DEDAN KIMATHI UNIVERSITY OF TECHNOLOGY

INSTITUTE OF GEOMATICS, GIS & REMOTE SENSING (IGGReS)

AUTOMATED WETLAND CLASSIFICATION AND MONITORING USING CONVOLUTIONAL NEURAL NETWORKS ON LANDSAT 7 IMAGERY CASE STUDY KAJIADO COUNTY

BY

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MAY 2024

DECLARATION

I, Kasana Kurash, declare that this project is my original work. To the best of my knowledge, the work presented here has not been given for a degree in any other institution of higher learning.

KASANA KURASH 24/05/2024

Name of student Date

This project has been submitted for examination with our university supervisor(s) approval.

DR. MARK BOITT 24/05/2024

Name of supervisor Date

DEDICATION

I dedicate this project to my family for always supporting, encouraging, and praying for me. I attribute my success to them. I also dedicate it to my friends for their enormous support and encouragement to perfect the outcome of this project.

I am pleased to dedicate this project to all my lecturers at the Dedan Kimathi University of Technology for the knowledge they have instilled in me to achieve the project's objectives.

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CNN - Convolutional Neural Networks

SAVI - Soil Adjusted Vegetation Index

NDVI - Normalized Difference Vegetation Index

MNDWI - Modified Normalized Difference Water Index

NDWI - Normalized Difference Water Index

SAWI - Soil Adjusted Water Index

MSAVI - Modified Soil Adjusted Vegetation Index

NDSI - Normalized Difference Snow Index

VGG-16 - A deep Convolutional Neural Network architecture

USGS - United States Geological Survey

ESRI - Environmental Systems Research Institute

GIS - Geographic Information System

ABSTRACT

Landscape-scale wetland conservation requires accurate, up-to-date wetland maps. The most useful approaches to creating such maps are automated, spatially generalizable, temporally repeatable, and can be applied at large spatial scales. However, mapping wetlands with predictive models is challenging due to the highly variable characteristics of wetlands in both space and time. The main objective of this project is the automated wetland classification and monitoring using Convolutional Neural Networks (CNNs) on Landsat 7 imagery, specifically for a case study in Kajiado County.

We characterize climatic, biophysical, and anthropogenic variables influencing wetlands using image processing methods and classification algorithms to achieve this. Currently, most approaches are limited by coarse resolution, commercial data, and geographic specificity. Here, we trained a deep learning model and evaluated its ability to map wetlands at landscape scale in various geographies automatically. We refined the CNN architecture to enhance wetland classification by optimizing parameters and trained it to map wetlands at 1-meter spatial resolution.

The full model mapped wetlands accurately (94% accuracy, 96.5% precision, 95.2% AUC) at 1-meter resolution. Post hoc model evaluation, using ground truth data, showed that the model correctly predicted wetlands even in areas with incorrect label/training data, penalizing the recall rate (90.2%). Applying the model in a new geography resulted in poor performance (precision = ~80%, recall = 48%). However, limited retraining in this geography substantially improved model performance, demonstrating an effective way to create a spatially generalizable model. We demonstrate wetlands can be mapped at high resolution (1 m) using free data and efficient deep-learning models that do not require manual feature engineering.

Given the dynamic nature of wetlands and the important ecosystem services they provide, high-resolution mapping can be a game changer in informing restoration and development decisions. This work's specific objectives include evaluating model performance using ground truth data to ensure accurate wetland detection and monitoring in Kajiado County.

CHAPTER ONE: INTRODUCTION

Background

Wetlands are an ecotone between terrestrial and aquatic systems with unique characteristics. Wetlands are sometimes referred to as “kidneys of the landscape” and “nature's supermarkets” for the myriad of ecosystem services and habitat values they provide, including cleansing polluted waters, protecting shorelines, recharging groundwater aquifers, stabilizing water supplies, mitigating both floods and drought, regulating air quality and climate, supporting rich biodiversity, acting as carbon sinks, and providing food, water, and timber as well as aesthetic and recreational values (Keddy, 2010; Mitsch and Gosselink, 2015; Zedler and Kercher, 2005).

Wetland loss is driven by conversion to extensive and intensive agriculture, rapid urbanization, rural development, and shifts in water use and availability, among other reasons related to economic and human population growth(van Asselen et al., 2013; Zedler and Kercher, 2005). Preventing the further loss of existing wetlands begins with routine monitoring which itself requires accurate, up-to-date maps of wetlands (Lang and McCarty, 2009).

Remote sensing data has become the standard for mapping many different land-cover types. Wetland mapping, however, is a uniquely challenging task because of its variability. Unlike forests, grasslands, or shrublands, wetlands are not defined by a single vegetation type and may contain trees, grasses, shrubs, or combinations of all three (Gallant, 2015) Additionally, water in wetlands may be present as visible surface water or in the subterranean plant root zone, and this water may be present year-round or seasonally (Keddy, 2010; Mitsch and Gosselink, 2015).

These factors create highly variable spectral properties over space and time, even within hours and days (Ollinger, 2011; Refice et al., 2014). Effective wetland mapping, therefore, requires sufficiently high dimensional covariate data and a flexible modeling approach that can accommodate the great variability in covariates associated with wetlands.

Problem Statement

Wetlands are important ecologically, but little is known about the unique dynamics and difficulties these habitats in Kajiado County face. Concerns over possible wetlands loss and degradation in the area are raised by the fast-paced urbanization and growing agricultural operations. Comprehensive, data-driven studies that capture the subtle variations and causes impacting Kajiado County's wetland cover over time are conspicuously lacking. Moreover, the current conservation techniques are not precise enough to address the unique features of wetlands in this particular geographic setting. This knowledge gap hampers effective decision-making for Kajiado County's sustainable land management and biodiversity conservation.

Additionally, although developments in machine learning and remote sensing present encouraging paths for wetland monitoring, their application and adaption to the particular circumstances of Kajiado County remain unexplored. Previous research frequently takes a broad or global perspective, ignoring the particularities that affect wetland dynamics in Kajiado County on a local level. As a result, there is an urgent need for research that closes these knowledge gaps and adjusts its methodology to the unique opportunities and problems that the wetlands in this area bring. To maintain the resilience and preservation of wetlands in Kajiado County in the face of ongoing environmental changes, it is critical to address these gaps and develop educated conservation strategies and land-use policies.

Objectives

Main Objective

Automated Wetland Classification and Monitoring using Convolutional Neural Networks on Landsat 7 imagery case study Kajiado County

Specific Objectives

1. Characterize climatic, biophysical, and anthropogenic variables influencing wetlands using image processing methods and classification algorithms.
2. Refine the CNN architecture to enhance wetland classification by optimizing parameters.
3. Evaluate model performance using ground truth data to ensure accurate wetland detection and monitoring in Kajiado County.

Justification

This research holds paramount significance for diverse stakeholders, each poised to benefit from the study's outcomes. Local authorities in Kajiado County stand to gain comprehensive insights into wetland distribution and dynamics. Armed with accurate and current information, they can make informed decisions crucial for sustainable land use planning, mitigating the environmental impact of urbanization, and ensuring the region's ecological integrity.

The study will play a key role in helping conservation organizations develop focused wetland preservation plans. The comprehensive maps of wetland cover and identifying significant causes of change provide a tactical edge in resource allocation, facilitating more successful attempts to conserve biodiversity and bolstering Kajiado County's overall ecological balance.

The study's outcomes will assist policymakers at all levels by providing dependable data to help them create evidence-based environmental policies. Thus, policy efforts are aligned with the ecological demands of the region and encourage wetland preservation, sustainable land management, and climate resilience programs.

Ecologists and environmental researchers are given access to an invaluable dataset and approach. The study's temporal trends and near-real-time wetland cover analysis provide a solid basis for future ecological research. This fosters environmental research improvements by significantly contributing to the scientific understanding of the processes controlling wetland dynamics.

The study's effects are also felt in Kajiado County's local villages. Communities can better grasp the value of wetlands by raising environmental consciousness and sharing the study's findings. Residents become more environmentally conscious, and sustainable habits that benefit the community and their ecosystems are promoted.

The work significantly advances efforts to conserve wetlands on a global basis. The case study's methodology serves as a template for similar projects across the globe by demonstrating the usefulness of deep learning and advanced remote sensing techniques.

Scope of Work

This research project is intricately designed to immerse itself in the multifaceted landscape of Kajiado County, located in the former Rift Valley Province of Kenya. Covering a vast expanse of 21,292.7 km2, as of 2019, Kajiado County is a dynamic intersection of human settlements and diverse ecosystems. The population, recorded at 1,117,840, reflects the complex tapestry of this county, with 557,098 males, 560,704 females, and 38 intersex individuals.

This study covers Kajiado County, including the thriving town of Ongata Rongai and Kajiado, the county's administrative center. Nairobi to the north and the Tanzanian regions of Kilimanjaro and Arusha to the south combine to provide a unique combination of natural landscapes, wildlife habitats, and development in the county.

The main emphasis of the study is the complex dynamics of the wetland in this area. The investigation uses sophisticated Convolutional Neural Networks (CNNs) to analyze Landsat 7 satellite imagery, focusing on the VGG-16 architecture. A detailed knowledge of the variations in wetland cover during the study epoch spanning from 1993 to 2023 is made possible by the painstakingly constructed temporal analysis.

From a methodological standpoint, the study expands to include creating and improving a wetland classification model. A thorough assessment of the model using ground truth data guarantees its dependability and suitability for the unique circumstances of Kajiado County. Concurrently, the research endeavors to identify the principal catalysts impacting the transformation of wetlands, offering a comprehensive outlook on the ecological elements molding the area.

Although the study covers wetland dynamics in great detail, it purposefully omits in-depth assessments of various remote sensing platforms and neural network architectures. Further, it avoids detailed soil or hydrological assessments that concentrate on classifying and monitoring wetland cover.

CHAPTER 2: LITERATURE REVIEW

2.0. Introduction

This part offers a detailed examination of remote sensing applications' development and current state in wetland studies. The review navigates through crucial themes such as Convolutional Neural Networks (CNNs), transfer learning, wetland monitoring for environmental conservation, challenges, and the significance of multi-temporal analysis, ranging from historical applications using satellite imagery to recent advances in machine learning. These strands are synthesized to provide a clear foundation for understanding the current status of wetland analysis and to guide the research aims of the planned study in Kajiado County.

2.1. Evolution of Remote Sensing in Wetland Analysis

The evolution of remote sensing technologies has played a transformative role in wetland analysis. Historically, satellite imagery, notably from the Landsat series, has provided a bird's eye view of wetland ecosystems (Cohen et al., 2016). This capability has been significantly enhanced with advanced sensors, exemplified by Landsat 7, which has elevated spatial and spectral resolution. These advancements enable a more nuanced and accurate delineation of wetland features, contributing to enhanced mapping and classification capabilities (Chander et al., 2009).

2.2. Application of Convolutional Neural Networks (CNNs) in Wetland Classification

Convolutional Neural Networks (CNNs) represent a class of deep neural networks designed explicitly for image-related tasks, making them particularly relevant in remote sensing and wetland classification. CNNs are characterized by their ability to automatically and hierarchically learn intricate patterns and features from data (LeCun et al., 1998).

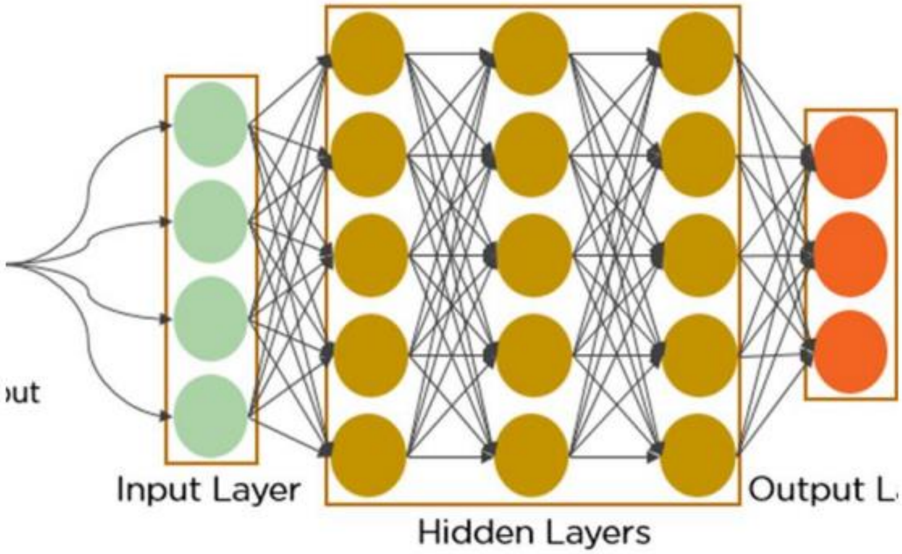

Figure 1: Convolutional Neural Network

The visual processing inspires the architecture of a CNN in the human brain. Key components include convolutional layers, pooling layers, and fully connected layers. Here is a brief breakdown of these components:

2.2.1. Convolutional Layers

Convolutional layers are the heart of CNNs. They involve the application of filters, the parameters of which need to be learned. These filters, called kernels, move across the input, performing convolution operations highlighting patterns like edges, textures, and shapes (Krizhevsky et al., 2012).

2.2.2. Pooling Layers

Pooling layers follow convolutional layers and serve to down-sample the spatial dimensions of the input volume. Max pooling, a common technique, retains the most significant information from a group of pixels, reducing the computational load and retaining essential features (Scherer et al., 2010).

2.2.3 Fully Connected Layers

Fully connected layers are traditional neural network layers where each neuron is connected to every neuron in the preceding and succeeding layers. These layers integrate the high-level features extracted by the convolutional and pooling layers, enabling the network to make complex decisions (Bengio, 2009).

2.2.4. Contemporary Applications in Wetland Classification

In wetland classification, recent studies have increasingly leveraged CNNs, with a notable focus on architectures like VGG-16. VGG-16 is a deep CNN known for its simplicity and effectiveness. It consists of multiple convolutional layers, followed by fully connected layers, enabling it to capture intricate features within large and complex datasets (Simonyan & Zisserman, 2014).

