As shown in figures 4.1, 4.2 and 4.3, from 1987 to 2000, there was a significant decrease in vegetation cover, suggesting a decline in the health and density of vegetation during that period. This could be attributed to various factors such as land degradation, climate variability, or human activities.

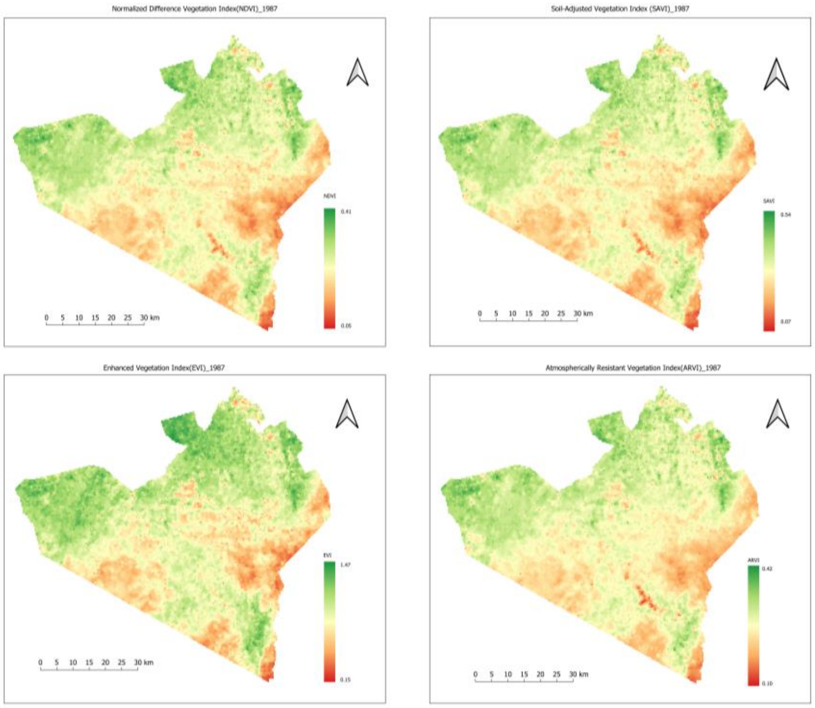

FIGURE 4.1: VEGETATION INDICES_1987

As illustrated in Figure 4.2 below, a discernible reduction in vegetation is evident in comparison to the conditions depicted in Figure 4.1 above. The majority of Narok County's regions exhibited signs of vegetation degradation, underscoring the presence of drought-related patterns within the county.

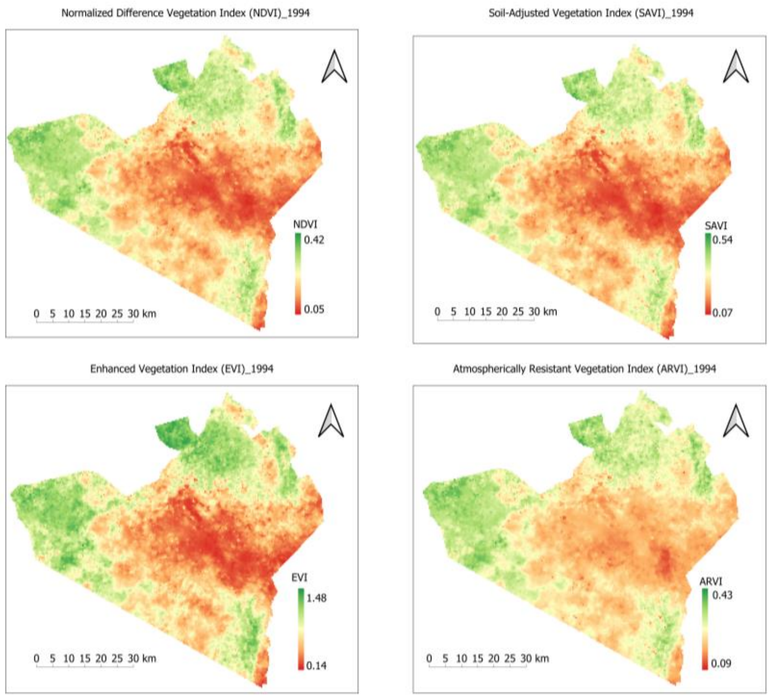

FIGURE 4.2: VEGETATION INDICES_1994

In 2000, Kenya encountered one of its most severe droughts. As depicted in Figure 4.3, a pronounced decline in vegetation cover is evident. The prevailing arid conditions and insufficient rainfall led to a notable reduction in the vitality and density of vegetation throughout Narok County.

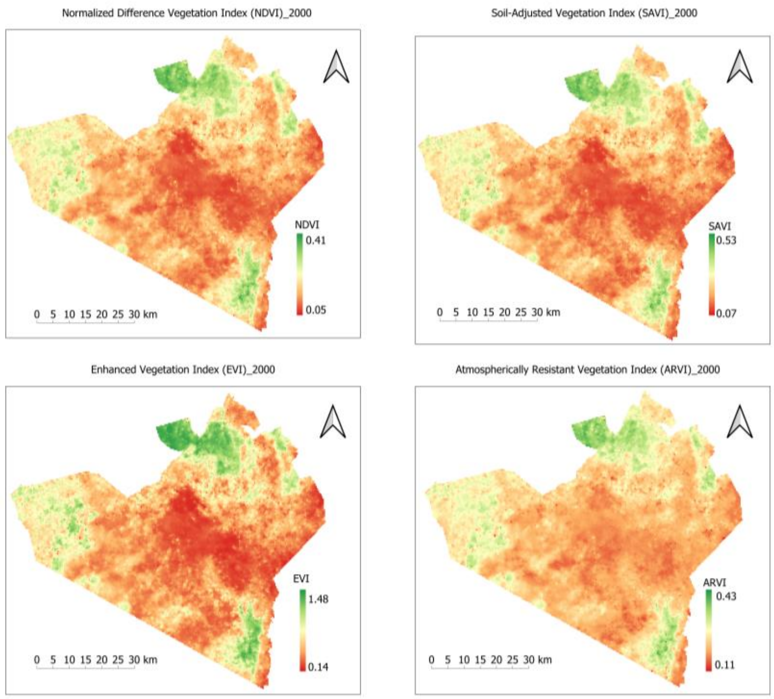

FIGURE 4.3: VEGETATION INDICES_2000

In 2008, as shown in figure 4.4 below, a larger area of Narok County experienced healthier vegetation cover, indicating a positive shift in the overall vegetation conditions. This could be attributed to various factors, including improved land management practices, conservation efforts, or favorable weather patterns during that specific year.

