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Dedication

First and foremost, I dedicate this master's thesis to GOD for his unwavering guidance, protection, and blessings throughout this journey.

Secondly, to my dearest parents and siblings for their financial, emotional, psychological, and spiritual support over these past years. Their advice, “just pray and do it, everything will be fine” has been my encouragement throughout my academic journey. To them, I owe my entire academic success and achievements.

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ABSTRACT

This study analyzes vegetation degradation, a proxy for land degradation, across Northern Ghana and quantifies the relative influence of climatic and anthropogenic drivers. To identify significant vegetation degradation trends, a 500 m resolution Normalized Difference Vegetation Index (NDVI) time series from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor ranging from 2004 to 2024 was analyzed using Sen's slope and the Mann-Kendall test. A principal component analysis (PCA) of climate (precipitation, temperature, solar radiation, soil moisture, actual evapotranspiration), anthropogenic factors (population density, built-area extent, night-lights) and surface topography data (slope and elevation) variables was performed to extract the main gradients associated with variance in NDVI. A multiple linear regression of NDVI against the first three principal components yielded NDVI residual maps showing where observed vegetation change diverges from what would be expected using these drivers.

Results indicated that 64.6% of the study area is heavily degraded, 26.9% restored, and 8.5% is stable. The PCA analysis implied that the first two components, mostly determined by moisture availability and temperature variation, explained 67.35% of the total variance, while the third, determined by population density, explained 14.28%. The residual mapping reveals local greening within known irrigation schemes and protected-area boundaries, explicitly highlighting the importance of targeted land-management practices.

By incorporating trend analysis with multivariate driver decomposition and residual mapping, the framework presented in this study provides a replicable method for disentangling natural and anthropogenic drivers of land-change processes, even in relatively data-poor regions, and will help better inform land-restoration efforts.

Keywords: Vegetation degradation; land degradation; MODIS-NDVI; Residual analysis; Northern Ghana

RÉSUMÉ

Titre: La dégradation des terres et ses facteurs de causalité dans le nord du Ghana

Cette étude analyse les indicateurs de la dynamique de la végétation pour la dégradation des sols dans le nord du Ghana et quantifie l'influence relative des facteurs climatiques et anthropiques. Afin d'identifier les tendances significatives, une série chronologique MODIS NDVI d'une résolution de 500 m couvrant la période 2004-2024 a été générée et analysée à l'aide de la pente de Sen et du test de Mann-Kendall. Une analyse en composantes principales (ACP) des variables climatiques (précipitations, température, rayonnement solaire, humidité du sol, évapotranspiration réelle, altitude) et anthropiques (densité de population, étendue des zones bâties, éclairage nocturne) a été réalisée afin d'extraire les principaux gradients associés à la variance du NDVI. Une régression linéaire multiple du NDVI par rapport aux trois premières composantes principales a permis d'obtenir des cartes résiduelles du NDVI montrant où les changements observés dans la végétation s'écartent de ce qui serait attendu compte tenu de ces facteurs.

Les résultats ont indiqué que 64,6 % de la zone d'étude est fortement dégradée, 26,9 % restaurée et 8,5 % stable. L'analyse PCA montre que les deux premières composantes, principalement déterminées par la disponibilité en eau (précipitations, humidité du sol, évapotranspiration, rayonnement solaire) et les variations de température, expliquent 67,35 % de la variance totale, tandis que la troisième, déterminée par la densité de population, explique 14,28 %. La cartographie des résidus révèle un verdissement local au sein des systèmes d'irrigation connus et des limites des zones protégées, mettant explicitement en évidence les pratiques de gestion des terres ciblées.

En intégrant l'analyse des tendances à la décomposition multivariée des facteurs et à la cartographie des résidus, ce cadre fournit une méthode reproductible pour démêler les processus naturels et anthropiques de changement foncier, même dans les régions relativement pauvres en données, et contribuera à mieux informer les efforts de restauration des terres.