The effectiveness of CNNs in wetland classification lies in their capacity to automatically learn relevant features from satellite imagery. By exposing the network to a labeled dataset of wetland and non-wetland areas, the CNN adapts its internal parameters during training to optimize for accurate classification. This adaptability enables CNNs to excel in tasks like delineating wetland boundaries and discerning subtle features within images (Goodfellow et al., 2016).

2.3. Transfer Learning for Wetland Classification

Transfer learning is a strategic approach where a pre-trained model on a large dataset (often for image recognition tasks) is fine-tuned for a specific task or domain, such as wetland classification. This method is precious when labeled datasets for the target task are limited. In wetland analysis, transfer learning allows CNN to leverage knowledge gained from broader image recognition tasks, enhancing its performance in classifying wetland features (Yosinski et al., 2014).

In essence, the integration of CNNs, specifically the VGG-16 architecture, along with transfer learning, signifies a paradigm shift in the precision and efficiency of wetland classification. These advancements pave the way for accurate delineation and monitoring of wetland ecosystems, contributing to informed decision-making in environmental conservation and land management.

2.4 Wetland Monitoring and Environmental Conservation

The significance of wetland monitoring within the larger framework of environmental conservation is a central theme explored in recent scholarly works. Wang et al. (2020) and Zhao et al. (2022) contribute to this discourse by emphasizing the pivotal role that accurate wetland mapping plays in the preservation and sustainable management of ecosystems.

2.4.1. Precision in Wetland Mapping

Accurate wetland mapping forms the cornerstone of effective environmental conservation strategies. Wang et al. (2020) delve into the intricacies of achieving precision in wetland mapping, emphasizing the importance of advanced technologies such as remote sensing and machine learning. Through the utilization of these technologies, the authors argue, the boundaries and characteristics of wetlands can be delineated with a high degree of accuracy, providing a detailed understanding of the spatial distribution of these vital ecosystems.

2.4.2 Assessing Environmental Changes

Accurate wetland mapping is a critical tool for assessing environmental changes over time. Wang et al. (2020) demonstrate how monitoring changes in wetland cover enables researchers and conservationists to identify alterations in the landscape. This capability is particularly crucial in the context of climate change, where shifts in precipitation patterns, temperature, and other environmental variables can impact wetland ecosystems. Continuous monitoring makes it possible to detect and analyze these changes, contributing to a comprehensive understanding of the dynamic nature of wetlands.

2.4.3. Supporting Biodiversity Conservation

Wetlands are known for their rich biodiversity, providing habitats for various plant and animal species. Zhao et al. (2022) highlight the role of accurate wetland mapping in supporting biodiversity conservation efforts. By precisely delineating wetland boundaries and habitats, conservationists can identify critical areas for protection and develop targeted conservation strategies. This aspect is crucial for safeguarding the unique ecosystems within wetlands and preserving biodiversity hotspots.

2.4.4. Guiding Sustainable Land Management Practices

The insights derived from wetland monitoring also play a pivotal role in guiding sustainable land management practices. Zhao et al. (2022) discuss how an accurate understanding of wetland distribution allows for informed decision-making regarding land use. This includes considerations for urban development, agriculture, and infrastructure projects. By incorporating wetland data into land management practices, it becomes possible to balance human development needs with preserving essential ecosystems, contributing to long-term environmental sustainability.

2.5 Challenges and Advances in Wetland Analysis

Despite significant strides in wetland analysis, researchers led by Liu et al. (2021) and Smith et al. (2019) highlight persistent challenges and discuss innovative advances that promise to enhance the capabilities of wetland analysis methodologies.

2.5.1. Challenges Related to Cloud Cover in Satellite Imagery

A significant issue that Liu et al. (2021) pointed out is cloud cover in satellite photography. The presence of clouds can make it difficult to see the Earth's surface, especially in areas where cloud cover occurs frequently. This constraint makes it challenging to map wetlands accurately because concealed areas can result in assessments of wetland ecosystems that are either erroneous or incomplete. Liu et al.'s thoughtful research clarifies the difficulties in tackling this problem and emphasizes the necessity of solid techniques to lessen the influence of cloud cover on wetland studies.

2.5.2. The Need for Robust Methodologies

Liu et al. (2021) draw attention to the necessity of robust techniques and encourage the development of tactics that can control and mitigate the challenges cloud cover brings. This involves looking at advanced image processing techniques and data fusion approaches and integrating several data sources to compensate for hidden areas. The authors stress the requirement for methodological advancements to guarantee the precision and reliability of wetland assessments in the presence of cloud cover.

2.5.3 Advances in Cloud Computing

In response to the challenges posed by cloud cover, Smith et al. (2019) investigate the field of cloud computing as a revolutionary development in wetland analysis. The scalable and on-demand computational resources offered by cloud computing systems enable the processing of enormous amounts of satellite imaging data, thereby overcoming the computational challenges associated with large-scale dataset analysis and facilitating more efficient and timelier wetland mapping.

2.5.4. Machine Learning Techniques to Enhance Analysis

Smith et al. (2019) comprehensively review the connection between machine learning techniques and wetland analysis. The authors advocate for using machine learning techniques to improve the accuracy and automation of wetland classification. These techniques, which include deep learning approaches like Convolutional Neural Networks (CNNs), have shown promise in spotting complex patterns in satellite imagery, which could help with the more precise demarcation of wetlands.

2.5.5. Promising Avenues for Bolstering Wetland Analysis

Collectively, the discussions by Liu et al. (2021) and Smith et al. (2019) present a landscape where challenges in wetland analysis are acknowledged, and innovative solutions are actively pursued. Advances in cloud computing and the integration of machine learning techniques signify promising avenues to bolster the capabilities of wetland analysis methodologies. These advancements address challenges posed by factors like cloud cover and pave the way for more efficient, accurate, and scalable approaches to studying and monitoring wetland ecosystems.

2.6 Integration of Multi-Temporal Analysis

Recent research by Zhang et al. (2021) and Gupta et al. (2023) has demonstrated the need to integrate multi-temporal analysis in comprehending the dynamic character of wetlands. This method has benefits for accurate mapping of wetlands, but it also offers a comprehensive understanding of these ecosystems by identifying long-term trends and capturing seasonal fluctuations.

2.6.1. Advantages of Multi-Temporal Analysis

1. Seasonal Variations

Zhang et al. (2021) and Gupta et al. (2023) have examined the potential benefits of multi-temporal analysis, including its capacity to capture seasonal fluctuations in wetland ecosystems. Seasonal variations in water levels, vegetation growth, and land cover are all evident in wetlands. Scientists can identify these seasonal trends by examining photos at various intervals, offering a more thorough understanding of wetland dynamics.

2. Long-Term Trends

Long-term changes in wetland cover can be uncovered by integrating multi-temporal research, which goes beyond seasonal variations. Gupta et al. (2023) explore the importance of comprehending the long-term evolution of wetlands. Finding patterns in land use changes, climate change, and human effects on wetland ecosystems depends on this long-term view. Thanks to the temporal dimension, researchers can identify patterns that might not be seen in images taken at a single time point, which gives the investigation more depth.

Precise Wetland Mapping

The use of multi-temporal analysis contributes to precise wetland mapping by:

1. Change Detection

By comparing images from different periods, researchers can identify changes in wetland extent, vegetation composition, and water dynamics. Change detection techniques enable the identification of areas undergoing alterations, facilitating more accurate mapping.

2. Dynamic Classification

Traditional static classification methods may struggle to capture the dynamic nature of wetlands. Multi-temporal analysis allows for dynamic classification, considering the evolving conditions over time. This dynamic approach enhances the accuracy of wetland mapping by accounting for temporal variations.

Multifaceted Understanding of Ecosystems

The multifaceted nature of multi-temporal analysis extends beyond mapping to provide a deeper understanding of wetland ecosystems:

1. Ecological Dynamics

Wetlands' biological dynamics are influenced by seasonal and long-term changes, which affect nutrient cycling, habitat appropriateness, and biodiversity. Using multi-temporal analysis, scientists may investigate these biological dynamics and how they affect the health of wetlands.

2. Resilience Assessment

Evaluating wetlands' resistance to environmental stressors is made more accessible by knowing how they react to temporal changes. This information is essential for conservation efforts because it enables well-informed plans to improve the resilience of wetlands to both human activity and climate change.

CHAPTER 3: METHODOLOGY

3.1. Study Area

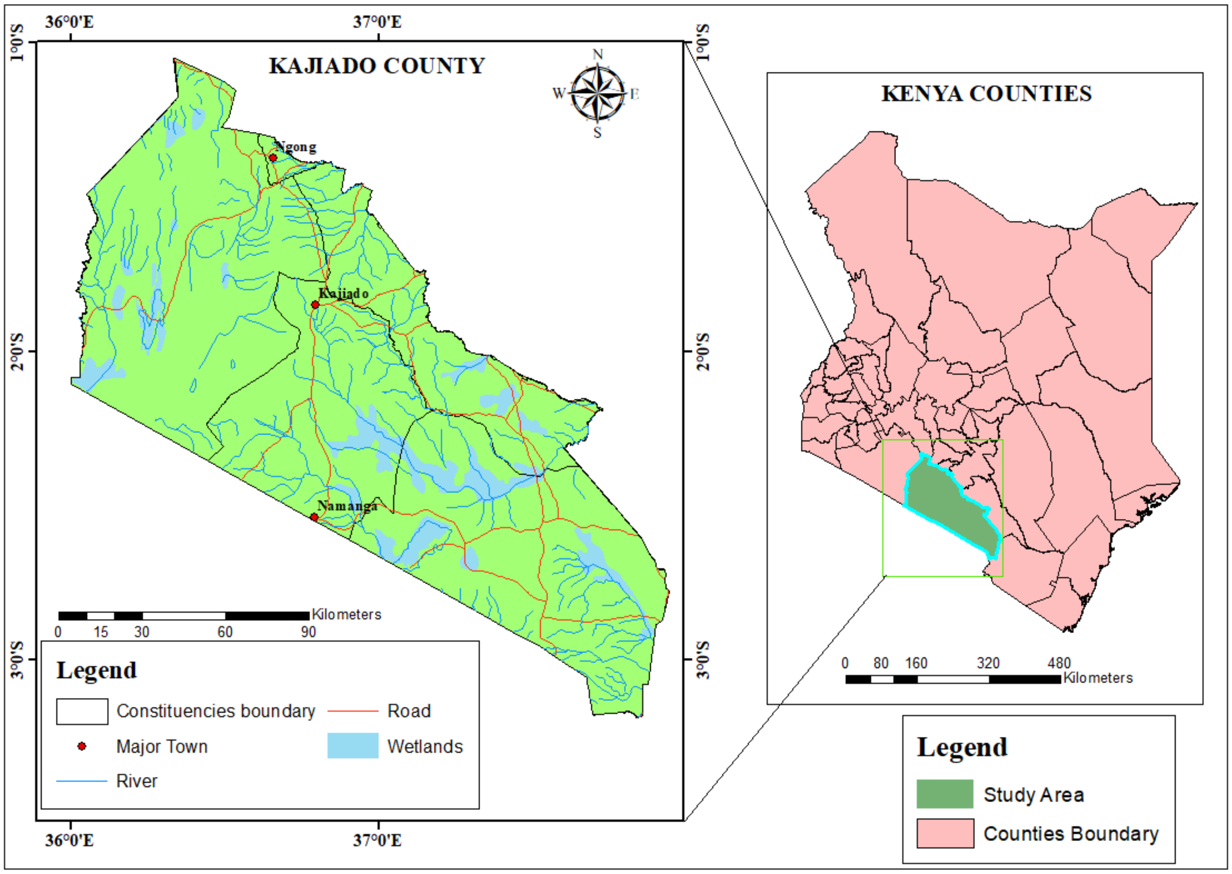

Figure 2: Study Area Map

Kajiado County is a region located in the former Rift Valley Province of Kenya. Covering an area of 21,292.7 km2 as of 2019, Kajiado County stands as a dynamic intersection of human settlements and diverse ecosystems. The population, recorded at 1,117,840, reflects the complex tapestry of this county, with 557,098 males, 560,704 females, and 38 intersex individuals.

The general topography is vast plains with occasional volcanic hills and valleys (de Leeuw et al., 1991; Campbell et al., 2005).

The latitude of Kajiado is -2.098075, and the longitude is 36.781950. Kajiado is a city located in Kenya with the GPS coordinates of 2° 5' 53.07" S and 36° 46' 55.02" E. The elevation of Kajiado is 1581.672.