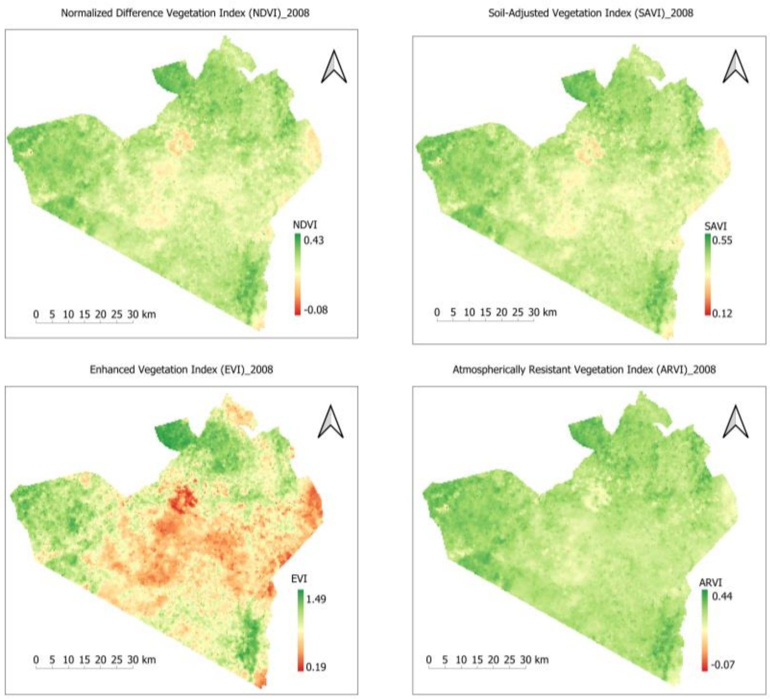

FIGURE 4.4: VEGETATION INDICES_2008

However, from 2014 to 2022, there was a recorded drop in vegetation cover, indicating a decline in the health and density of vegetation once again. This decline could be influenced by factors such as prolonged drought periods, land-use changes, or other environmental stressors impacting the vegetation.

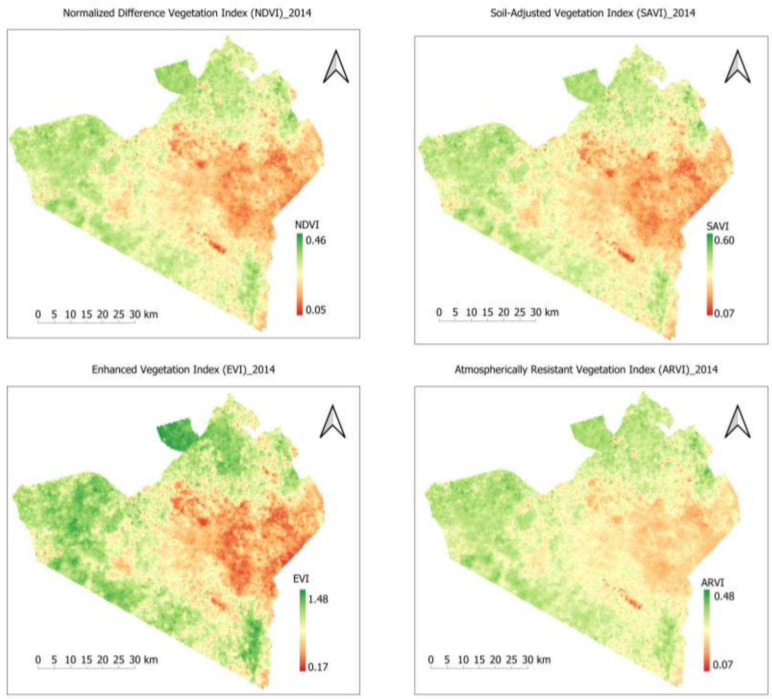

FIGURE 4.5: VEGETATION INDICES_2014

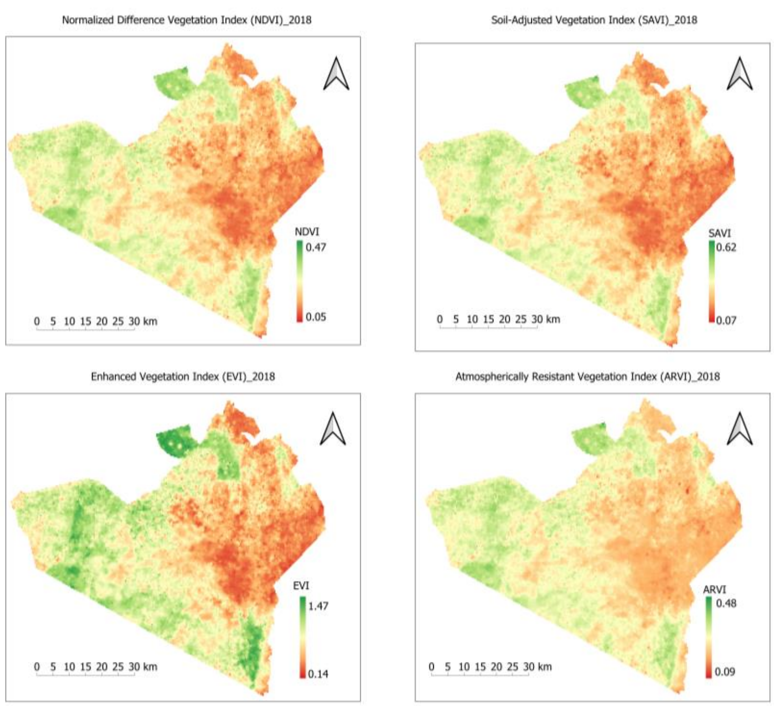

FIGURE 4.6: VEGETATION INDICES_2018

As presented in Figure 4.7 below, there is a notable reduction in vegetation cover. This decline in vegetation cover signifies the occurrence of drought within the county. In 2022, Kenya faced a drought situation caused by a sequence of five consecutive below-average rainy seasons since late 2020.

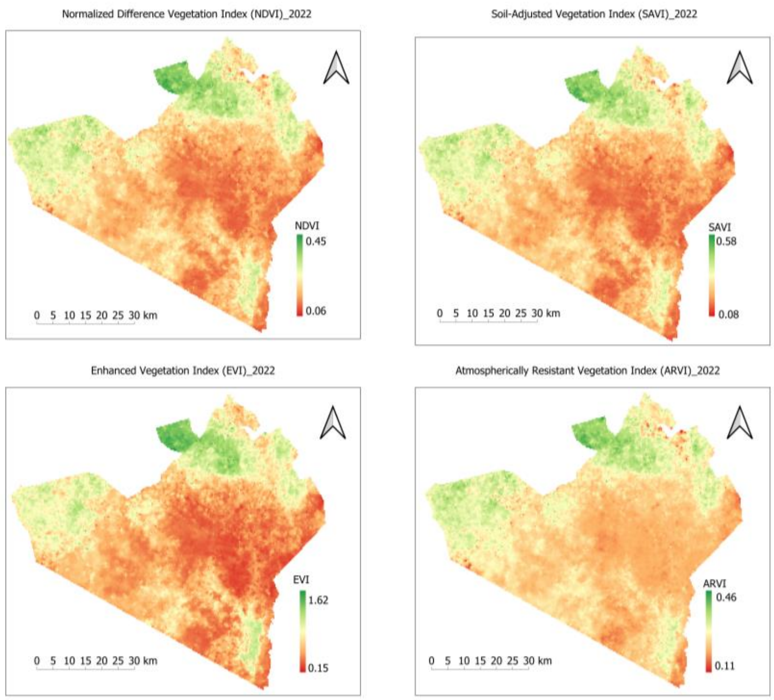

FIGURE 4.7: VEGETATION INDICES_2022

4.2 Drought Indices

The computation of drought indices from satellite imagery revealed that the Vegetation Condition Index (VCI) and Normalized Difference Water Index (NDWI) exhibited similar trends as the vegetation indices. Figures 4.8, 4.9, and 4.10 illustrate a decrease in vegetation cover from 1987 to 2000, aligning with the observed trends in VCI and NDWI.