Mots clés: dégradation de la végétation; dégradation des terres; MODIS-NDVI; analyse des résidus; nord du Ghana

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Acronyms and Abbreviations

AHP	Analytic Hierarchy Process
BDD	Both-Driven Degradation
BDR	Both-Driven Restoration
CBNRM	Community-based natural resource management
CDD	Climatic-Driven Degradation
CDR	Climatic-Driven Restoration
CO_2	Carbon Dioxide
CNN	Convolutional Neural Network
DEM	Digital Elevation Model
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization
GDP	Gross Domestic Product
GEE	Google Earth Engine
GGWI	Great Green Wall Initiative
GIMMS	Global Inventory Monitoring and Modelling System
GIS	Geographic Information System
HDD	Human-Driven Degradation
HDR	Human-Driven Restoration
IPBES	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
LD	Land degradation
LDN	Land Degradation Neutrality
MARS	Multivariate Adaptive Regression Splines
MENA	Middle East and North Africa
MODIS	Moderate Resolution Imaging Spectroradiometer
NAP	National Adaptation Plan
NDVI	Normalized Difference Vegetation Index
PC	Principal Component
PCA	Principal Component Analysis
RESTREND	Residual trend
SDG	Sustainable Development Goal
SLM	Sustainable Land Management
SRTM	Shuttle Radar Topography Mission
SVM	Support Vector Machine
UNCCD	United Nations Convention to Combat Desertification
UN	United Nations
UNEP	United Nations Environment Programme
USGS	United States Geological Survey

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Introduction

I. Context

Land degradation (LD) is one of the greatest environmental challenges caused by climate change, resulting mainly from anthropogenic activities. LD leads to a series of economic and social problems due to its negative impact on soil productivity and food availability, biodiversity, and ecosystem functioning (Perović et al., 2021). Loss of vegetation is one of the most critical types of land degradation, and in semi-arid and savannah landscapes it is of utmost concern since vegetation is an important component that allows for ecological equilibrium and sustains local populations (Dallimer et al., 2011; Zhou et al., 2014). Areas like Northern Ghana also experience setbacks to their vegetation systems due to variations in weather conditions, including extended periods of drought and unpredictable rainfall pattern, as well as human-induced factors such as deforestation, overgrazing, and unsustainable use of the land. Ecosystem resilience and production are impacted by these combined effects of rising rates of vegetative cover and soil quality degradation (Kooch et al., 2022).

Badiee et al. (2024) defined vegetation degradation as the “temporary or permanent reduction in the density, structure, species composition, or productivity of vegetation cover.” This can either be loss of biomass, i.e., a decrease in the density or greenness of the canopy, or loss of quality, like modification of the species composition. These subtler forms of degradation also pose a serious problem for an environmentally sensitive area such as Northern Ghana, for land productivity and ecological stability are closely tied to the health of the vegetation. In order to monitor vegetation degradation at larger scales, both regionally and globally, reliable, frequent, and long-term monitoring is needed. In this sense, remote sensing technologies represent an important approach, as they can provide spatiotemporally continuous data for all geographical scales from local to global.

One of the most popular vegetation indices employed for assessing the conditions of land surfaces is the Normalized Difference Vegetation Index (NDVI). NDVI is an effective measure of vegetation strength and cover that takes advantage of the difference in spectra reflectance in the red and near-infrared bands. This index is particularly appreciated for both its ability to minimize radiometric and atmospheric variations and its high sensitivity to the vegetation dynamics (Huang et al., 2021). Despite the fact that NDVI is an indicator of vegetation cover, it is commonly used as a proxy of land degradation for large-scale environmental analyses, particularly in areas with sparse data (Chen et al., 2023; Evans & Geerken, 2004; Wessels et al., 2004). The development of cloud-based geospatial platforms, such as Google Earth Engine (GEE), has allowed for easier access and faster processing of long-term NDVI datasets to improve the identification of spatial and temporal trends in vegetation health (Gorelick et al., 2017). The Mann-Kendall trend test and Sen's slope estimator are commonly used to understand long-term trends in NDVI, such as the significance and direction of these changes (Yue & Wang, 2004).

While NDVI has been increasingly used for monitoring vegetation, the integration of trend analysis with residual analysis and multivariate methods such as PCA for understanding the drivers of vegetation degradation in Northern Ghana has been limited. Although trajectories of NDVI are often assumed to be related to land degradation, the intricate interaction between NDVI dynamics and climatic and anthropogenic driving forces is in most cases not thoroughly articulated at the local scale. This hinders the possibility to develop well-targeted and impactful land management interventions grounded on solid evidence. This study aims to enhance understanding of vegetation degradation dynamics in Northern Ghana by:

- Mapping the spatial distribution and temporal trends of vegetation degradation using MODIS NDVI time series data; and
- Identifying the major climatic and anthropogenic drivers influencing vegetation dynamics through Principal Component Analysis (PCA) and residual trend analysis.

By integrating satellite-based trend detection with statistical analysis of driving factors, the study seeks to contribute to evidence-based land restoration planning and sustainable resource management in degradation-prone savannah landscapes.