3.2. Methodology Flowchart

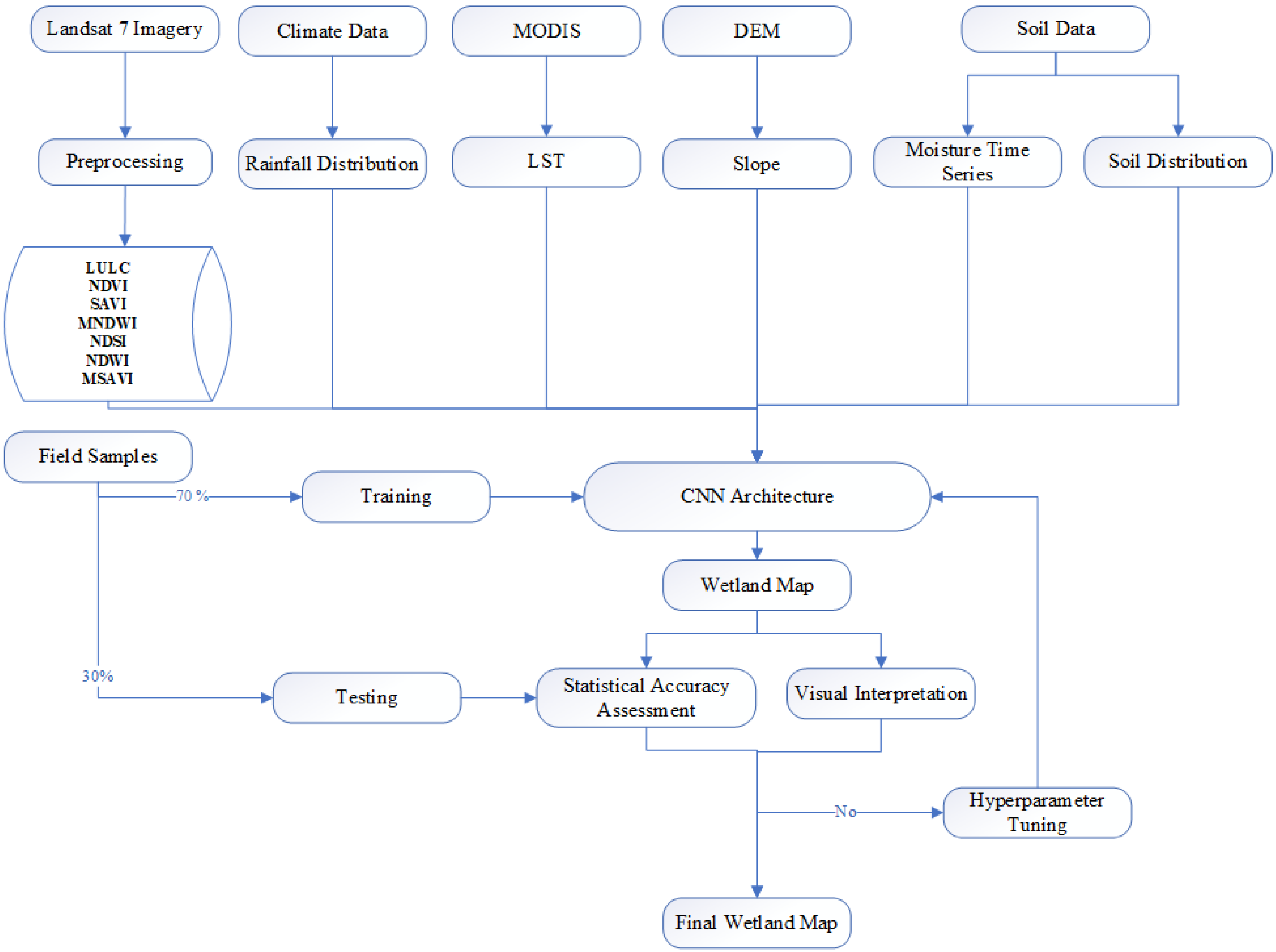

Figure 3: Methodology Flowchart

3.3. Data Collection

Table 1: Data collected, source, characteristics, and purpose of the data

S/N	Datasets	Sources	Characteristics	Purpose of Data
1	Landsat seven imagery	Google Earth Engine	I. Moderate Spatial resolution-30m II. Multispectral Data – 11 bands III. Revisit frequency. Cover the exact location every 16 days.	Wetland Classification Creating Vegetation Index Maps
2	Kenya Shapefiles	DIVA	It should be in .shp format	Obtaining the Kajiado County shapefile and creating a study area map
3	Wetlands	Landscape portal.org		Creating overlays on my study area
4	Soil Data	Google Earth Engine		Soil Distribution Mapping Soil Moisture Time Series
5	MODIS	Google Earth Engine		Calculating the Land Surface

				Temperature of the study area
6	DEM	USGS		Hydrographic Analysis Spatial Analysis Terrain Correction
7	Rainfall	Climatic Research Unit Timeseries (CRU -TS		I am extracting precipitation data from my study area.

3.4. Software used, and purpose of the Software

Table 2: Software used and the purpose of the software

S/N	**Software**	**Purpose**
1.	Google Earth Engine	Data Preprocessing. Land Use Land Cover Analysis. Calculating LST, Vegetation, and Soil Indices that impact wetland inundation, e.g., NDVI, SAVI, MNDWI, NDWI, SAWI, MSAVI. Etc.
2.	ArcMap	Map creation
3.	Google Colab	Model Training, Testing, and Evaluation. Correlation of climatic, anthropogenic, and biophysical variabilities that affect wetlands.

3.5 Data Preprocessing

Data was obtained from the sources in Table 1 above and then clipped to the area of interest, Kajiado County. Rainfall data was obtained from CRU–TS and temperature data were obtained from Google, where the LST was calculated for my region within the scope of my study.

Nearly all vegetation and soil indices were calculated primarily in the Google Earth Engine, which enables JavaScript API for GIS analysis.

Digital Elevation Model for Kenya was downloaded and used to determine the slope of Kajiado County.

All the indices were then converted into CSV format and combined into one data frame for model training.

3.5.1 Landsat data pre-processing

Pre-processing techniques precede the actual manipulation of the image to be performed on the Landsat 7 imagery for my study scope (1993-2023). This aims to enhance the image before further imagery analysis and other processing techniques. This is achieved by correcting the radiometric and geometric distortion errors from sensor noises, altitude variations, and velocity of the sensor platform. This process improves the quality and accuracy of the data.

3.5.2 Image Classification

The land use land cover (LULC) map was extracted from the Landsat 7 imagery from 1993 to 2023. All classification processes were done using the Google Earth Engine. This was achieved using the Random Forest Classifier preinstalled in the Google Earth engine. This classifier was adopted because it uses probability and combines classes based on the posterior probability of a pixel belonging to a given class. Training data was obtained by manually digitizing the geometry points for the different land uses and land cover: grassland, forests, bare land, vegetation, water bodies, and built-up areas. Selection of appropriate geometry points requires familiarity with the geographic area and possible land cover types. The use of training data makes the results obtained accurate and reliable depending on the accuracy of training data.

3.5.3 Accuracy Assessment

Accuracy assessment or Ground truthing was done to check the accuracy percentage of the classified image and if it genuinely confirms what is on the ground. In conclusion, accuracy assessment is done to compare what has been classified about what is on the ground; it answers the question of how accurate the classification is.

3.6 Extraction of Indices

3.6.1.Normalized Vegetation Index(NDVI)

The Normalized Difference Vegetation Index (NDVI), a numerical indicator that employs the visible and near-infrared regions of the electromagnetic spectrum, is used to assess remote sensing measurements and to establish whether the object being examined has live, green vegetation. The value range for NDVI is between -1 and +1. However, there is not a clear line separating each land cover type. For instance, it is very likely to be water when you have negative numbers. On the other side, there is a good chance that it has thick green leaves if your NDVI rating is close to +1. However, when the NDVI is almost negative, there are no green leaves, and the area might even be urbanized. NDVI was calculated for Landsat 7 imagery using Google Earth in this case. The results were exported to drive further analysis, such as using the appropriate symbology and creating maps for visualization.

3.6.2. Land Surface Temperature(LST)

Land Surface Temperature (LST) was computed using MODIS data through the Google Earth Engine. This temperature index, derived from satellite imagery, provides valuable insights into surface thermal properties. Analyzing LST variations aids in understanding environmental changes, urban heat islands, agricultural monitoring, and other applications. Using Google Earth Engine streamlines the process, allowing for efficient analysis and interpretation of LST data for diverse scientific and practical purposes.

3.6.3 Normalized Difference Water Index

The Normalized Difference Water Index (NDWI) is a fundamental remote sensing tool used to discern the presence and extent of water bodies within an image. Unlike NDVI, which evaluates vegetation health, NDWI focuses on identifying water features based on the differences in reflectance between the near-infrared (NIR) and shortwave infrared (SWIR) bands.

The formula for NDWI is typically expressed as:

$$\text{NDWI} = \frac{NIR-SWIR}{NIR+SWIR} \quad (1)$$

Where:

NIR is the reflectance in the near-infrared band

SWIR is the reflectance in the shortwave infrared band.

With NDWI, water bodies typically yield high positive values due to their strong absorption of NIR radiation and relatively low reflectance in the SWIR range. In contrast, non-water features such as vegetation and bare soil tend to produce lower or even negative NDWI values.

The NDWI scale ranges from negative values representing non-water features to positive values indicating water bodies. The distinct contrast in values facilitates the delineation of water boundaries and aids in various applications, including hydrological mapping, flood monitoring, and wetland delineation.

Utilizing Landsat seven imagery within the Google Earth Engine platform, NDWI calculations are efficiently performed, enabling researchers to extract valuable information about water bodies' spatial distribution and dynamics. These results are then utilized for further analysis, such as mapping water bodies and assessing changes in their extent over time, contributing to a comprehensive understanding of hydrological processes and water resource management.

3.6.4. Soil Adjusted Water Index

The Soil-Adjusted Vegetation Index (SAVI) is a modification of the Normalized Difference Vegetation Index (NDVI) that corrects for variations in soil brightness, particularly in areas with high soil reflectance. It is beneficial in regions with sparse vegetation or where soil brightness significantly affects NDVI values.

The formula for SAVI is:

$$\text{SAVI}= \frac{\boldsymbol{NIR-Red}}{(\boldsymbol{NIR+Red+L})\times(\boldsymbol{1+L})} \quad (2)$$

Where:

NIR is the reflectance in the near-infrared band.

Red is the reflectance in the red band.

L is the soil brightness correction factor, typically set to 0.5, but can be adjusted based on local conditions.

The SAVI index compensates for soil brightness by introducing a soil-adjustment factor (L) in the denominator, reducing the influence of soil reflectance on the index. This adjustment enhances the sensitivity of SAVI to variations in vegetation cover, making it particularly suitable for assessing vegetation health in areas with mixed land cover or high soil brightness.

SAVI values range from -1 to +1, similar to NDVI, with higher values indicating denser vegetation cover and lower values corresponding to less vegetation or bare soil. By accounting for soil brightness, SAVI provides a more accurate assessment of vegetation vigor and density than NDVI in areas with significant soil background influence.

3.6.5 Modified Adjusted Water Index

The Modified Normalized Difference Water Index (MNDWI) is a variation of the Normalized Difference Water Index (NDWI) that enhances water feature detection by leveraging the green and shortwave infrared (SWIR) bands. It is particularly effective in identifying and discriminating open water bodies from other land cover types.

The formula for MNDWI is:

$$MNDWI=\frac{(Green-SWIR)}{(Green+SWIR)} \qquad (3)$$

Where:

Green is the reflectance in the green band.

SWIR is the reflectance in the shortwave infrared band.

Unlike NDWI, MNDWI uses the difference and sum of reflectance values in specific spectral bands to highlight water features. However, by utilizing the green band and the SWIR band, MNDWI further enhances water detection capabilities, especially in areas with vegetation.

MNDWI values typically range from negative to positive, with higher values indicating the presence of water bodies and lower or negative values corresponding to non-water features. This index is widely used in hydrological studies, wetland mapping, and land cover classification, where accurate delineation of water bodies is essential.

3.6.7 Soil Adjusted Water Index

The Soil Adjusted Water Index (SAWI) is a modified version of the Normalized Difference Water Index (NDWI) that accounts for soil background effects, particularly in arid and semi-arid regions where soil brightness can significantly impact water detection. SAWI is designed to enhance the delineation of water bodies by adjusting for soil reflectance variations, thereby improving the accuracy of water feature detection.

The formula for SAWI is:

$$SAWI=\frac{(NIR-SWIR)}{(NIR+SWIR+L)} \qquad (4)$$

Where:

NIR is the reflectance in the near-infrared band.

SWIR is the reflectance in the shortwave infrared band.

L is the soil brightness correction factor, typically set to 0.5.

Like NDWI, SAWI utilizes the difference and sum of reflectance values in specific spectral bands to highlight water features. However, by incorporating a soil brightness correction factor (L) in the denominator, SAWI reduces the influence of soil background effects on water detection, thereby improving the accuracy of water body delineation.

SAWI values range from negative to positive, with higher values indicating the presence of water bodies and lower values corresponding to non-water features. This index is handy in regions with significant soil brightness variations, where accurate water detection is essential for various applications such as hydrological studies, land cover classification, and environmental monitoring.

3.6.8 Modified Soil Adjusted Vegetation Index

The Modified Soil-Adjusted Vegetation Index (MSAVI) is an enhanced version of the Soil-Adjusted Vegetation Index (SAVI) that further improves vegetation detection in areas with high soil brightness. By incorporating a soil brightness correction factor, MSAVI minimizes the influence of soil reflectance on vegetation index calculations, thereby providing more accurate assessments of vegetation health.

The formula for is: $\mathbf{MSAVI} = (\mathbf{2} \times \boldsymbol{NIR} + \mathbf{1} - \surd))/\mathbf{2}$ (5)

Where:

NIR is the reflectance in the near-infrared band.

Red is the reflectance in the red band.

MSAVI adjusts the numerator and denominator components of the SAVI formula to reduce sensitivity to soil brightness while preserving sensitivity to vegetation. This adjustment enhances the contrast between vegetation and soil, making MSAVI particularly effective in areas with diverse land cover types and varying soil conditions.

MSAVI values typically range from -1 to +1, with higher values indicating healthier vegetation cover and lower values corresponding to less vegetated or bare soil areas. This index is widely used in agricultural monitoring, land cover classification, and environmental studies where accurate assessment of vegetation health is crucial for decision-making and resource management.