The Standardized Precipitation Index (SPI) was calculated specifically for a one-month period (SPI-1). Positive SPI values were recorded in 1987, 1994, 2008, and 2014, indicating above-median precipitation and wet conditions during those years. Conversely, dry conditions were identified in 2000, 2008, and 2022 based on SPI calculations.

Land surface temperature exhibited variations over the years, with the highest recorded temperature of 32.64 degrees Celsius in 2000 (figure 4.10). On the other hand, the lowest temperatures of 28.44 degrees Celsius were observed in 2014 (figure 4.12). The red shows areas experiencing high thermal stress/ drought while the blue represents areas with low thermal stress.

The computation of the Soil Moisture Index over the years revealed values ranging from 0 to 1. Values approaching zero indicated areas experiencing water deficit or low soil moisture content, while values nearing 1 indicated region with high moisture content in the soil.

The Temperature Condition Index shows significant variability in drought intensity during the study period. The color gradient of each pixel represents the drought level. Green corresponds to the lowest value, red to the most intense.

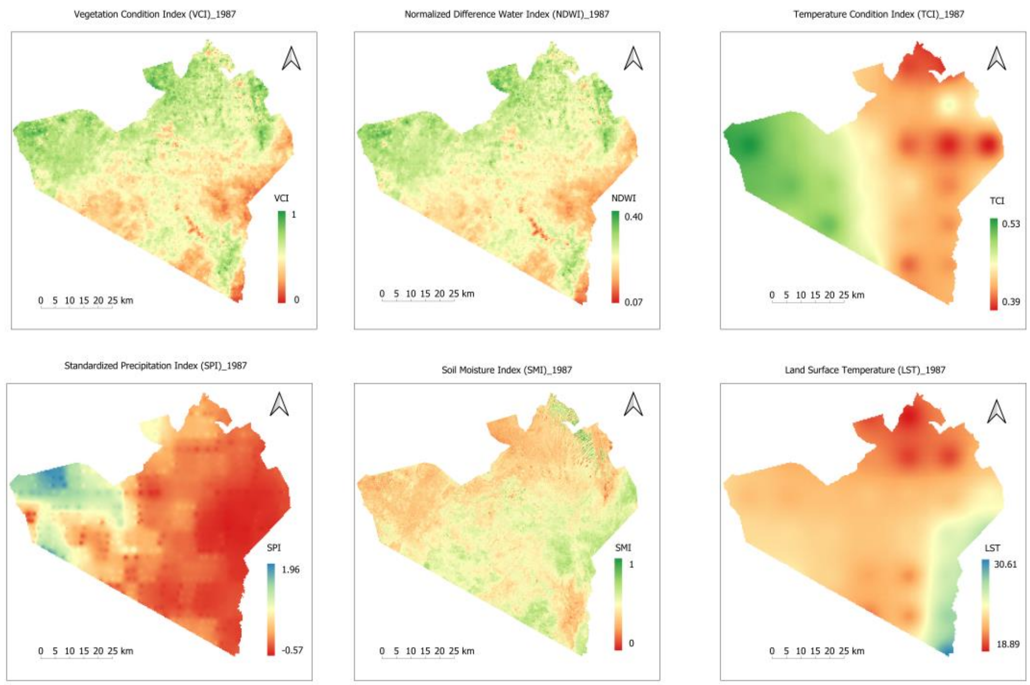

FIGURE 4.8: DROUGHT INDICES_1987

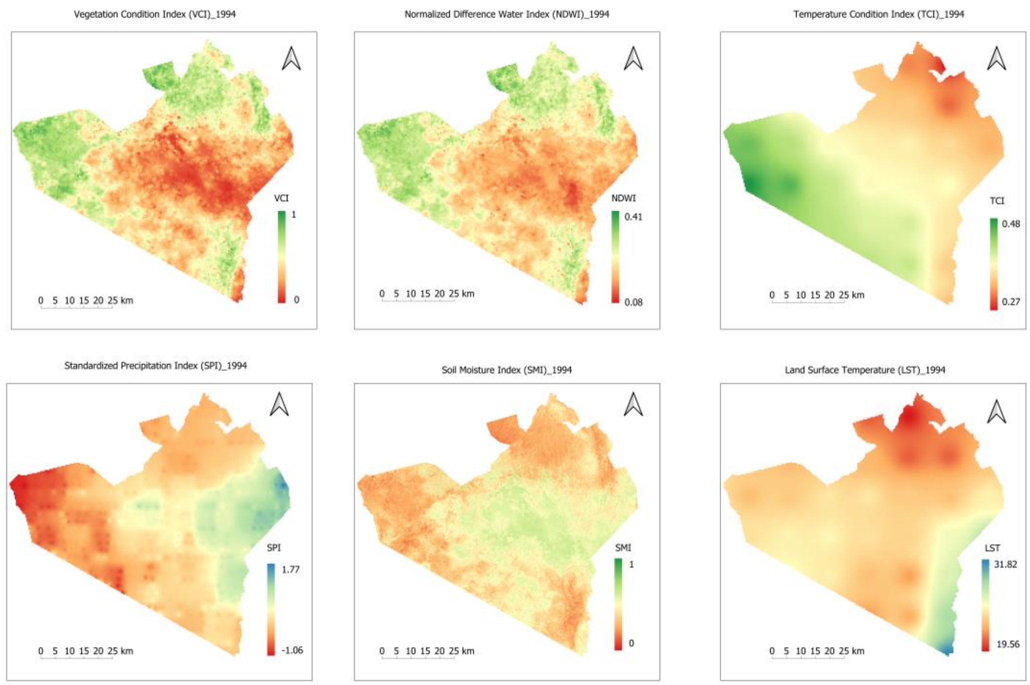

FIGURE 4.9: DROUGHT INDICES_1994

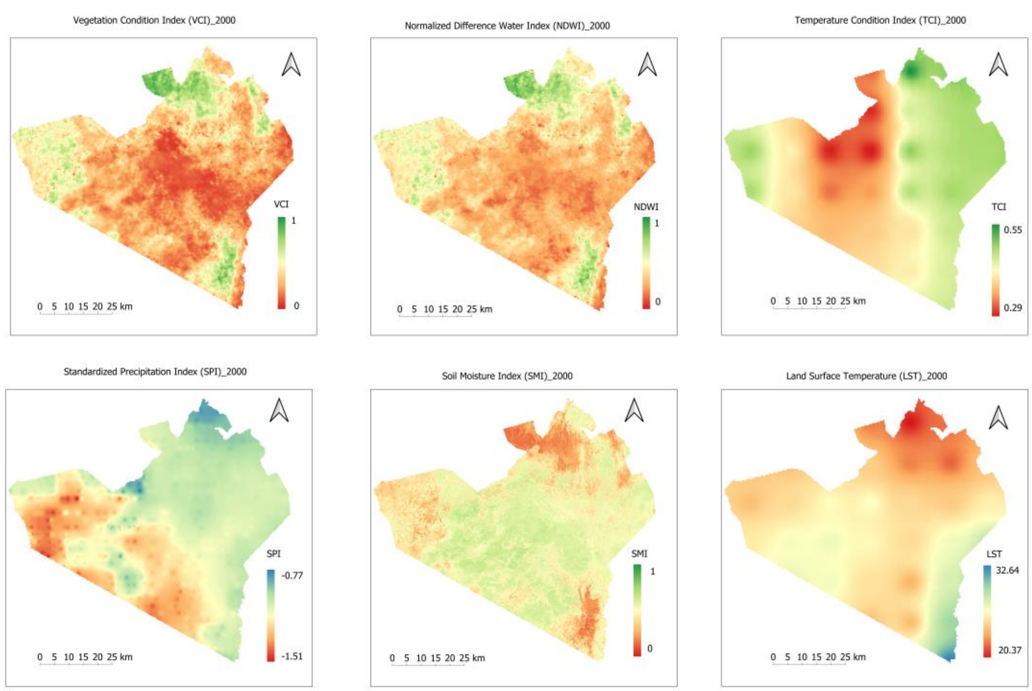

FIGURE 4.10: DROUGHT INDICES_2000

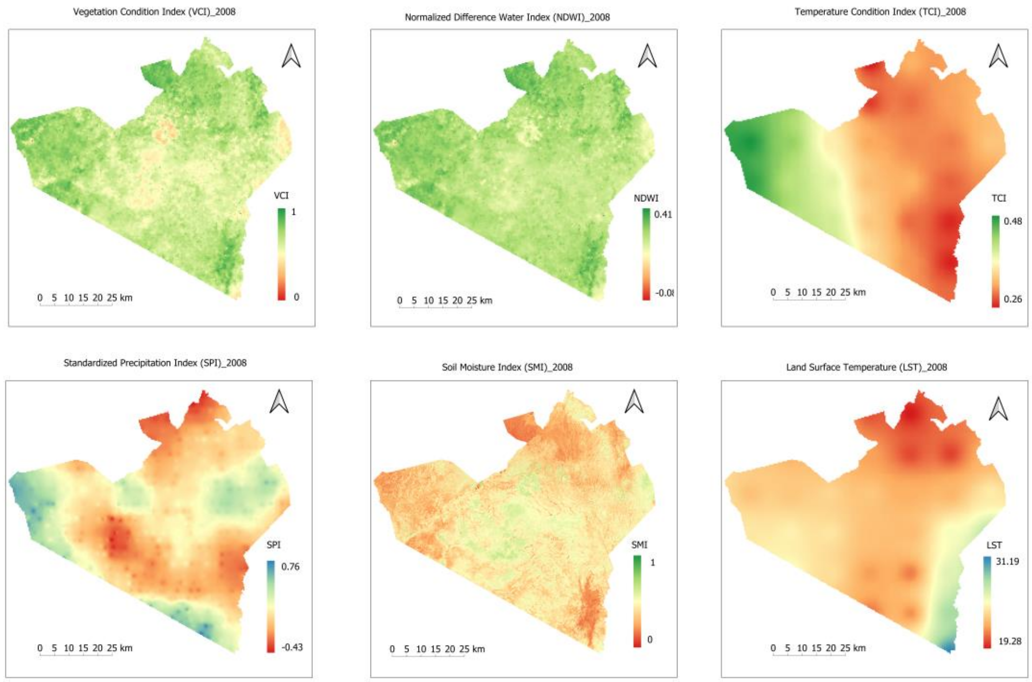

FIGURE 4.11: DROUGHT INDICES_2008