II. Problem Statement

Land degradation poses a significant global environmental challenge, impacting ecosystem services, food security, and biodiversity (UNCCD, 2022). In Africa, land degradation and desertification processes are due to human and climatic variability (UNEP, 2008). About 65% of the continent's agricultural land suffers from soil erosion and/or chemical and physical degradation of soils in Africa. In addition, 31% of the continent's pasturelands and 19% of the forests and woodlands in the continent are also classified as degraded (UNEP, 2008). While overgrazing has been one of the chief causes of degradation in Africa, at present variability of rainfall and long-term drought are the principal factors (UNEP, 1999). According to IPBES et al. (2018), land degradation is particularly extensive in Sub-Saharan Africa, and estimates suggest that between 20% and 50% of the land is being degraded, affecting 200 million people (Snel & Bot, 2003). Particularly in West Africa, land degradation is exacerbated by climatic stress such as drought and unpredictable rainfall, leading to substantial socio-economic impacts and biodiversity loss (IPCC, 2019). In these regions, deforestation, overgrazing, and unsustainable agricultural practices have been identified as key drivers of land degradation (FAO, 2016).

Ghana, especially its northern regions, faces severe challenges related to land degradation, which threat the agricultural productivity and livelihoods of local communities (Yiran et al., 2012). Existing studies, while extensive, often focus on either trend analyses using NDVI time series or assessments of degradation risk based on various factors. However, there is a lack of integrated research that combines these approaches to provide a holistic understanding of land degradation dynamics in Ghana.

This study aims to fill these gaps by deploying a novel methodological framework that integrates Sen's slope estimator and Mann-Kendall test analysis with Principal Component Analysis (PCA) regression modeling and residual NDVI trend mapping. This approach identifies areas of vegetation degradation due to both climatic and anthropogenic factors and locate degradation hotspots in northern Ghana. By using NDVI as a proxy for land degradation, the study also aims to provide insights into ecosystem productivity loss. This enables long-term regional monitoring and supports the design of targeted sustainable land management interventions in support to the achievement of SDG 15, focused on protecting, restoring and promoting sustainable use of terrestrial ecosystems.

III. Research questions, hypotheses, and objectives

To guide this research well, one main research question, hypothesis, and objective were formulated, along with two specific research questions, two hypotheses, and two corresponding objectives.

a. Research Questions

The main research question is: What is the extent of vegetation degradation and its major driving factors in northern Ghana?

The specific research questions are the following.

i. Where are the hotspots of vegetation degradation in northern Ghana?

ii. What factors contribute most significantly to vegetation degradation in northern Ghana?

b. Research Hypotheses

The main hypothesis related to the main research question is that vegetation degradation in northern Ghana varies spatially across the region and is driven by climatic and human factors, serving as a proxy for land degradation.

The specific hypotheses to be confirmed are:

i. The hotspots of vegetation degradation in northern Ghana is concentrated in specific areas rather than being uniformly distributed across the region.

ii. The primary drivers of vegetation degradation in northern Ghana are climatic and anthropogenic factors.

c. Main and Specific Objectives

The main objective of this study is to assess the spatial distribution and driving factors of vegetation degradation in Northern Ghana from 2004 to 2024 using NDVI as a proxy for land degradation.

The specific objectives are to:

i. Map the vegetation degradation hotspots in northern Ghana using NDVI trend analysis.

ii. Determine the most significant driving factors contributing to vegetation degradation in northern Ghana.

Chapter 1: Literature Review

Land degradation (LD) has become a global concern, threatening ecosystem resilience, agricultural productivity, and livelihoods, particularly in arid and semi-arid regions (Bai et al., 2008). Capturing the complex reality of LD and its various typologies requires not only a multidimensional understanding of ecological, climatic, and socio-economic conditions but also a multi-discursive approach that considers popular narratives and perceptions of the LD process itself (Leach et al., 1999). In recent years, research institutions have increasingly focused on defining LD, identifying its drivers, and developing robust methods for its assessment and monitoring. This review provides a comprehensive background on the core concept of land degradation, the models used to assess it, and the scientific methods commonly employed for diagnosing and characterizing its manifestation. Special reference is given to the African context, with a specific focus on the scale, drivers, and impacts of land degradation in Ghana. Methodological advancements are also highlighted, particularly the use of remote sensing, time-series analysis, and multivariate techniques such as principal component analysis. Finally, the review outlines the policy and management implications discussed in the scientific literature, establishing the foundation for how this study contributes to the field and identifying critical gaps in existing research.