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1 Results

4.1.1 Land Use Land Cover

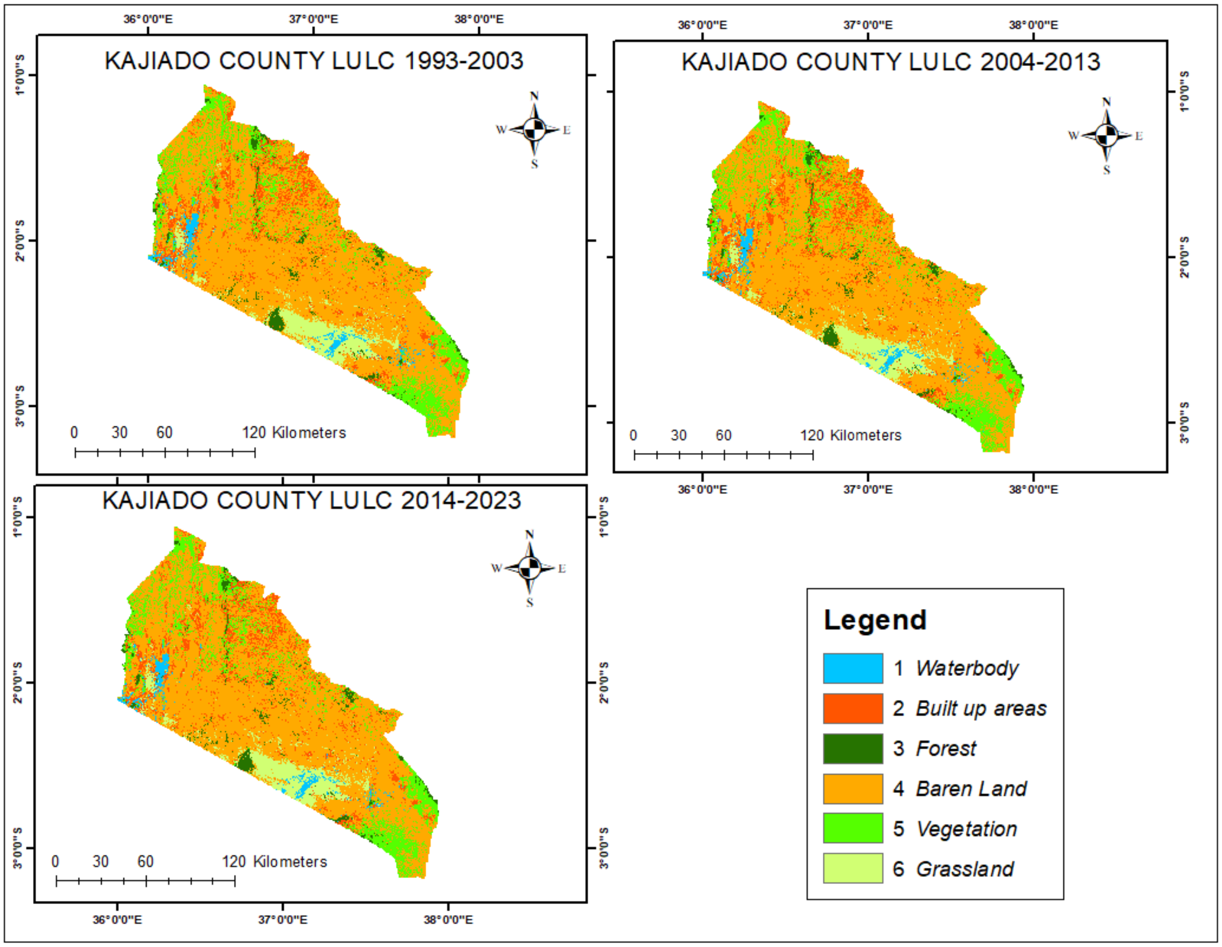

Figure 4: Land Use Land Cover Map

Figure 4 above illustrates the Land Use/Land Cover (LULC) map of Kajiado County. It categorizes the landscape into water bodies, built-up areas, forests, vegetation, bare land, and grassland obtained primarily from the Google Earth engine. The dominant land cover type in my study area is barren land. Among these, water bodies and vegetated areas are prominent, indicating potential locations of wetlands such as marshes, swamps, and saline lakes. Built-up areas have a lower potential for natural wetlands, while bare land and grassland areas may still contain temporary or seasonal wetlands. Overall, the LULC map provides valuable information for identifying and classifying wetlands in the study area.

4.1.2 Land Surface Temperature

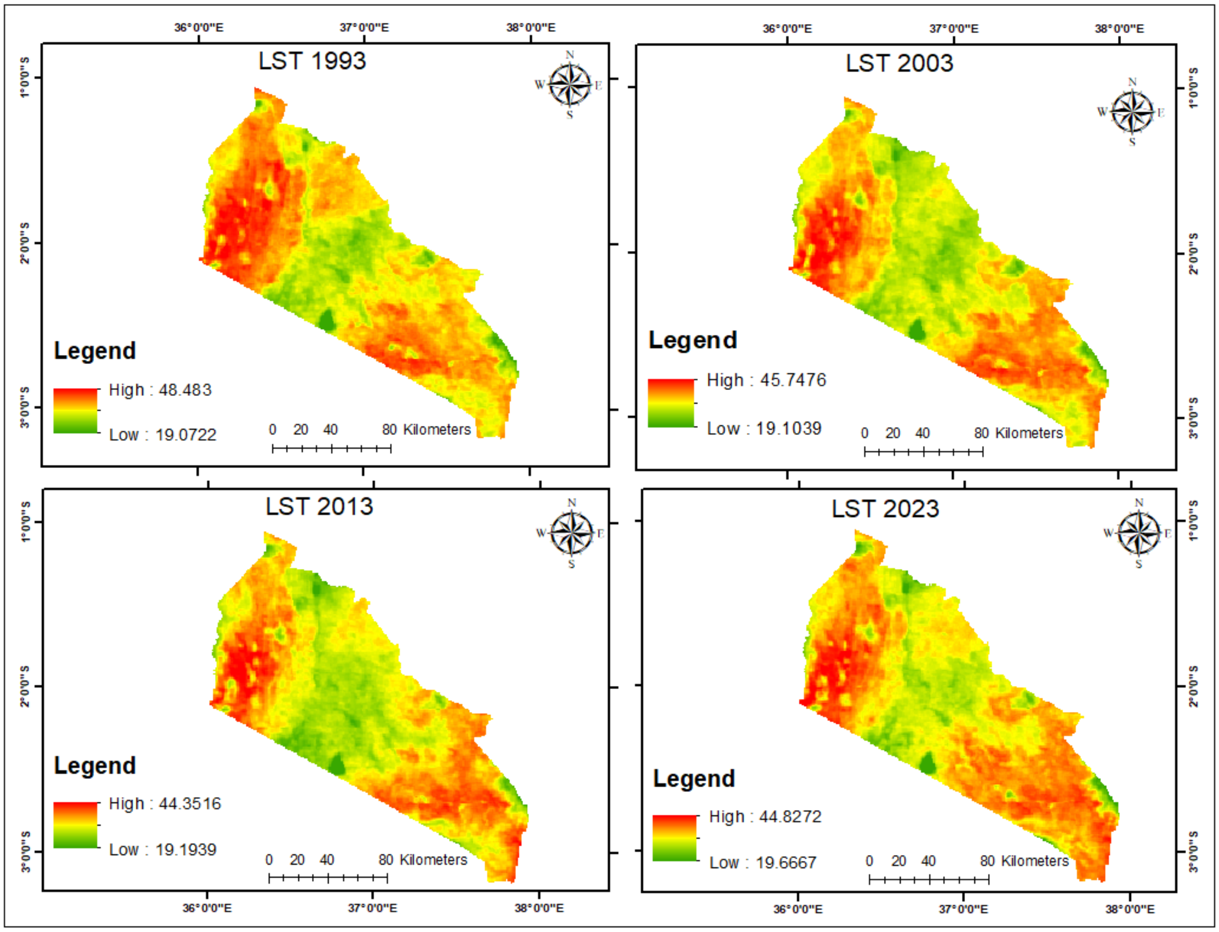

Figure 5: Land Surface Temperature

The Land Surface Temperature (LST) ranges for the study period exhibit a gradual decrease over time. In 1993, the LST ranged from 48.48°C to 19.0722°C, indicating relatively high temperatures. By 2023, the LST range decreased from 44.8272°C to 19.6667°C, suggesting a decrease in surface temperatures over the years. This trend may reflect changes in land cover, urbanization, or climatic conditions impacting the thermal characteristics of the study area. Analyzing LST data provides valuable insights into temporal trends and spatial variations in surface temperature, which are essential for understanding the dynamics of wetland ecosystems and their response to environmental factors.

4.1.3 NDVI

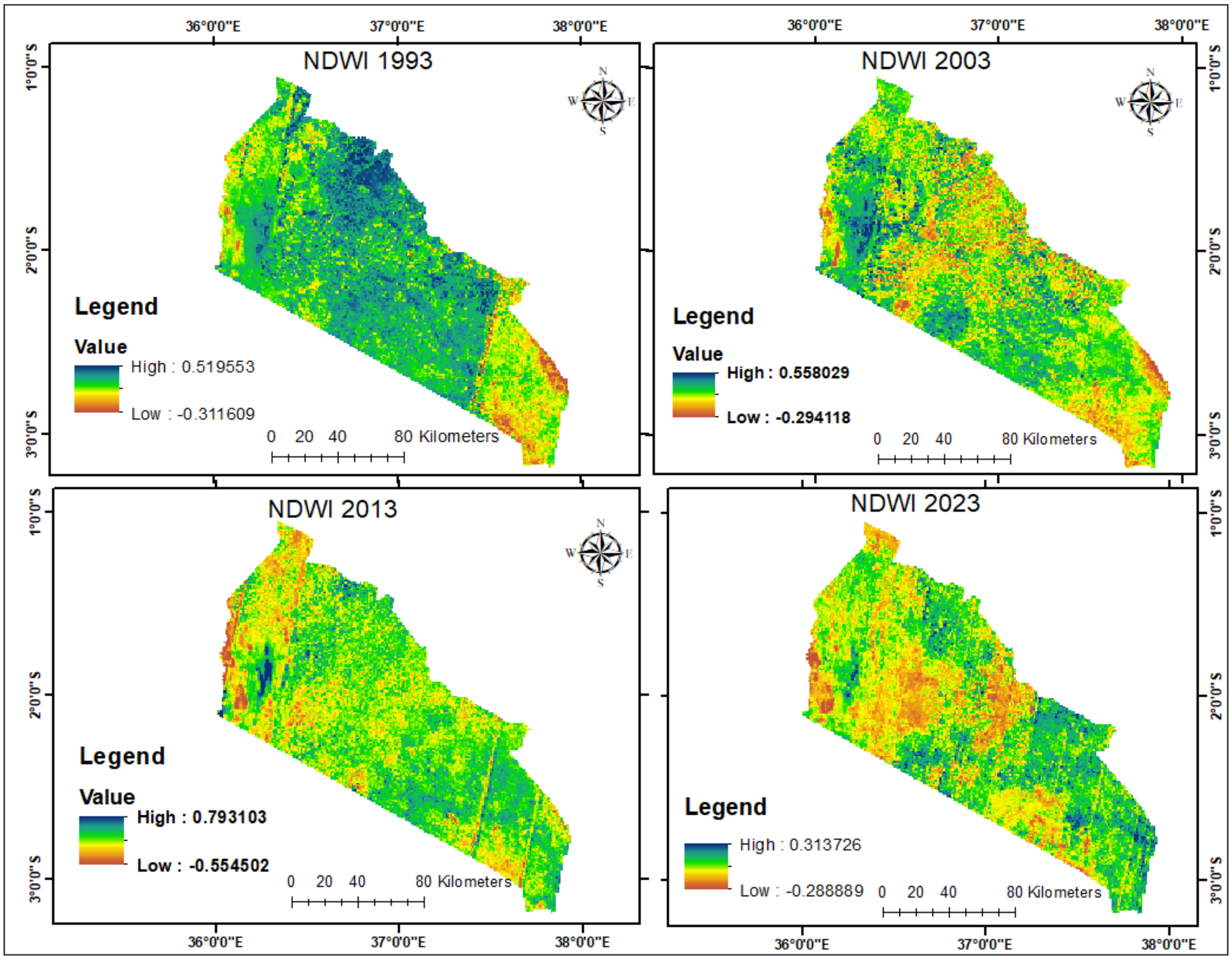

Figure 6: Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) ranges within the study period exhibit fluctuations, indicating changes in vegetation density over time. In 1993, NDVI ranged from 0.519553 to -0.311609, suggesting moderate to dense vegetation cover in some areas and sparse vegetation or bare soil in others. By 2023, the NDVI range decreased from 0.313726 to -0.288889, indicating a potential decline in vegetation density or changes in land cover. These fluctuations in NDVI reflect variations in vegetation health and distribution, which are crucial for assessing the condition of wetland habitats and monitoring ecosystem changes over time. Analyzing NDVI data provides valuable information for understanding the dynamics of vegetation and its influence on wetland ecosystems within the study area.

4.1.4 MNDWI

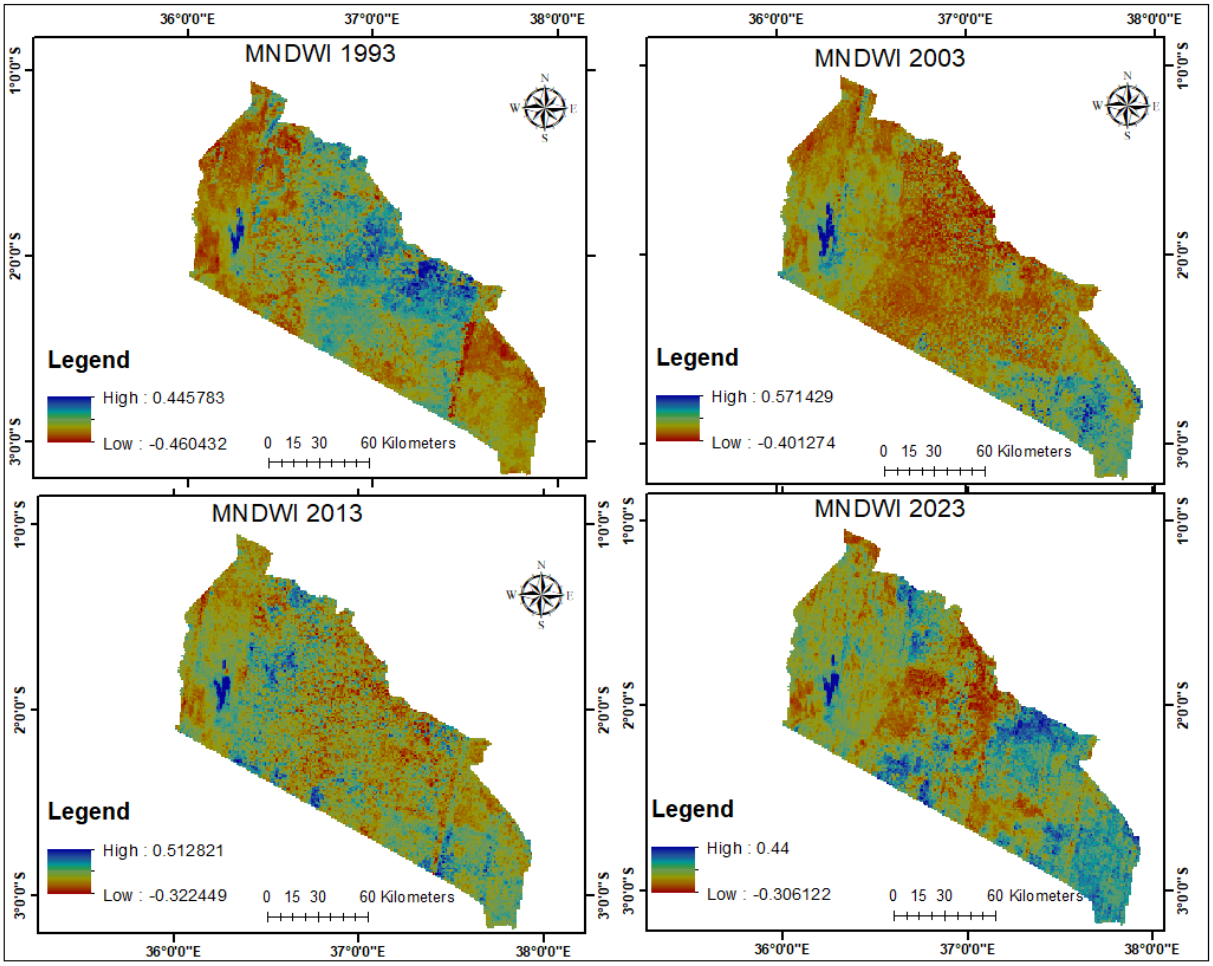

Figure 7: Modified Normalized Difference Water Index

The Modified Normalized Difference Water Index (MNDWI) ranges for the study period reveal variations in water body presence and characteristics over time. In 1993, the MNDWI ranged from 0.445783 to -0.460432, indicating significant variability in water and non-water features. By 2023, the range adjusted to 0.44 to -0.306122, showing a slight decrease in the variability. These changes reflect shifts in the extent and condition of water bodies and wetlands in the study area. Higher MNDWI values generally correspond to open water features, while lower and negative values indicate non-water surfaces. Analyzing MNDWI data helps identify and monitor changes in wetland and water body extent, providing critical insights for wetland classification and management.