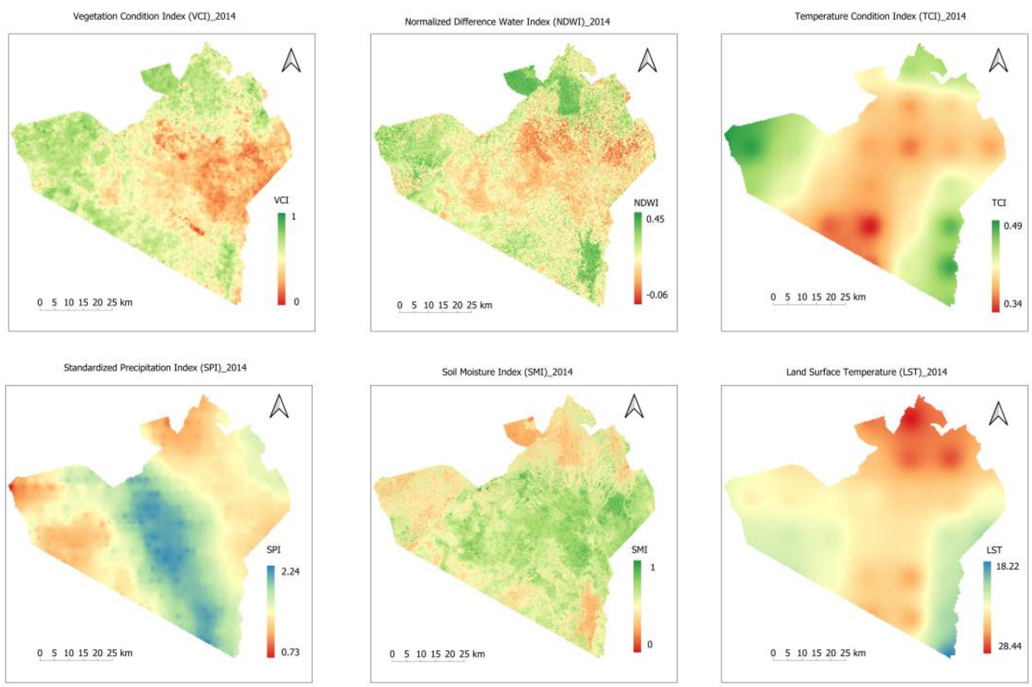

FIGURE 4.12: DROUGHT INDICES_2014

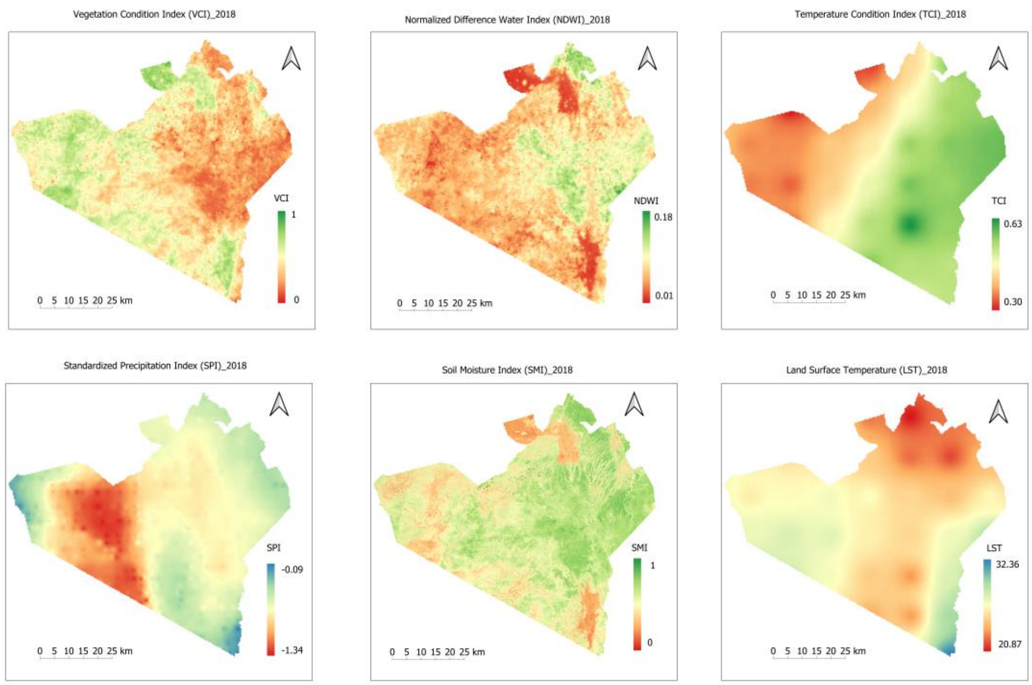

FIGURE 4.13: DROUGHT INDICES_2018

The VCI map reveals the health and vigor of vegetation in response to water availability. Areas with VCI values closer to 1 signify healthier vegetation, whereas values nearing 0 indicate stressed or deteriorated vegetation. Figure 4.14 below, suggests widespread vegetation stress due to limited moisture availability.

Lower NDWI values suggest reduced water availability, aligning with the drought conditions. The range of NDWI values indicates varying levels of moisture stress across different areas, substantiating the widespread impact of the drought.

Higher TCI values reflect warmer temperatures, which, when combined with limited rainfall, contribute to increased evaporation rates and heightened drought stress.

The LST map illustrates land surface temperature, with higher values indicating hotter and potentially drier conditions. The range of LST values underscores the elevated temperatures associated with drought, exacerbating evapotranspiration and contributing to water scarcity.

The SPI map quantifies rainfall deficits or surpluses. Positive SPI values above 0 indicate wetter conditions, while negative values below 0 indicate drier conditions. The positive SPI values in certain regions point to localized wetter periods, while negative values elsewhere correlate with the drought's impact.