1.1 Conceptualizing Land Degradation

1.1.1 Definition of LD and its indicators

According to D'Odorico and Ravi (2023), land degradation is defined as the process by which land's ability to provide ecosystem services is diminished. This is manifested through the over-exploitation of soil resources, loss of ecosystem production, changes in vegetation composition, and reductions in soil water-holding capacity. Land degradation results in significant economic losses, particularly in developing countries. For instance, it is estimated that land degradation causes a 3-6% loss in the global agricultural gross domestic product (GDP), amounting to approximately ~US$490 billion per year (Pacheco et al., 2018).

As stated in the 1994 report of the UNCCD, identifying the main causes of land degradation—such as climate variability and human-induced disturbances—is essential to reinforce national strategies aimed at combating desertification and promoting land rehabilitation. Ibrahim et al. (2015) described land degradation as a long-term decline of vegetation cover and primary productivity in a given area. Since drylands are prone to temporary declines in primary productivity, such declines serve as strong indicators of land degradation. A decrease in vegetation density is also one of the most widely accepted indicators for evaluating the land degradation process, as noted by Kundu and Dutta (2021).

In this context, NDVI has become a commonly used proxy for detecting vegetation changes due to its sensitivity to vegetation greenness. For example, Ibrahim et al. (2015) used NDVI data to assess land degradation and its relationship to climate variables across sub-Saharan West Africa over a 30-year period, finding a strong association between vegetation loss and rainfall variability. Similarly, Kang et al. (2017) used the Moderate Resolution Imaging Spectroradiometer (MODIS) NDVI data to monitor land degradation in the Tumen River Basin from 2000 to 2015. Their study confirmed NDVI as an effective tool for long-term monitoring of land degradation processes driven by vegetation change.

Although NDVI does not capture every aspect of land degradation, its utility as a proxy has made it a dominant indicator in remote sensing–based land degradation studies.

1.1.2 Key frameworks used in LD assessment

In 2015 the United Nations (UN) established the 17 Sustainable Development Goals (SDG) fundamental to the 2030 agenda, which seek to mobilize international action (United Nations General Assembly, 2015). One of the main objectives of Goal 15.3 is a land degradation-neutral (LDN) world to help curb and revert the current trends of land degradation. Unfortunately, as stated by O'Mara (2012) and Markos et al. (2023), grassland degradation represented one of the main threats to this goal. It is even more closely tied with no poverty (Goal 1), zero hunger (Goal 2), good health and well-being (Goal 3), and climate action (Goal 13). Since the 1990s, some attempts to assess global land degradation have been carried out by Oldeman et al. (1990). And in recent years, an increasing number of scholars have also done work with degradation monitoring in order to respond to and support SDG15.3, like that of Xoxo et al. 2022.

1.2 Land Degradation in Africa & Ghana

1.2.1 Land Degradation in Africa

Land degradation is a pervasive environmental issue across Africa, impacting the continent's ability to sustain its biodiversity and meet the needs of its growing population. A recent assessment by the United Nations Convention to Combat Desertification (UNCCD, 2022) highlights that land degradation undermines ecosystem services, exacerbating food insecurity and poverty. With twothirds of the continent's land classified as desert or drylands, Africa is particularly susceptible to degradation (IPCC, 2019). Human activities, including deforestation, overgrazing, and inappropriate agricultural practices, combined with climatic factors such as prolonged droughts and irregular rainfall patterns, contribute significantly to this challenge (Gupta, 2019)

1.2.2 Land Degradation in West Africa

West Africa faces distinct challenges related to land degradation, which threaten the region's agricultural viability and economic resilience. According to Nkonya et al. (2016), the Sahel region, in particular, experiences severe land degradation rates due to both climatic stressors and anthropogenic pressures. The expansion of agricultural frontiers, driven by population growth and increased food demand, has intensified deforestation and unsustainable land management practices (Adolph et al., 2023). As a result, soil fertility declines, leading to reduced agricultural productivity and increased vulnerability of rural communities to climatic variations.

1.2.3 Land Degradation in Ghana

In Ghana, land degradation is especially pronounced in the northern regions, where erratic rainfall and extended droughts contribute to persistent environmental stress (Yiran et al., 2012). Like other African countries, Ghana possesses high levels of degraded lands. According to the 2017 UNCCD report, 35% of its lands are under threat of desertification. Grasslands, woodlands, and forests are lost to land degradation, while natural water bodies dry up due to extreme droughts and sedimentation of water sources. The same report estimated the annual cost of land degradation in Ghana at 1.4 billion dollars, equivalent to 6% of the Gross Domestic Product (GDP) of Ghana. Ashaley (2013) revealed that degradation levels are concentrated in the Upper East, one of the poorest regions in the country. Under these circumstances, land degradation has become a growing issue of concern.