4.1.5 NDWI

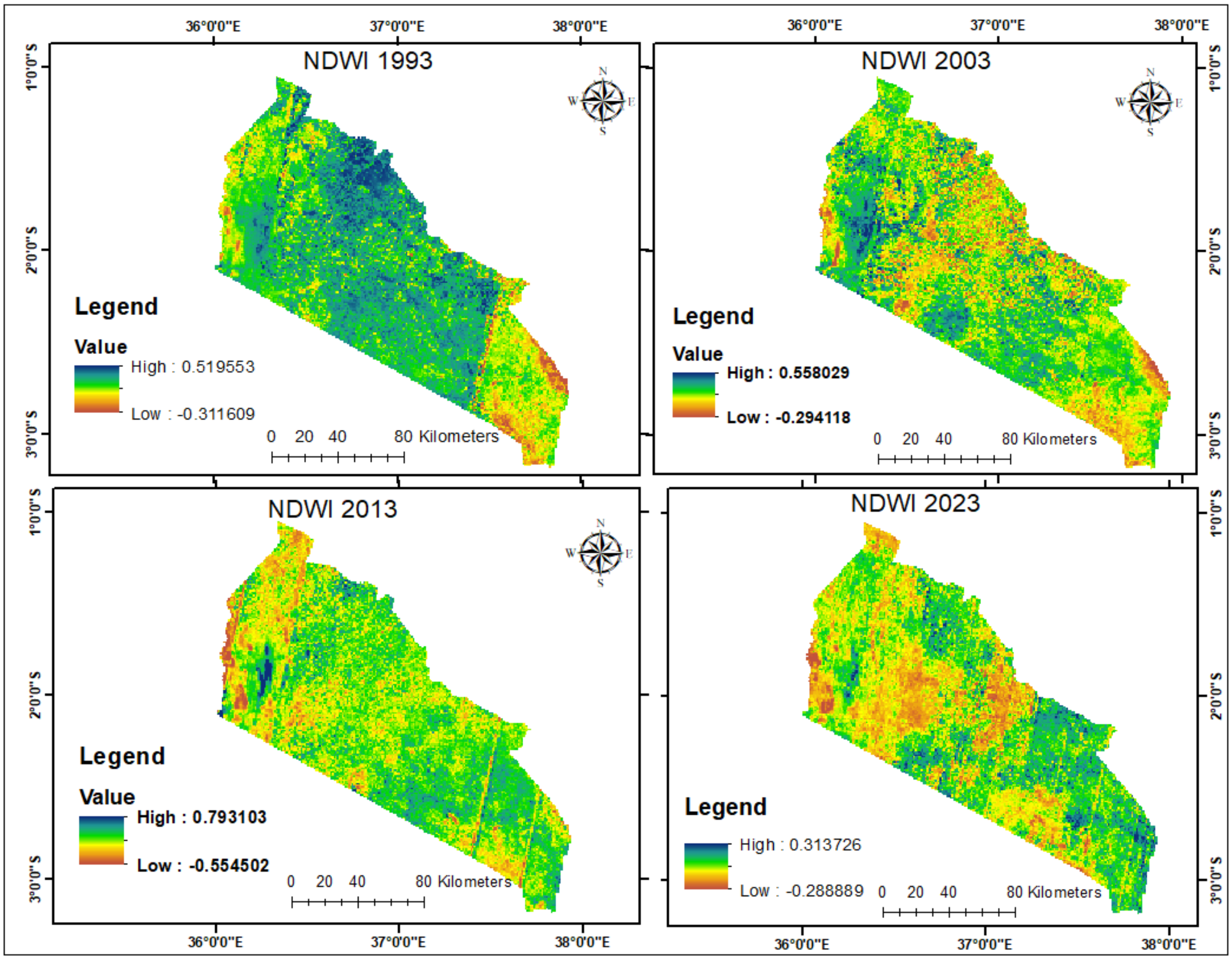

Figure 8: Normalized Difference Water Index

Figure 8 above shows the Normalized Difference Water Index (NDWI). The ranges of NDWI within the study period highlight significant changes in water presence and conditions over time. In 1993, the NDWI ranged from 0.519553 to -0.311609, indicating varying water content and surface moisture levels. By 2023, the range shifted from 0.313726 to -0.288889, showing a decrease in the index's variability. These changes suggest alterations in the extent and quality of water bodies and wetland areas. Higher NDWI values typically indicate water-rich areas, while lower and negative values denote less moisture or dry land. Analyzing NDWI data provides crucial information for tracking water dynamics, which is essential for effective wetland classification and monitoring in the study area.

4.1.6 SAWI

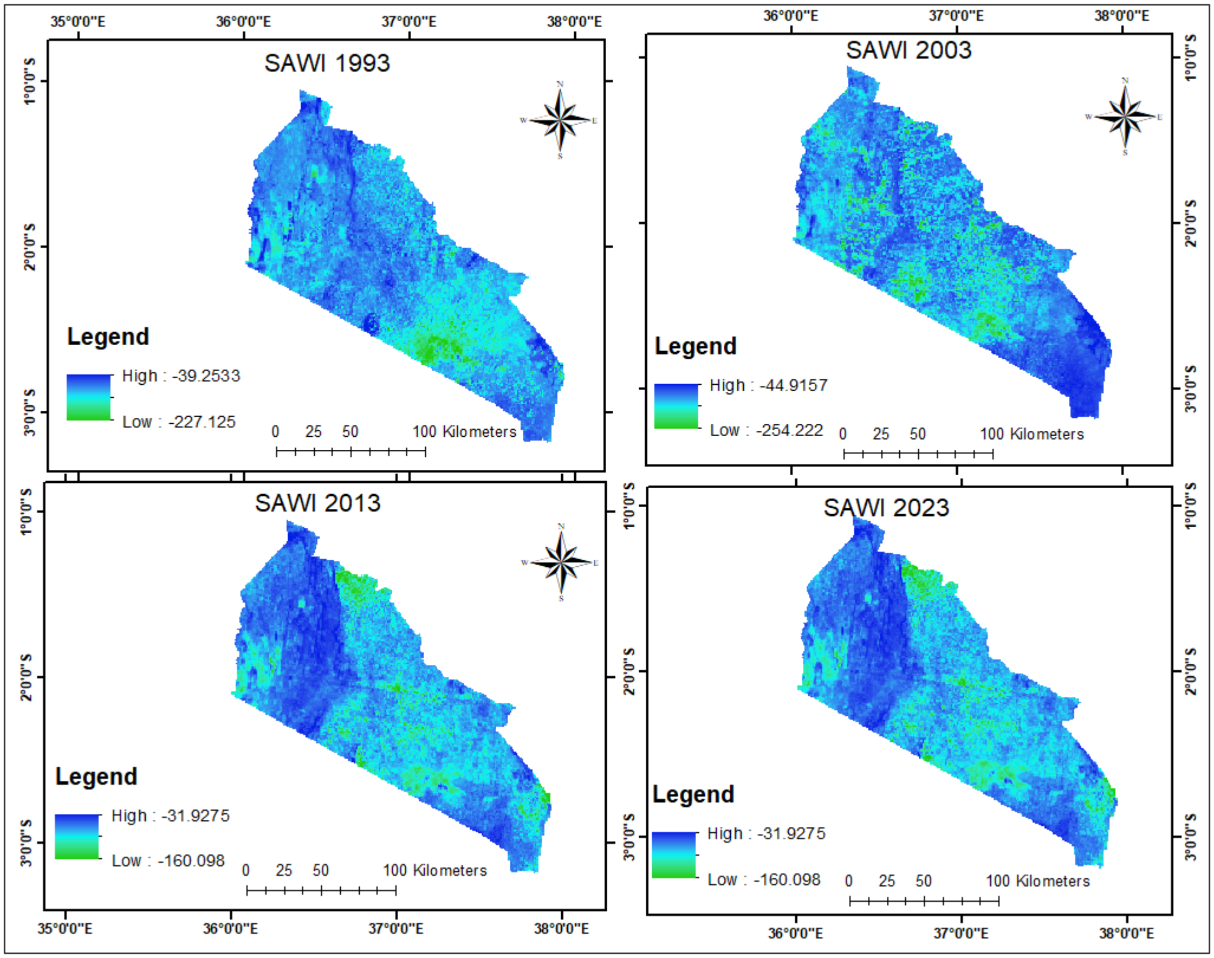

Figure 9: Soil Adjusted Water Index

The Soil Adjusted Water Index (SAWI) ranges within the study period illustrate significant variations in soil moisture and water content over time. In 1993, the SAWI ranged from -39.2533 to -227.125, indicating substantial variability in soil moisture levels. By 2023, the range shifted slightly from -31.9275 to -160.098, showing a reduction in the variability of soil moisture. These changes suggest alterations in the soil water content and potential impacts on wetland conditions. Lower SAWI values generally reflect higher soil moisture content, which is critical for maintaining healthy wetland ecosystems. Analyzing SAWI data helps in understanding soil moisture dynamics and their influence on wetland health and distribution, providing essential insights for wetland classification and management in the study area.

4.1.7 NDSI

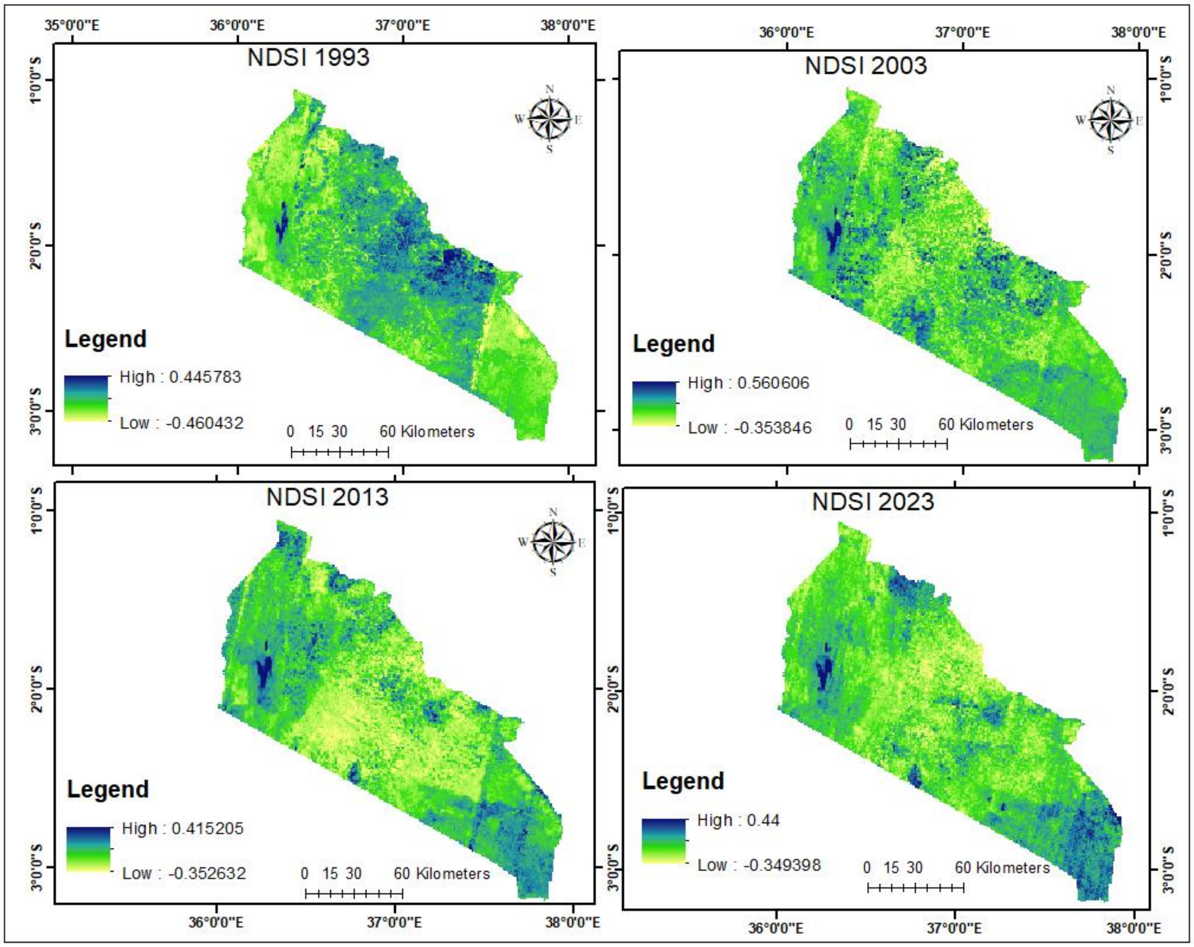

Figure 10: Normalized Adjusted Snow Index

The Normalized Difference Soil Index (NDSI) ranges within the study period reflect changes in soil characteristics and bare land conditions over time. In 1993, the NDSI ranged from 0.445783 to -0.460432, indicating significant variability in soil and bare land features. By 2023, the range adjusted slightly to 0.44 to -0.349398, showing a reduction in variability. These changes suggest shifts in soil exposure and the extent of bare land areas. Higher NDSI values typically indicate exposed soil and bare land, while lower and negative values denote vegetation cover or moist soil. Analyzing NDSI data provides valuable insights into soil conditions and land cover dynamics, which are essential for understanding and classifying wetland areas in the study region.