The SMI map indicates soil moisture levels, with higher values suggesting greater moisture content. The lower SMI values in certain areas indicate reduced soil moisture, intensifying the drought's impact on vegetation and ecosystems.

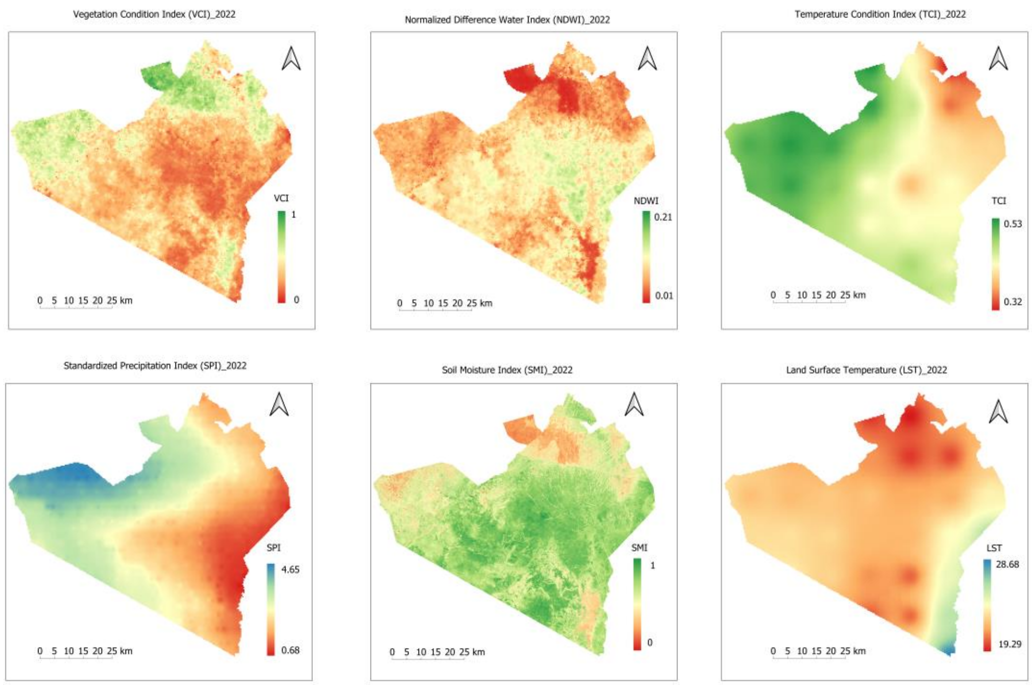

FIGURE 4.14: DROUGHT INDICES_2022

4.3 Correlation Analysis

4.3.1 Exploratory Regression Analysis

Exploratory regression refers to the process of using regression analysis as an exploratory tool to understand the relationships between variables in a dataset. The goal is not necessarily to build a predictive model but to gain insights into the data and understand how the variables are related to each other. It helps in identifying patterns, trends, and potential associations between variables.

The output of this process shows the percentage influence of each independent variable on the dependent variable. Figure 4.15 shows the influence of each drought indicator on individual vegetation index.

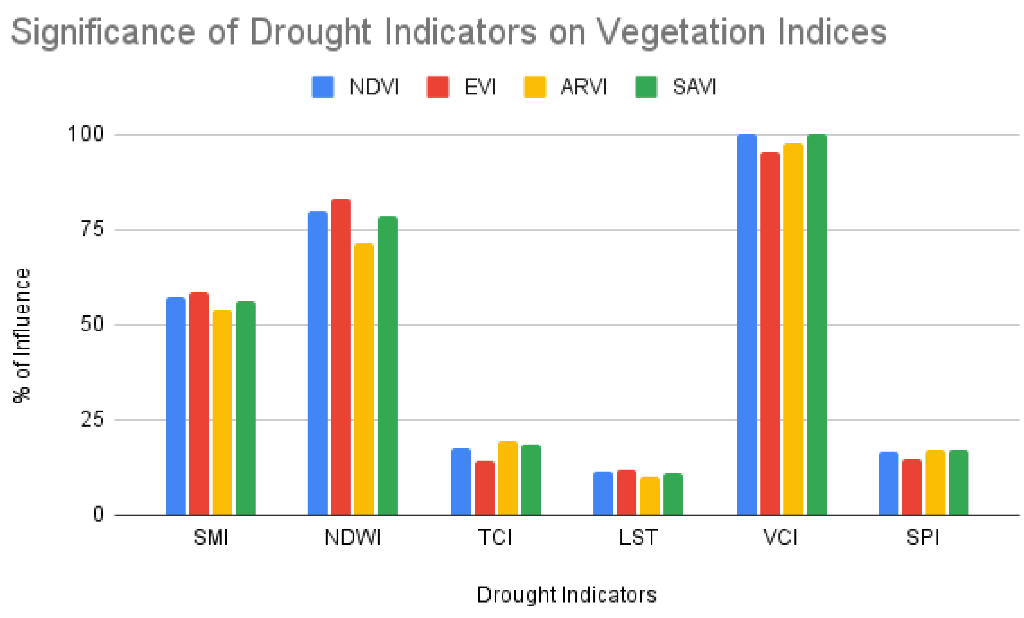

FIGURE 4.15: SIGNIFICANCE OF DROUGHT INDICES ON VEGETATION INDICES

Cumulative Drought Index

A cumulative drought index is a metric that combines various indicators of drought severity over a specific period, providing a comprehensive measure of the cumulative effects of drought. From exploratory analysis, cumulative drought index in this study takes into account soil moisture index, vegetation condition index and normalized difference water index. To calculate the cumulative drought index, the three drought indicators were aggregated as sum.