1.3 Land Degradation Assessment Methods

Different approaches to measuring land degradation have included qualitative measures like expert assessment and land users' perceptions and quantitative measurements like field observations, productivity estimates, and modeling. The most common among them are remote sensing (satellite) and Geographic Information System (GIS) for land use and land cover change detection (Symeonakis, 2022). These technologies are often accompanied by ecological assessments and measurements of soil properties, allowing a more complete assessment of degradation processes (Reed et al., 2008). The use of multispectral satellite data, such as vegetation indices, and digital elevation models (DEMs), together with geostatistical methods have made the analysis of land degradation even possible in terms of monitoring spatial and temporal dynamics of land degradation (Gül & Erşahin, 2019).

In light of the complex interaction between environmental and socio-economic processes that compose land degradation, the need for robust analytical and statistical frameworks that are able to model the trajectories of such systems through time and space is pressing.

Various approaches have been adopted to separate man-made from natural land degradation. Machine learning algorithms (Torabi Haghighi et al., 2021; Basu et al., 2021) have been shown to be highly predictive but are also highly context dependent, as they often necessitate large training datasets. Geostatistical analyses proposed in Chen et al. (2019) and Prăvălie et al. (2021) provide useful information on spatial patterns but can miss the dynamics of the temporal component. Further, Li et al. (2021) attempted to fill this gap by applying time series methods such as residual trend analysis to separate anthropogenic influences from climatic fluctuations, while other approaches like multi-criteria frameworks such as the Analytic Hierarchy Process applied by Sandeep et al. (2021) added expert knowledge, yet they bring in subjectivity. Dimensionality reduction techniques such as principal component analysis (PCA) can also be used as a complementary approach to summarize complex environmental data, focusing on dominant drivers (Ontel et al., 2023).

As an example, Torabi Haghighi et al. (2021) used multiple machine learning models, such as Support Vector Machine (SVM), Multivariate Adaptive Regression Splines (MARS), Generalized Linear Model (GLM), and Dragonfly Algorithm, to produce maps of LD risk in the Pole-Doab watershed of Iran. In a similar way, Feizizadeh & Blaschke (2013) have applied AHP in a GIS environment to evaluate land suitability and land degradation risk factors for Tabriz County, Iran.

Principal component analysis (PCA) is one of the few approaches that has been shown to successfully eliminate multicollinearity between variables that are themselves correlated (e.g., precipitation, temperature, solar radiation) and represent their overall influence on vegetation shifts. PCA allows the generation of composite indicators that provide information on spatial patterns of degradation drivers by extracting alternate components that account for a high percentage of the variance of the input variables (Ontel et al., 2023).

1.4 Remote Sensing and Modeling Approaches for Assessing Vegetation Degradation Change

The monitoring and assessment of vegetation degradation have shifted from relying solely on biophysical measurements to approaches that incorporate both climatic and anthropogenic factors, as well as considerations of spatial and temporal scale (Reed et al., 2011). Temporal datasets of vegetation indices derived from remote sensing, along with statistical modeling techniques such as regression analysis, are frequently utilized to comprehend trends in vegetation degradation and its root causes (Huang et al.,2022). The increased availability and use of Earth observation data has enhanced our capacity to detect vegetation dynamics associated with climate and human pressures (Bai et al., 2008; Reynolds & Stafford, 2002).

In particular, drylands require observational data capable of capturing both long-term trends and short-term disturbances over extensive areas (Cherlet et al., 2018). For this reason, remote sensing datasets are key in methodologies for monitoring vegetation degradation, as they provide objective, repeatable, and synoptic observations (Vogt et al., 2011). Instruments such as the Moderate-Resolution Imaging Spectroradiometer (MODIS) have been instrumental in providing consistent biophysical indicators, benefiting from high frequency and moderate spatial resolution (Didan, 2015). Among the most commonly used proxies for monitoring vegetation degradation are vegetation indices such as the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI), which, though primarily measures of vegetation greenness, are often used as proxies for broader land degradation trends (Chen et al., 2023; Wessels et al., 2004). In particular, NDVI has proven useful in locating degradation hotspots, assessing the impact of drought, and accompanying early warning systems (Ji & Peters, 2003).