4.1.8 SAVI

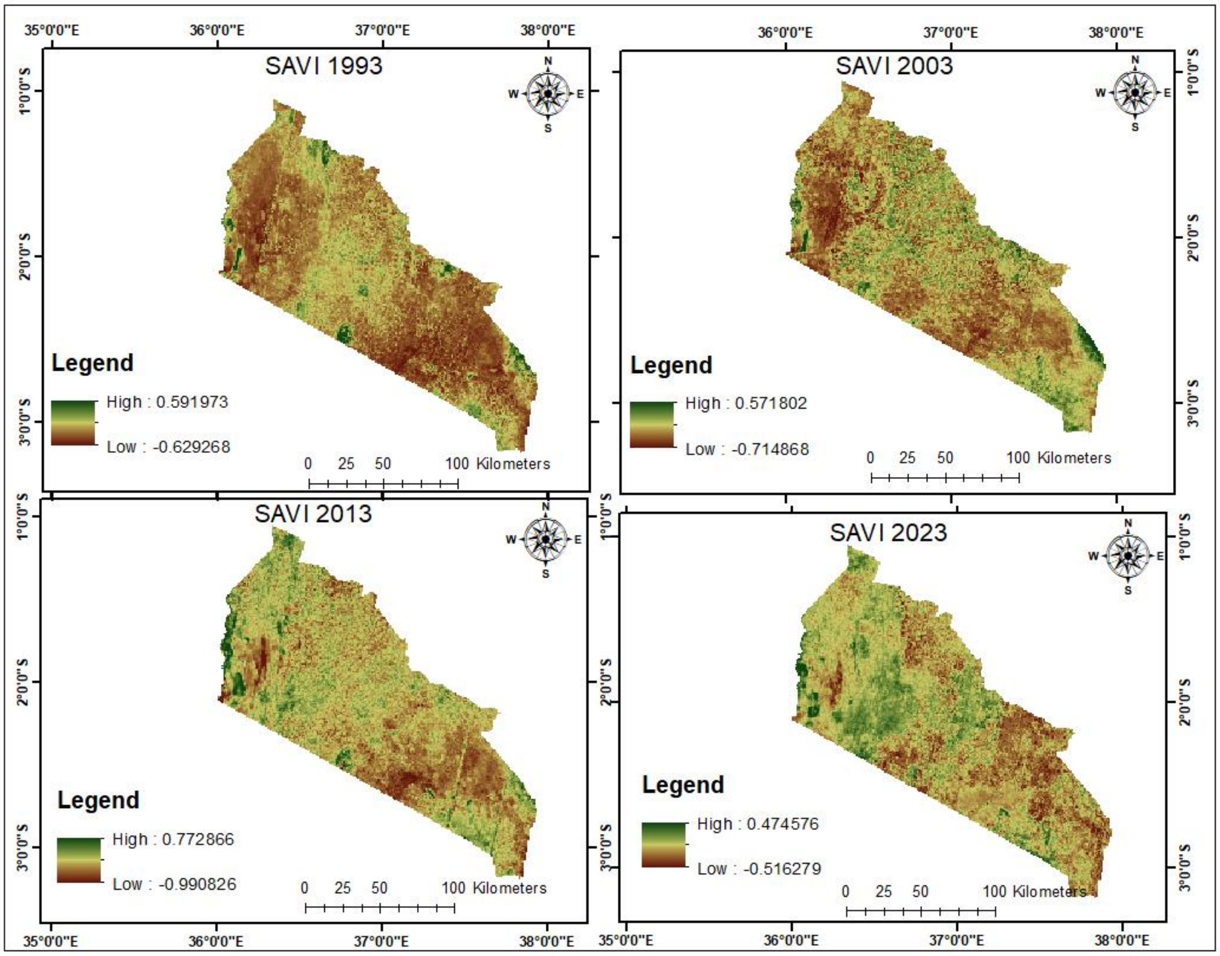

Figure 11: Soil Adjusted Vegetation Index

The Soil Adjusted Vegetation Index (SAVI) ranges observed throughout the study period indicate significant changes in vegetation density and soil brightness correction. In 1993, the SAVI values ranged from 0.591973 to -0.629268, reflecting a wide range of vegetation cover and soil brightness. By 2023, the SAVI range shifted from 0.474576 to -0.516279, showing a reduction in both vegetation density and variability. These changes suggest fluctuations in vegetation health and soil exposure over time. Higher SAVI values point to denser, healthier vegetation, whereas lower and negative values indicate sparser vegetation or exposed soil. Analyzing SAVI data provides valuable insights into vegetation dynamics and soil conditions, which are crucial for accurately classifying and monitoring wetlands within the study area.

4.1.9 MSAVI

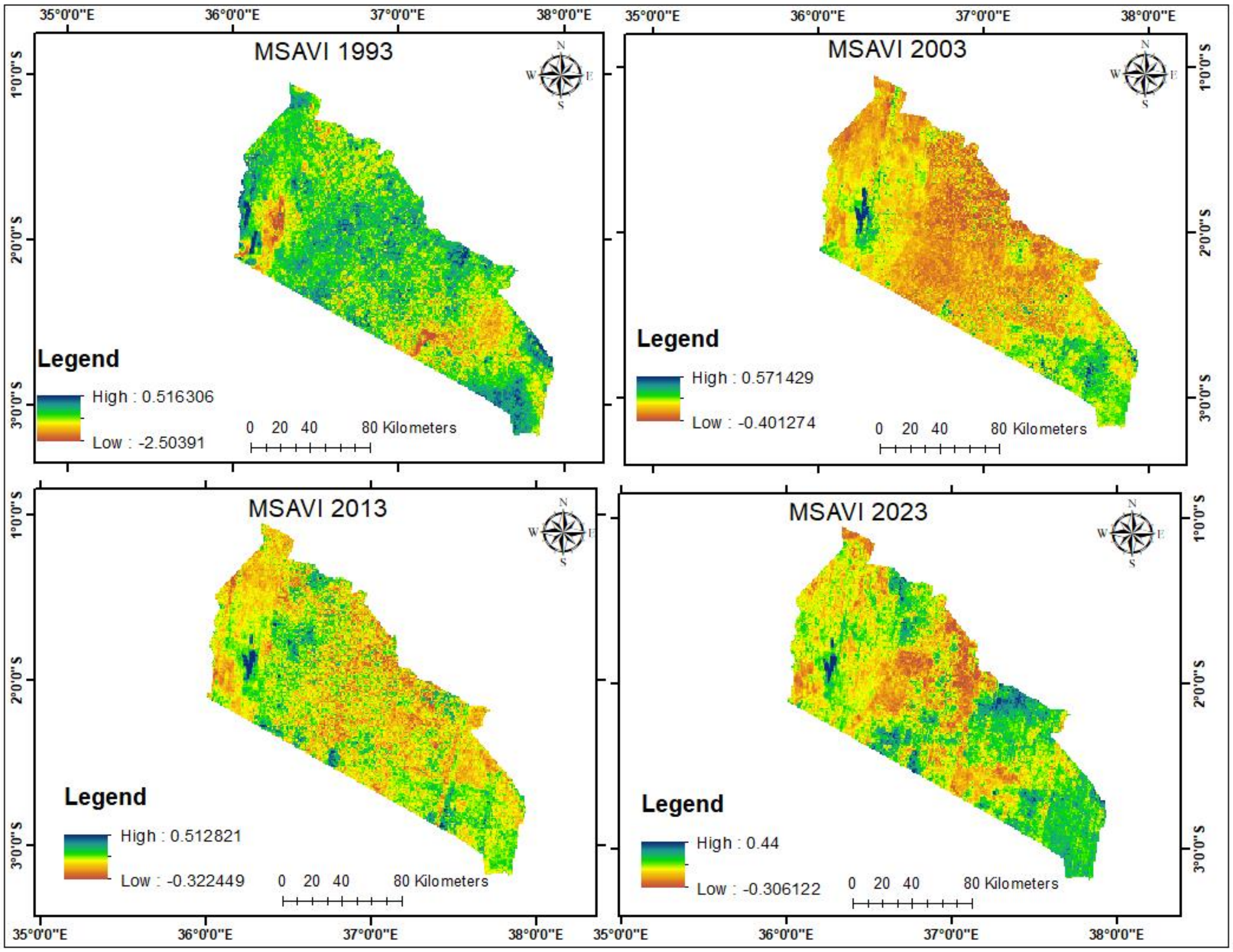

Figure 12: Modified Soil Adjusted Vegetation Index

The Modified Soil Adjusted Vegetation Index (MSAVI) ranges observed over the study period reveal notable changes in vegetation density and soil brightness. In 1993, MSAVI values varied from 0.516306 to -0.250391, indicating a broad spectrum of vegetation cover and soil conditions. By 2023, the range adjusted from 0.44 to -0.306122, suggesting a decrease in the variability of vegetation density and soil exposure. These fluctuations reflect alterations in plant health and the extent of bare soil areas. Higher MSAVI values are indicative of denser, healthier vegetation, while lower and negative values signify sparser vegetation or exposed soil. Examining MSAVI data is essential for gaining insights into vegetation and soil dynamics, which are pivotal for the accurate classification and monitoring of wetlands in the study area.