From the sum aggregation, it follows that the maximum drought will be 3 and minimum will be 0. Higher index values indicate less severe or no drought conditions, while lower values represent severe drought events. Table 4.1 below shows the drought categories.

TABLE 4.1: DROUGHT CATEGORIES

Value	Category
0	No-Drought
> 0 to <1	Mild Drought
≥ 1 to < 2	Moderate Drought

≥ 2 to < 3	Severe Drought
≥ 3	Extreme Drought

4.3.2 Regression Analysis

The aim of this project is to explore the relationship between drought indicators and vegetation indices. To accomplish this, regression analysis was employed, a statistical technique that allows modeling and quantification of the association between a dependent variable and one or more independent variables. In particular, this study utilizes Ordinary Least Squares (OLS) regression to estimate the parameters of the model.

Variable distribution

To gain insights into the distribution of vegetation indices and drought index in Narok County, a histogram analysis was conducted. The histograms provide visual representations of the frequency distribution of the variables.

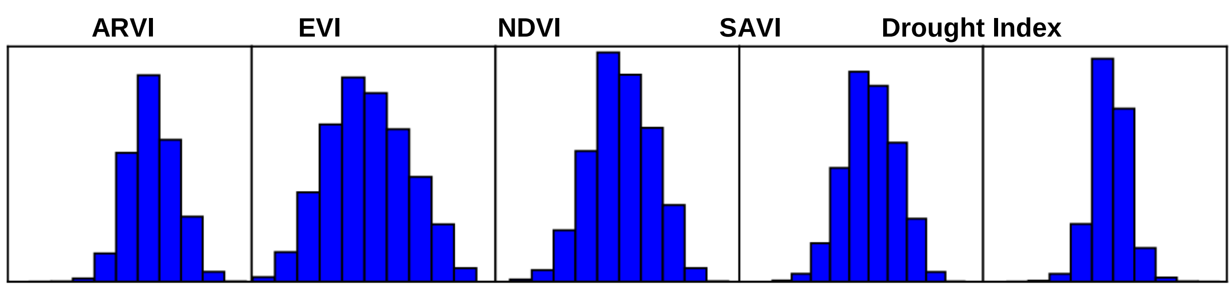

FIGURE 4.16: HISTOGRAM SHOWING VARIABLE DISTRIBUTION

From the histograms, it can be observed that the distribution of drought index and vegetation indices is approximately bell-shaped and symmetric, indicating a normal-like distribution. This suggests that the drought index and vegetation indices values in the study area are representative of the broader range.

Variable relationship

To examine the correlation between drought indices and vegetation indices, scatter plots were created. Scatter plots visualize the distribution of data points and help identify any patterns or trends between the variables. Figure 4.17 shows the relationship between the cumulative drought index and the vegetation indices. The observation that data points are clustered predominantly along the diagonal line of the scatterplots indicates a positive relationship between the vegetation indices and the drought indicators. This alignment signifies that as vegetation indices increase, there is a corresponding increase in the values of the drought indicators.

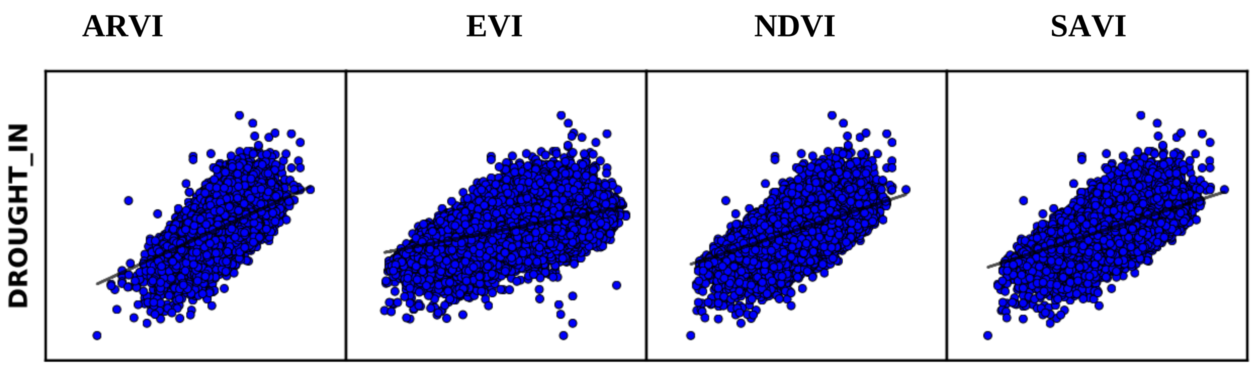

FIGURE 4.17: SCATTERPLOTS SHOWING VARIABLE RELATIONSHIPS

Histogram of residuals

To assess the validity of the regression model, an examination of the residuals was performed. The residuals represent the differences between the observed drought index values and the predicted drought index values from the OLS regression model. The figure below displays a histogram of the residuals obtained from the regression model. The histogram provides insights into the distribution and characteristics of the model's errors.