A recent study using the long-term Global Inventory Modeling and Mapping Studies (GIMMS) NDVI dataset for the Middle East and North Africa (MENA) region found that over 40% of the area remains vulnerable to land degradation and desertification, with less than 5% showing signs of regeneration (Li et al., (2023). Climate variability and recurrent drought became the primary driver of degradation, with secondary drivers such as forest fires and socioeconomic stressors being of less importance (Faour et al., 2016). Moreover, methodologies like the residual trend analysis (RESTREND) have been developed to separate human-induced land degradation from shifts in vegetation related to inter-annual climate variation, providing useful insight into the nature of human influence (Evans & Geerken, 2004; Ibrahim et al., 2015). Spatial logistic regression modeling has also been carried out to quantify the influence of specific driving forces in the dynamics of degradation and to spatially characterize the probability of land degradation risk (Dubovyk et al., 2013).

1.5 Relevant Variables Used in Assessing Vegetation Health

Numerous studies have demonstrated the importance of various environmental and anthropogenic variables in evaluating vegetation health and land degradation. For instance, Chen et al. (2023) utilized NDVI data alongside temperature, precipitation, and evapotranspiration indicators to assess vegetation health and land degradation trends in Balochistan, Pakistan. This study underscores the significance of climatic variables in understanding vegetation dynamics.

Similarly, Kang et al. (2021) explored the influence of temperature, precipitation, solar radiation, relative humidity, and CO_2 concentration on NDVI changes across China. Their research highlighted the complex interactions between vegetation dynamics and climate factors, emphasizing the multifaceted nature of ecological assessments.

Topographic data, such as the Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM), has been extensively employed in studies related to soil erosion, watershed analysis, and terrain-induced degradation risks (Farr et al., 2007). This dataset provides essential information for understanding how elevation and terrain affect land degradation processes.

Moreover, the impacts of human activities on land degradation have been extensively studied. Cherif et al. (2023) monitored land degradation in Greece and Tunisia, taking into account anthropogenic factors such as population density and land use changes. This research illustrates the critical role of human-induced pressures in accelerating degradation processes.

These studies collectively highlight the diverse array of variables that must be considered in land degradation research, integrating both natural and anthropogenic factors to provide a comprehensive understanding of the issue.

1.6 Policy & Land Management Implications

The solution to land degradation, is an integrated policy response that is consistent with ecological and socioeconomic conditions. Ghana's National Action Plan (NAP) to combat desertification, strengthening the United Nations Convention to Combat Desertification (UNCCD), sets the stage for land degradation management that focuses on afforestation, sustainable land management

(SLM), and community involvement. But implementation is a big challenge due to a lack of funds, a weak enforcement of environmental codes, and fragmented institutional coordination, according to Ali Mekouar (2017).

At the continental level, projects such as the Great Green Wall Initiative (GGWI) seek to restore nearly 100 million hectares of degraded lands throughout the Sahel by 2030, as stated in the 2020 UNCCD report. While the GGWI was implemented inconsistently among Ghanaian regions, it presents potential for technical assistance and financial support avenues (Nkonya et al., 2016). Secured land tenure is another crucial issue, especially in Northern Ghana, since customary land ownership is often undocumented. Linked to this insecurity, it minimizes long-term investments to restore the land while forcing overuse of the resource (Snel & Bot, 2003; IPBES et al., 2018). Community-based natural resource management (CBNRM) has grown into the practical solution in the role of improving environmental stewardship.

Semi-arid regions that used indigenous knowledge systems alongside contemporary monitoring tools like remote sensing have improved early warnings and land-use planning (Vogt et al., 2011; Xoxo et al., 2022). Thus the success of degradation mitigation initiatives is contingent not only on technical measures but also on policy consistency, institutional capacity, and stakeholder participation. The inclusion of such remote sensing-derived measures as NDVI trend and residuals in national monitoring systems also has the potential to enhance evidence-based policy and effectively direct land restoration interventions (Higginbottom & Symeonakis, 2014). To be effective, these policies should rely on an accurate and spatially explicit understanding of degradation, such as the NDVI-PCA-RESTREND methodology employed in this study.

The review identifies a general agreement on the applicability of remote-sensing indices to land degradation mapping at large scales, along with critical open questions related to driver attribution and the interpretation of residual trends. This gap justifies the use of Sen's slope, Mann-Kendall trend tests, PCA, and residual analysis together, to assess vegetation degradation in northern Ghana and the associated driving factors, using NDVI as a proxy.

Chapter 2: Methodology

This chapter outlines the data sources used in this study. It describes the study area, preprocessing steps and the statistical methods applied. In addition, the chapter defines quality control protocols and classification criteria for identifying zones of degradation or restoration.