4.1.10 Rainfall

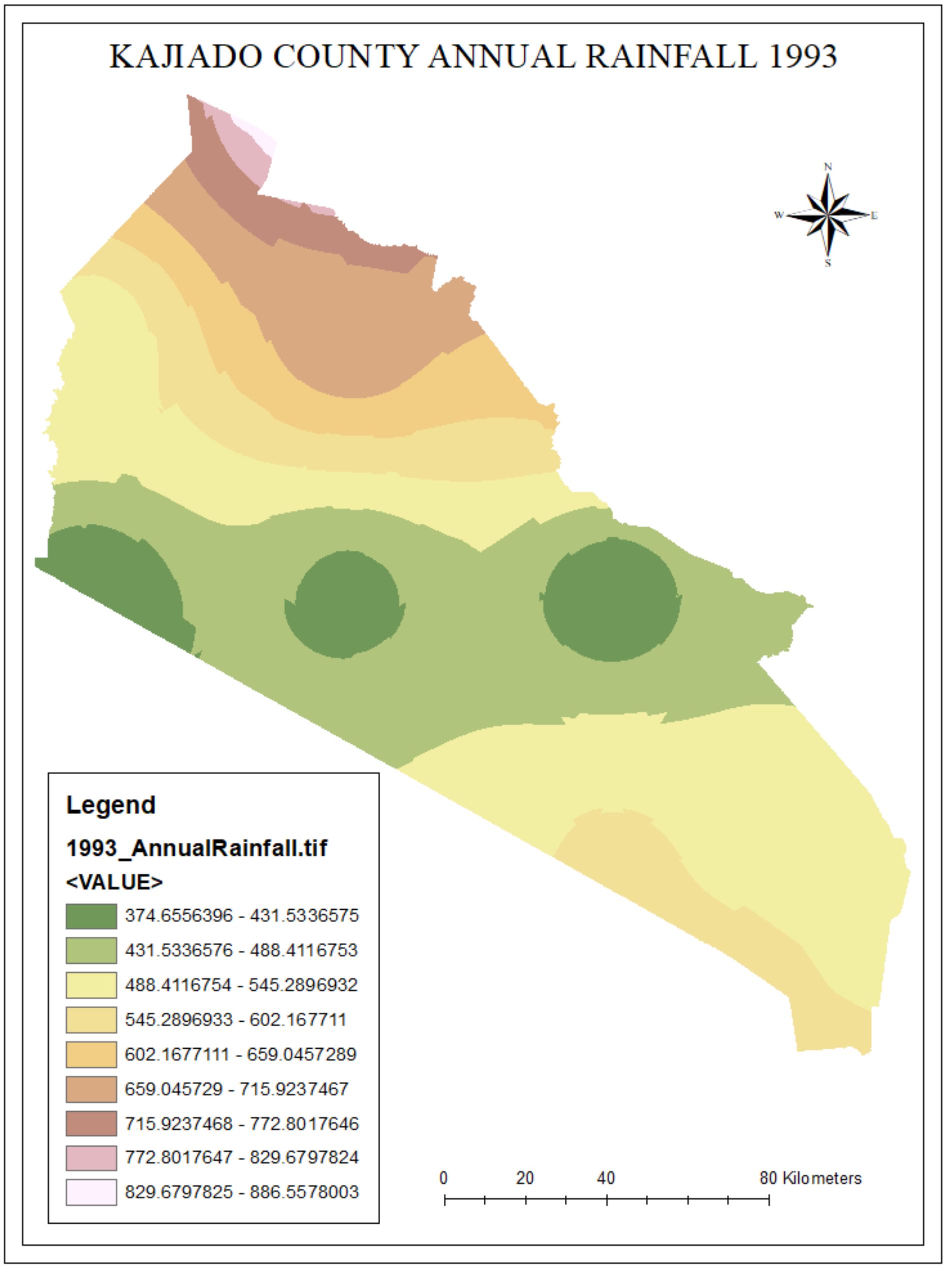

Figure 13: Rainfall distribution for the year 1993

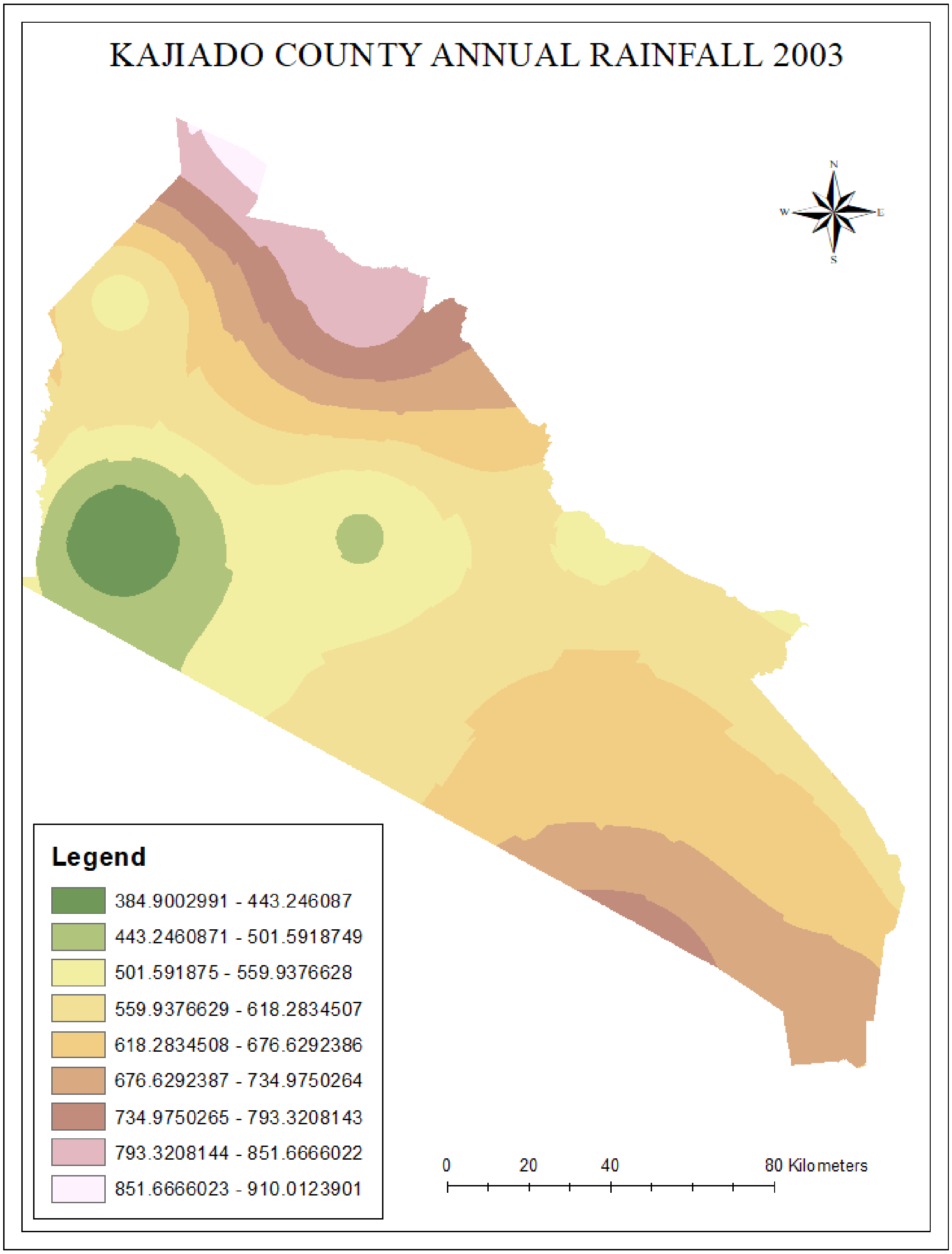

Figure 14: Rainfall distribution for the year 2003

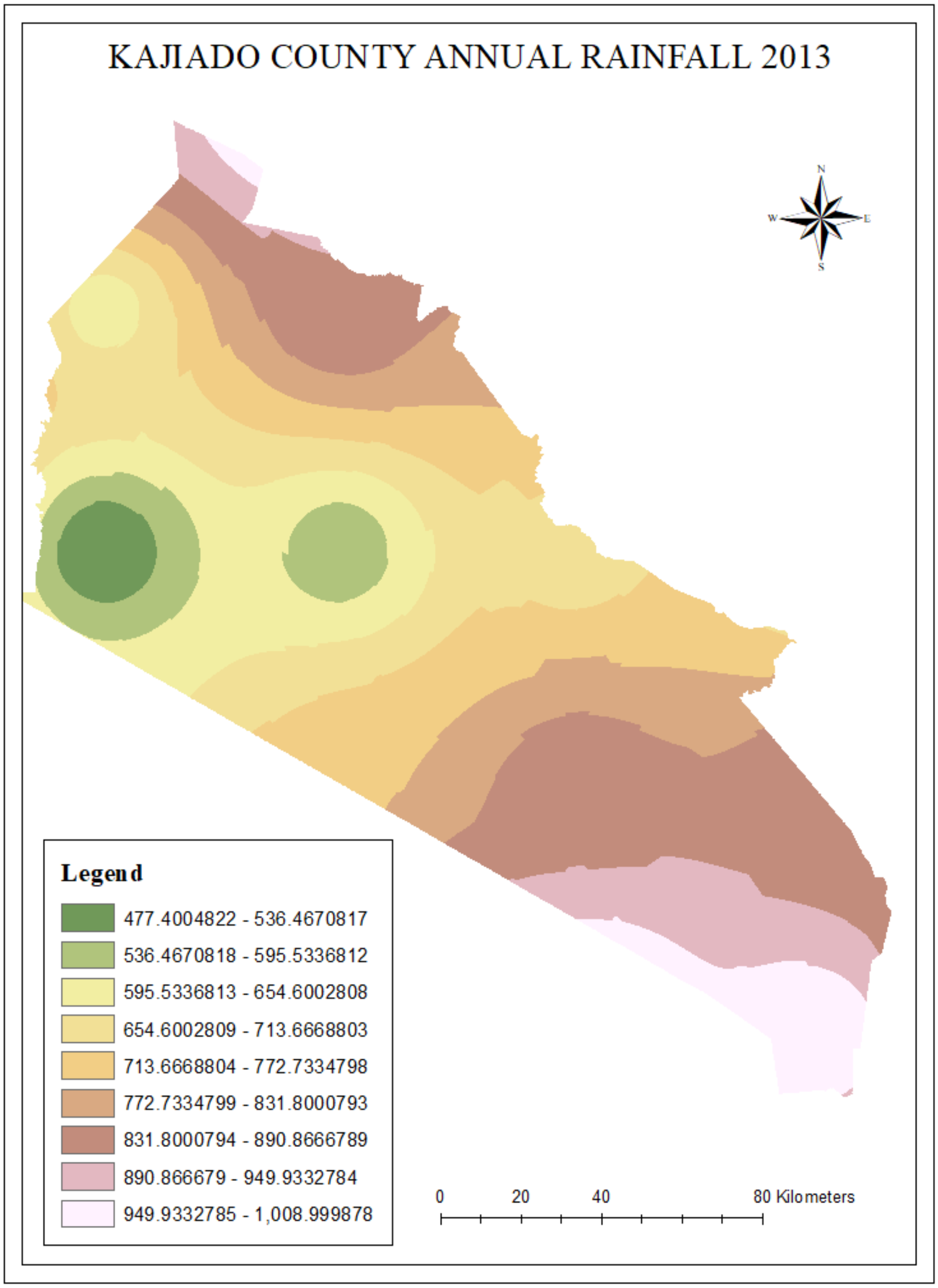

Figure 15: Rainfall distribution for 2013

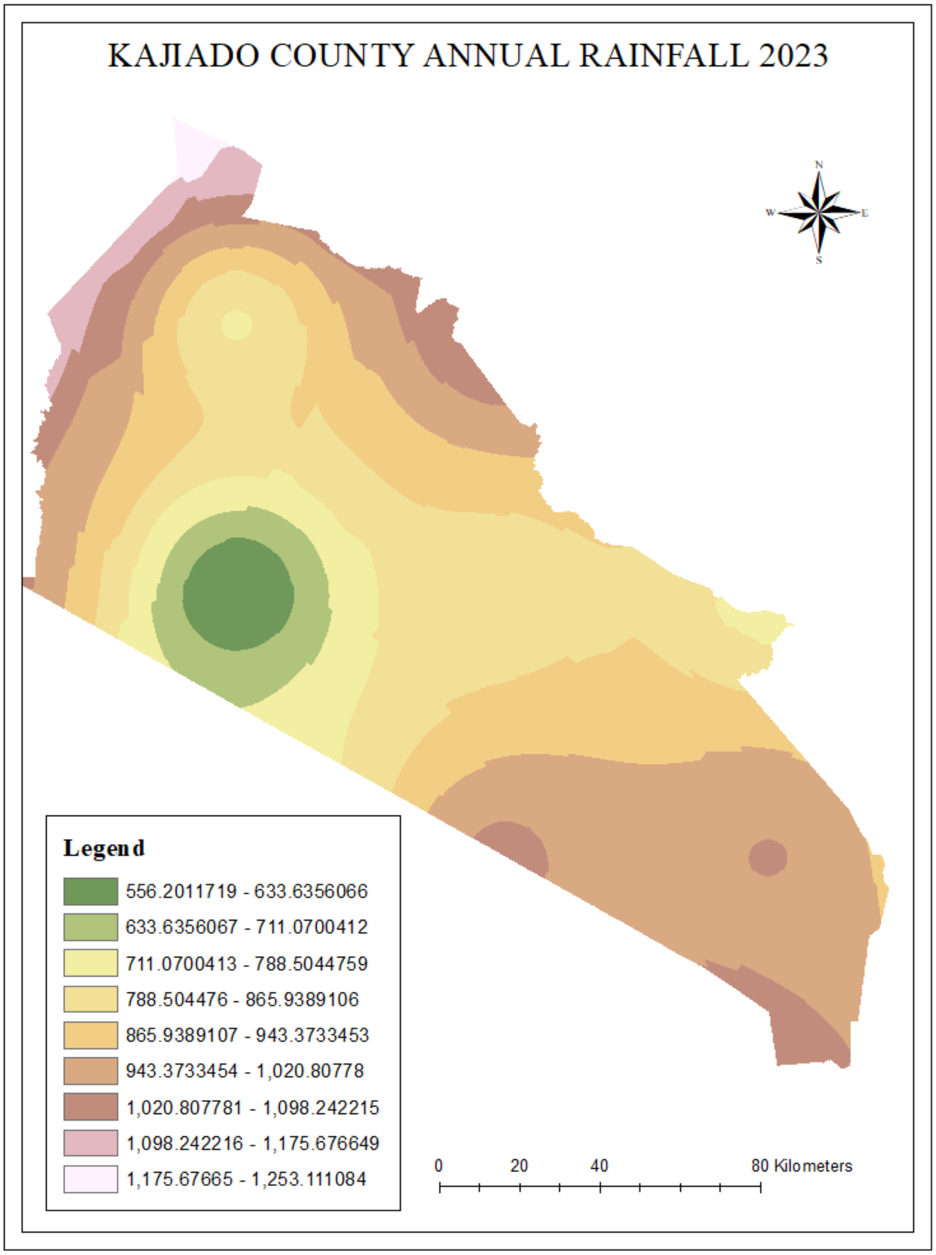

Figure 16: Rainfall distribution for 2023

4.1.11 Correlation

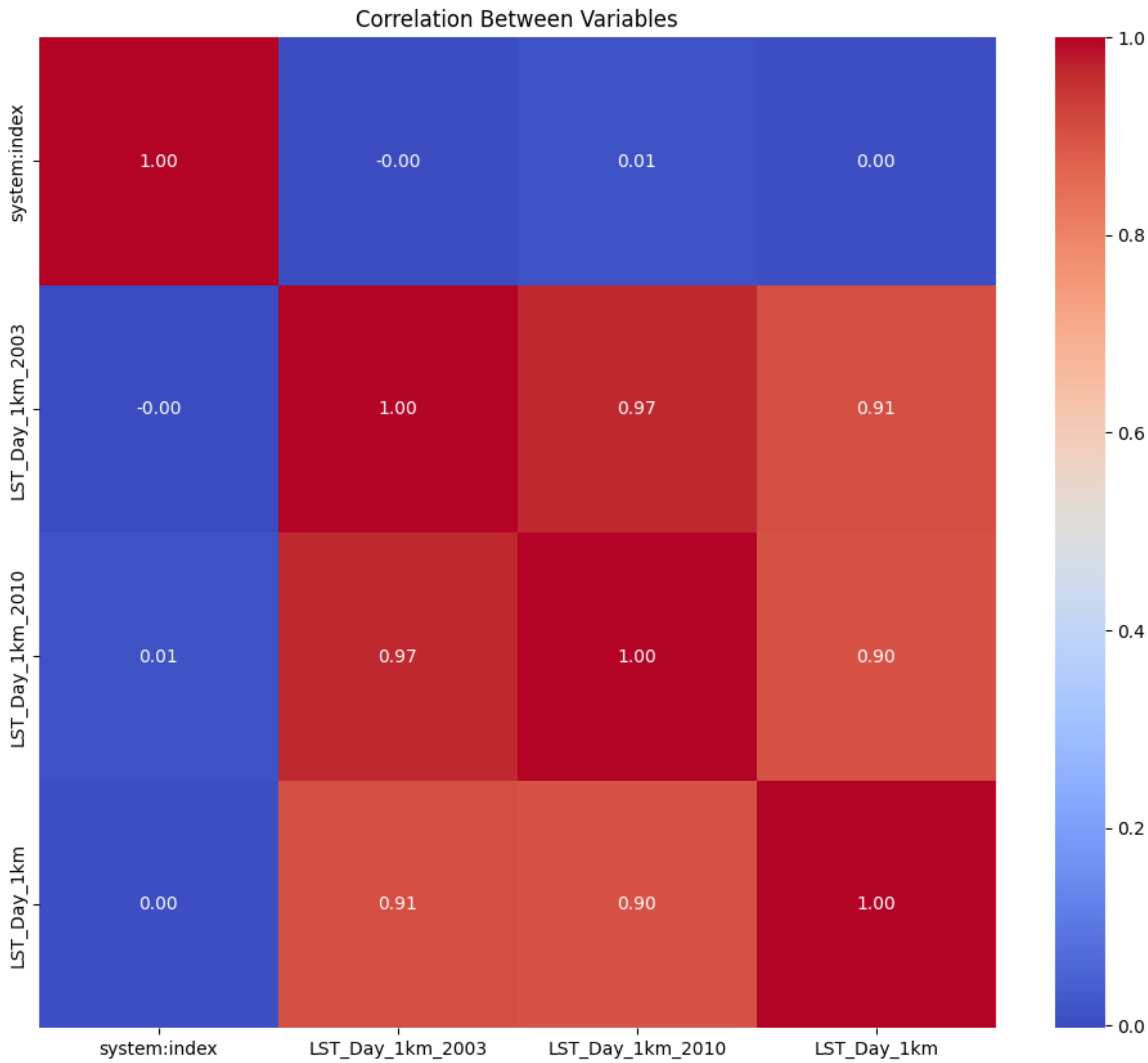

Figure 17: Correlation between the indices

4.1.12 Wetland Map

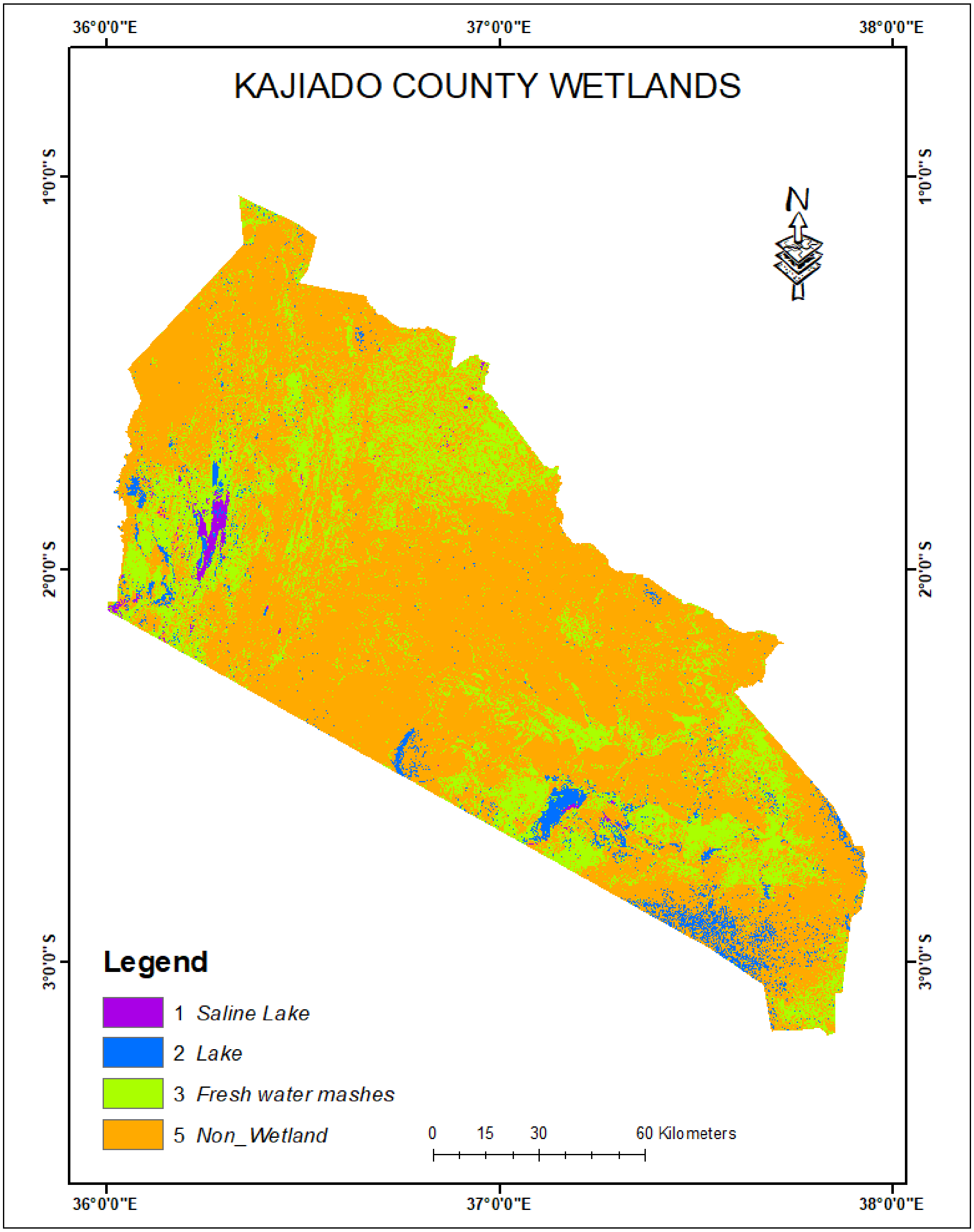

Figure 18: Wetland Cover Map

4.2 Discussion

Wetlands have been disappearing rapidly across the globe (Davidson, 2014) due to the drivers of economic and population growth including agricultural conversion, urbanization and rural development, and shifting water usage practices (van Asselen et al., 2013; Zedler and Kercher, 2005).

Without an effective means to monitor their extent and change over time, conservationists cannot protect and preserve the critical role wetlands play in supporting biodiversity and providing ecosystem services. Remote sensing data provide a natural solution to create up-to-date maps of wetlands, but leveraging such data has been historically challenging due to the highly variable nature of wetlands across space and through time (Gallant, 2015). Wetlands lack a characteristic spectral signature because they are not unified by one specific land-cover type or vegetation form and can have the widely variable presence of water in space and time (Keddy, 2010; Mitsch and Gosselink, 2015; Gallant, 2015).

Additionally, the boundary of a wetland may be too steep an environmental gradient to be captured effectively in coarse resolution remote sensing imagery. On the contrary, mapping boundaries using fine-resolution imagery can introduce human imprecision because determining wetland-upland boundary location is largely subjective (Gage and Cooper, 2010).

In this study, we developed an approach to wetland mapping at high spatial resolution using computer vision and publicly available remote sensing data that is robust across varied geographies and repeatable through time. We observed an accuracy of 92 % for a model using only publicly available remote sensing imagery and 94 % for a model including additional predictors. Such models can be used to create accurate, up-to-date maps that inform conservation policy, regulation, and prioritization. Under the current regulatory standard of field-delineated wetlands, a highly accurate prediction of wetlands could enable better avoidance of environmentally sensitive lands in planning infrastructure and development projects. It could also reduce the significant costs associated with the discovery of previously unmapped wetlands during project development.

Given the highly variable characteristics of wetlands in space and time, success in mapping wetlands with remote sensing data depends on carefully chosen training data, sampling approaches, and models. The vegetation and soil characteristics of a wetland depend on water availability which rapidly changes in both amount and spatial extent. Therefore, given the effect of temporally variable moisture regimes on the overall characteristics of a wetland and its spectral signatures, wetlands are a “moving target” (Gallant, 2015).

Furthermore, wetlands vary in terms of vegetation type, geography, and hydrology across large geographic extents, such as at a continental scale. Together, this spatial and temporal variation makes training a highly accurate predictive model a substantial challenge. We argue that, given these complexities in the data, deep learning models are well suited to producing unbiased and precise wetland maps using remote sensing data. This framework is efficient at capturing conditionality and non-linearities in the relationships between predictor and response variables, higher order of interactions among predictors, and can minimize feature engineering enabling mapping of large geographies.

A few features are desired in an efficient predictive model: reliability, generalizability, ability to predict at high spatial and temporal resolution, affordability, and minimal effort in the curation and processing of raw data. We trained VGG 16 model, a deep learning architecture that takes advantage of contextual information to segment images that (1) uses high spatial and temporal resolution data, (2) avoids the need to engineer the raw data, (3) and is efficient and reliable as judged based on model evaluation metrics and expert opinion. Since the model was trained with data obtained from three specific areas, it is not yet generalizable to a much broader geography.

4.2.1. Feature engineering and contextual information

Convolutional neural networks (CNNs), including VGG 16, are ideally designed for image segmentation of multispectral imagery. Reviewing several papers on wetland mapping using object-based image analysis (OBIA), a recent study (Dronova, 2015) concluded that the overall success of wetland assessment depended on feature extraction and the accuracy of image interpretation. Specifically, pixel-based models that do not account for contextual information were found to be inferior to object-based analyses. Pixel-based approaches fail to incorporate ecologically meaningful information from a pixel's neighborhood, and they are sensitive to unimportant local heterogeneity resulting in the infamous “salt and pepper” speckle (Dronova, 2015).

CNNs resolve both challenges simultaneously. Deep neural networks contain many layers that transform input data into higher-level features through a series of ‘hidden’ layers, exponentially expanding the feature space used to identify output classes. During model training, the model learns the necessary combinations of input variables and weights needed to predict outputs effectively, obviating the need for labor-intensive and expert-guided feature engineering and selection. Convolutional layers aggregate and summarize the characteristics of pixels within neighborhoods at multiple scales, thus extracting contextual information from the surrounding landscape to inform predictions (Ma et al., 2019). CNNs have been successfully used to map many different kinds of land-cover and features using remote sensing imagery (Kruitwagen et al., 2021; Parente et al., 2019; Shafique et al., 2022); thus, it is natural that mapping complex land-cover classes like wetlands should take advantage of computer vision.