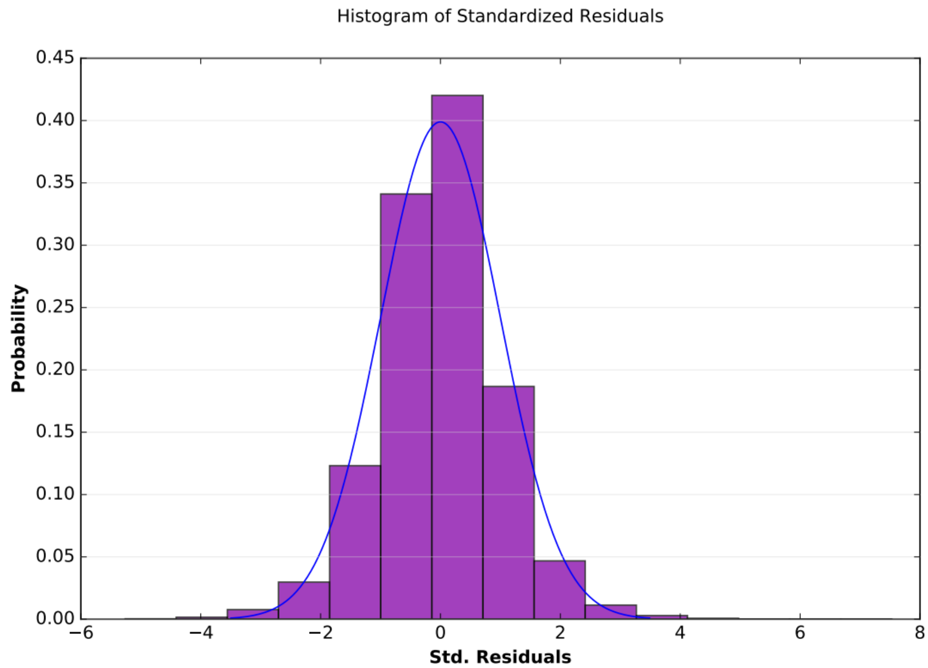

FIGURE 4.18: HISTOGRAM OF RESIDUALS

The histogram of residuals shows a roughly symmetric and bell-shaped distribution, indicating that the residuals follow a normal distribution. This suggests that the assumption of normality in the regression model is reasonable, supporting the reliability of the model's estimates.

The normal distribution of residuals implies that the model captures the underlying relationships between drought index and the vegetation indices adequately. The absence of significant deviations from normality suggests that the model's predictions are unbiased and reliable for this dataset.

4.4 Drought Monitoring Model

The model in this study can be represented as:

$$Y = c0 + c1*X1 + c2*X2 + c3*X3 + c4*X4 + e \quad (4.1)$$

Where c0 is the intercept, Y is the drought index value, c1, c2, c3 and c4 are ARVI, EVI, NDVI and SAVI coefficients respectively, X1, X2, X3 and X4 represent ARVI, EVI, NDVI and SAVI values respectively and e represents the error term. Table 4.2 presents the coefficients of vegetation indices spanning the period from 1987 to 2018.

TABLE 4.2: VEGETATION INDICES COEFFICIENTS

Parameter	1987	1994	2000	2008	2014	2018
C0	0.68	0.57	0.87	1.17	1.34	1.21
C1	-0.94	-0.72	-2.53	-1.96	-3.53	-2.62
C2	-0.27	-0.07	-0.26	-0.24	-0.27	-0.33
C3	-10.01	-13.61	-11.41	-17.46	-17.43	-12.71
C4	12.75	14.26	13.06	15.77	17.01	12.83

From the historical coefficient tabulation table above, average values between 1987 and 2018 for each coefficient were calculated to obtain the final model parameters that will be used in the model. The model will be in the form of;

Drought Index = 0.97 - 2.05X1 - 0.24X2 - 13.77X3 + 14.28X4 + 0.1

The data for the year 2022 will be used to validate the model. Figure 4.19 below shows a screenshot of the drought index model.

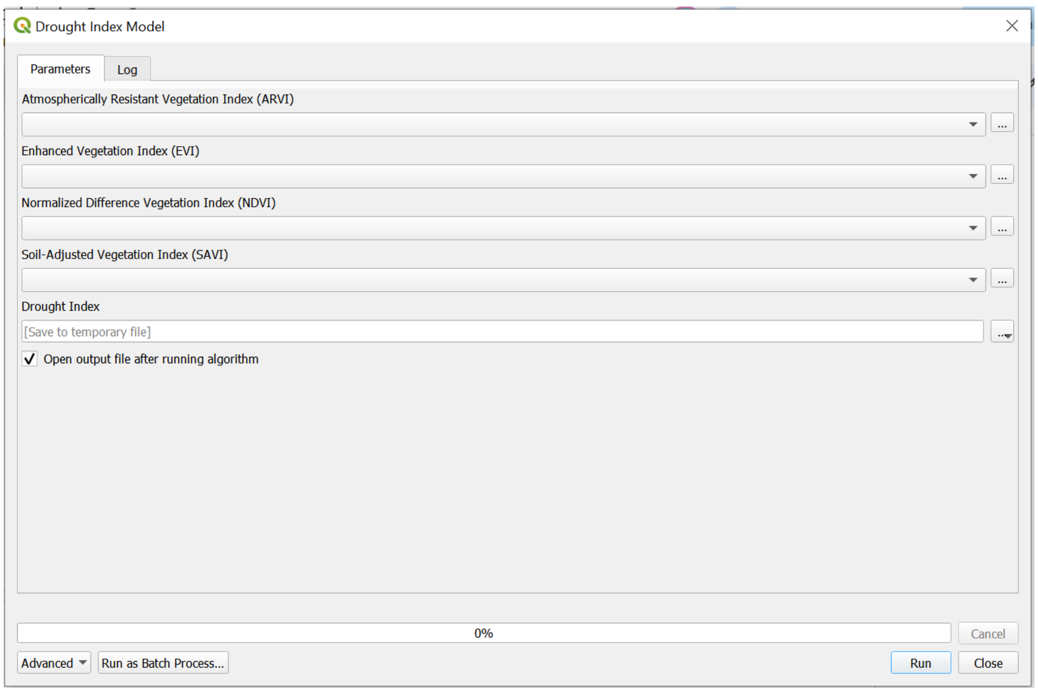

FIGURE 4.19: DROUGHT INDEX MODEL

4.5 Model Validation

To evaluate the precision of the model, a scatter plot of predicted versus the actual values of drought index for the year 2022 were plotted (see figure 4.20 below). The scatter plot serves as a visual tool to evaluate the performance of our regression model and assess its ability to accurately predict the drought index in Narok County. It helps us understand how closely the predicted values align with the actual values in our dataset.

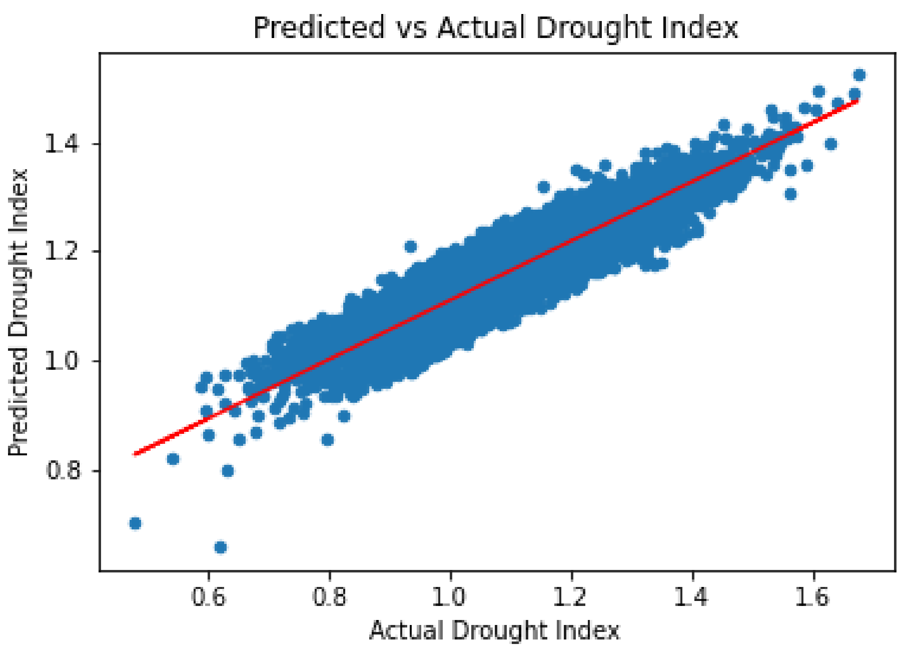

FIGURE 4.20: A GRAPH OF MODEL VALIDATION

R-Squared Value

The R-squared value, or the coefficient of determination, is a statistical metric that gauges the extent to which the predicted values account for the variability in the observed values. It assumes values between 0 and 1, with 1 denoting complete explanation of variance and 0 denoting no explanatory power.