2.1 Study Area

2.1.1 Description

This study was conducted in northern Ghana, a region characterized by semi-arid conditions and intensive land use. The area lies within the Guinea Savanna ecological zone, which covers approximately 147,900 km², representing around 62% of Ghana's total land area (≈ 238,500 km²) (FAO, 2001). The Guinea savanna zone spans between longitudes 2.8° W and 0.6° E and latitudes 8° N and 11° N (see Figure 1). It includes the Upper West, Upper East, Northern, Northeast, and Savanna regions, with respective populations of 901,502; 1,301,226; 2,310,939; 658,946; and 653,266 (Ghana Statistical Service, 2021).

2.1.2 Climatic characteristics

Mean monthly temperatures range from 24°C in December to 38°C in April, with relatively high humidity during the night and early morning in the rainy season. Annual rainfall is variable/irregular, ranging between 635 mm and 1350 mm (MOFA, 2021), with a unimodal seasonal rainfall pattern. These uncertain climatic conditions make climate a key factor contributing to land degradation in the region.

2.1.3 Vegetation conditions

The dominant vegetation consists of grassland interspersed with forest and riverine thickets (MLNR, 2022). Vegetation cover is composed of mixed formations of fire-resistant trees and shrubs. The region's economy is primarily based on smallholder agriculture, with over 80% of the population relying on agriculture for their livelihoods. The landscape is generally flat to gently undulating (1–3% slope) and is marked by broad river valleys and low-lying depressions.

Low soil organic matter, combined with overgrazing and intensive farming, accelerates land degradation. Human activities such as deforestation, overgrazing, unsustainable agricultural practices, and urbanization are major drivers of land degradation in Northern Ghana. Natural factors—such as droughts, floods, and wind erosion—also contribute significantly. Prolonged dry spells and erratic rainfall patterns lead to soil nutrient depletion and vegetation stress, while intense rainfall events result in surface runoff and erosion.