Feature engineering is the derivation of new predictor variables based on domain expertise has been a routine practice in remote sensing-based analysis; see (Jones, 2019; Lang et al., 2020) for an example of a feature computed with median first and bare earth intensities. For generalized linear models and other traditionally used machine learning models (e.g., random forest), the mapping of a response variable is less efficient with raw input variables (e.g., obtained from remote sensing data) than with features computed from the same set of raw input variables (e.g., NDVI). Depending on the response variable and the raw input variables, an approach for transforming raw variables into a useful feature (mostly some sort of algebraic operation) may need domain expertise. Deep learning is well known for its extensive search of competitive features in raw data and performs at least as well or better than manually created features given adequate data and epochs of model training, obviating the need for this labor-intensive process. As expected, CNNs have outperformed other methods in wetland mapping (DeLancey et., 2019; Liu and Abd-Elrahman, 2018)

4.2.2. Significance of high-resolution data

A review of various research papers using remote sensors in wetland research shows that 84 % of the studies used coarse and medium-resolution data whereas only 13 % used high-resolution imagery sources (Guo et al., 2017). Interestingly, a trend analysis found that studies with smaller spatial extent used higher resolution imagery than larger spatial extent studies did (Dronova, 2015). This collectively suggests that spatial extent is likely a bottleneck for using higher resolution imagery because of the size of data and lack of adequate computational resources. The significant limitations on computational resources as well as access to and storage of large volumes of data have been greatly reduced by the advent of cloud computing platforms such as Google Cloud Platform and Microsoft Azure and a variety of open data platforms such as Google Earth Engine and Microsoft's Planetary Computer.

A concomitant increase in the availability and usage of high-resolution remote sensing data is happening currently. This shift to high-resolution data has important implications in both model building and delivery of management-quality data products. Wetlands with sharp boundaries are more efficiently mapped by higher-resolution data. A landcover class results from a combination of ecological and other processes that operate at certain spatial resolutions. Therefore, a fine spatial resolution of remote sensing data is essential for the effective classification of land-cover classes that separate at a similarly fine spatial resolution. Such products will proliferate as more, higher-resolution data becomes available. Furthermore, properly delineating small wetlands is very challenging using moderate-resolution data, even when sub-pixel approaches are utilized (DeVries et al., 2017). Even though small wetlands provide important ecological services in human-modified landscapes (Vo et al., 2013), they are often omitted in regional inventories due to detection failure (Stein et al., 2012).

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

We showed that a reliable and accurate model for mapping wetlands at fine spatial resolution with freely available remote sensing data (Landsat 7) is possible without manual feature engineering. This finding is based on a model trained in four small geographies, and the effect of predictors on model performance may change once the model is retrained in a much larger geography. These findings collectively indicate that a trained VGG 16 model can effectively map wetlands with freely available multispectral data. Training a generalizable model requires data from a large and varied geography, without which deep learning-based models have limited spatial generalizability (also called transferability), as is true for any statistical model. On the contrary, a generalizable model learns to map input layers to wetland labels from variable geographies, which makes it suitable as a powerful tool for wetland mapping across a much larger geography, such as Kajiado County.

There are inherent problems in training and evaluating any automated wetland detection model using labels that are outdated or exclude modeled categories, as was the case with satellite imagery in the study area. This project aims to develop new approaches to automate the enhancement of Landsat data to better represent current conditions with improved accuracy and precision. Label inaccuracy as well as temporal and categorical mismatch between these labels and model outputs reflecting current conditions created uncertainty in the validation data used to assess model performance. The measures of precision and recall reported reflect the ability of our model to replicate Landsat data. We have reason to believe that the model may be better at mapping wetlands than suggested by these metrics.

5.2 Recommendations

We identify a need for future research to manually delineate wetland reference data to improve model evaluation. This temporal robustness observed in the model trained with input layers and wetland labels obtained more than a decade apart shows that model optimization extracts the signals in the data without being much affected by the noise introduced by the mismatch between wetland and its predictors.

In addition to manually delineating reference data and ensuring temporal robustness, future research should focus on improving model generalization across diverse geographies and wetland types. Integrating data from various remote sensing platforms, such as LiDAR and SAR, can enrich input datasets, enhancing classification accuracy. Efforts to improve the quality of training labels, including crowdsourcing and community-based validation, are crucial.

Furthermore, assessing the impacts of climate change on wetland dynamics using the model can aid in developing adaptive conservation strategies. Translating model outputs into actionable insights for policymakers and conservation managers will be key to informing restoration and development decisions. Establishing long-term monitoring programs that leverage the model's capabilities to track wetland health and changes will provide continuous feedback for effective management practices. By addressing these recommendations, future research can significantly advance wetland conservation efforts, ensuring the preservation of these vital ecosystems.

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