Within this project, the R-squared value attained for the comparison between actual and predicted values stands at 0.86. This suggests that around 86% of the variability in the actual values can be elucidated by the model's generated predictions.

With an R-squared value of 0.86, we can conclude that the model explains a substantial proportion of the variance in the actual values.

4.6 Discussions of the results

The results obtained from the analysis provide valuable insights into the relationship between vegetation indices and drought indicators, shedding light on their potential applications in drought monitoring and management. The discussion of these results highlights key findings and their implications for understanding and mitigating drought impacts.

The examination of vegetation indices, including SAVI, EVI, NDVI, and ARVI, offered valuable insights into the health and density of vegetation over the study period. These indices collectively provided a comprehensive view of the changes in vegetation cover and its response to varying environmental conditions.

The period from 1987 to 2000 witnessed a significant decrease in vegetation cover across the study area. This decline could be attributed to a combination of factors, including land degradation, climate fluctuations, and human activities. These findings align with the broader context of environmental challenges faced by arid and semi-arid regions.

In contrast, a drastic increase in vegetation cover was observed from 2000 to 2008. This rise in vegetation health suggests a potential recovery or improved environmental conditions during this phase, possibly influenced by more favorable climatic patterns, land management practices, or conservation efforts.

However, the subsequent years from 2014 to 2022, recorded a decline in vegetation cover once again. This decline could be attributed to factors such as prolonged drought periods, changes in land use, or other stressors impacting the ecosystem

The absence of a significant correlation between LST, TCI, and SPI-1 with vegetation indices suggests that temperature, thermal condition, and standardized precipitation index (SPI) for a specific time period may not directly influence vegetation health or vigor. Other factors, such as local climate conditions, soil properties, or the complex interactions between different variables, may contribute to this lack of correlation. Further investigation is required to understand the underlying mechanisms and identify additional factors influencing vegetation response to drought.

The observed correlation between SMI, VCI, and NDWI and vegetation indices indicates that soil moisture, vegetation condition, and water content play crucial roles in influencing vegetation health and density. These findings align with existing knowledge, highlighting the importance of water availability in sustaining vegetation growth and overall ecosystem functioning. The positive correlation suggests that decreases in soil moisture and vegetation condition are indicative of drought stress and may serve as valuable indicators for drought monitoring and early warning systems.

It is crucial to highlight that the outcomes obtained are specific to the study area (Narok County) and the analyzed time period. Generalizing these findings to other regions or different time frames requires caution, as environmental conditions and vegetation responses to drought can vary significantly. Further research, including a broader spatial and temporal analysis, is necessary to validate and extend these findings.

CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

In conclusion, this study focused on exploring the use of vegetation indices as indicators of drought conditions, taking a remote sensing perspective and utilizing Narok County as a case study. Drought, as a recurring natural phenomenon, poses significant challenges to various regions, including Narok County, impacting ecosystems, agriculture, and socioeconomic systems.

The review of vegetation indices demonstrates their effectiveness as reliable tools for mapping vegetation cover.

The findings indicate that vegetation indices derived from remote sensing data can be utilized to estimate vegetation cover. By analyzing the spectral responses of vegetation, including indices such as NDVI, EVI, ARVI, and SAVI, accurate estimations of vegetation cover can be obtained.

The utilization of remote sensing data to compute drought indices presents a valuable approach for quantifying and assessing drought conditions. By analyzing the spectral response of vegetation and other relevant variables, these indices provide valuable information on drought severity, duration, and spatial extent. This enables effective monitoring and analysis of drought patterns and facilitates informed decision-making in drought management.

By analyzing remote sensing data and vegetation indices, valuable insights were gained into the relationship between vegetation dynamics and drought occurrences in Narok County.

The findings revealed interesting patterns in the correlation between the vegetation indices and the climatic variables. While LST, TCI, and SPI-1 showed no significant correlation with the vegetation indices, SMI, VCI, and NDWI exhibited a significant correlation. This correlation suggests that vegetation indices can effectively capture and reflect drought-induced changes in vegetation health, biomass, and moisture content.

The lack of correlation between LST, TCI, and SPI-1 with the vegetation indices could be attributed to several factors. Time lag might play a role, as the immediate response of vegetation to changes in temperature or precipitation may not be captured by these variables. Additionally, other factors influencing LST and TCI, such as cloud cover or atmospheric conditions, could affect their correlation with vegetation indices. Moreover, SPI-1, being a precipitation-based index, might not capture the immediate response of vegetation to drought conditions.

On the other hand, the strong correlation observed between SMI, VCI, and NDWI with the vegetation indices highlights their suitability as indicators of drought conditions. The SMI, reflecting soil moisture content, provides insights into the availability of water for vegetation. The VCI, capturing vegetation vigor, indicates the health and condition of vegetation in relation to drought stress. The NDWI, sensitive to water content in vegetation, provides information on water availability and stress levels.

5.2 Recommendations

There is need for further research and evaluation of different vegetation indices to identify the most suitable indices for mapping vegetation cover accurately. This will enhance the understanding of vegetation dynamics and improve the effectiveness of drought monitoring and management.

To estimate vegetation cover using vegetation indices, it is recommended to develop robust models and algorithms that incorporate multiple indices and consider the specific characteristics of the study area. Regular validation and calibration of the estimation methods should be carried out using ground truth data to ensure accuracy and reliability

When computing drought indices using remote sensing data, it is recommended to integrate various relevant variables such as precipitation, temperature, and soil moisture alongside vegetation indices. This comprehensive approach will improve the accuracy and reliability of the computed drought indices, providing a holistic understanding of drought conditions.

To establish a robust correlation between vegetation cover and drought indicators, it is recommended to conduct in-depth statistical analysis and modeling. This should involve considering long-term trends, spatial variability, and incorporating multiple data sources. Regular monitoring and validation of the correlation should be undertaken to ensure its consistency and relevance over time.

By incorporating vegetation indices into drought monitoring and prediction systems, stakeholders, including policymakers, land managers, and researchers, can gain valuable insights into the severity, duration, and spatial extent of drought events. This information enables proactive drought management and mitigation efforts, leading to better resource allocation, improved land use practices, and more effective water resource management.

Further research and validation studies are necessary to strengthen the understanding and applicability of vegetation indices as indicators of drought. Conducting field studies, comparing remote sensing data with ground observations, and evaluating the performance of vegetation indices under different climatic and ecological conditions will enhance the reliability and confidence in their use for drought monitoring and prediction.

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