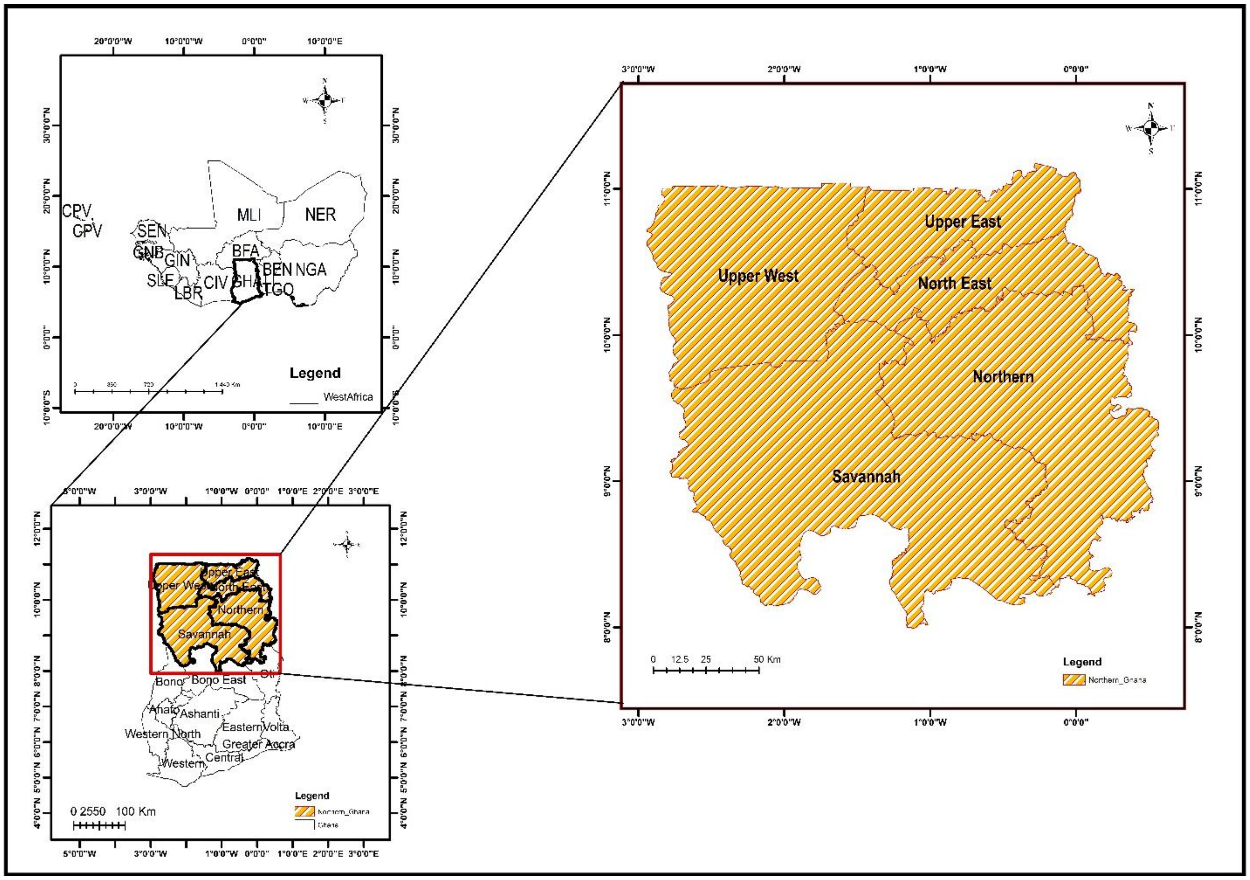

Figure 1: Study Area (Northern Ghana)

2.3 Datasets

Multiple spatial and environmental datasets were used for this study. The datasets were selected based on their associations with vegetation dynamics and their established use in previous land degradation research (Wessels et al., 2004; Bai et al., 2008; Evans & Geerken, 2004). The variables included average annual temperature (TMP), actual evapotranspiration (AET), solar radiation (SRAD), mean annual precipitation (MAP), NDVI, soil moisture, Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM), and a human pressure composite index incorporating population density, built-up areas, and nighttime lights (Table 1).

Table 1: Datasets

Dataset	Description	Spa. res.	Time period	Source
Mean annual precipitation (MAP)	Precipitation	4638.3m	2004-2024	IDAHO_EPSCOR/TERRACLIMATE
MODIS MOD13A1	(NDVI) Vegetation index	500m	2004-2024	MODIS/061/MOD13A1
SRTM DEM	Elevation and slope	30m	Static	USGS/SRTMGL1_003
Average annual temperature (TMP)	Temperature	4638.3m	2004-2024	IDAHO_EPSCOR/TERRACLIMATE
Soil	Soil Moisture	4638.3m	2004-2024	IDAHO_EPSCOR/TERRACLIMATE
Actual evapotranspiration (AET)	Actual water loss	4638.3m	2004-2024	IDAHO_EPSCOR/TERRACLIMATE
Solar radiation (SRAD)	Downward surface shortwave radiation	4638.3m	2004-2024	IDAHO_EPSCOR/TERRACLIMATE
Human composite index	Population, built-up areas and nighttime lights	92.77m 100m 463.83m	2000-2021	WorldPop/GP/100m/pop, JRC/GHSL/P2023A/GHS_BUILT_V, NOAA/VIIRS/DNB/MONTHLY_V1/VCMCFG

All datasets were assessed and pre-processed using Google Earth Engine (GEE) platform due to its robust cloud-based platform, which provides access to a vast array of geospatial datasets and powerful processing capabilities. This included steps such as spatial resampling and standardization of projections, efficiently handling large datasets and ensuring consistency.

Subsequent data analysis and mapping were performed using Python and ArcMap. Python facilitated further data manipulation and analysis, while ArcMap was utilized for creating detailed maps and visualizations. ArcMap's comprehensive spatial analysis tools allowed for precise cartographic outputs, aiding in the interpretation of spatial patterns in the study area.

2.4 Data Pre-processing & Analysis

To detect long-term vegetation trends across Northern Ghana, MODIS NDVI data was processed using the Google Earth Engine (GEE) platform for the period 2004 to 2024. The analysis focused on the growing season months from April to October. A boundary shapefile for Northern Ghana was used to define the study area and clip all data accordingly. Poor-quality NDVI observations were filtered out using the SummaryQA band, retaining only pixels with the highest quality (QA = 0). Monthly maximum NDVI values were computed for each growing season month and then averaged to obtain a yearly mean NDVI image for each year. To assess vegetation trends over time, the Sen's slope estimator was applied to the yearly NDVI time series to quantify the rate and direction of change. The Mann-Kendall test was used to evaluate the statistical significance of these trends, generating spatial layers for Kendall's tau coefficient, Z-score, and p-values (Al-Harbi et al., 2024). NDVI trends were then classified into greening, browning, or stable based on the slope direction and significance levels. Only pixels with statistically significant trends ($p < 0.05$) were used to identify degradation or restoration, while non-significant pixels were considered stable (Zhou et al., 2014). All final outputs, were exported in GeoTIFF format for map generation and further analysis in ArcMap and Python respectively.

These classifications were visualized through a trend classification map that defined areas of vegetation degradation, restoration, and stability across the study region. These steps are summarized in figure 2 below.

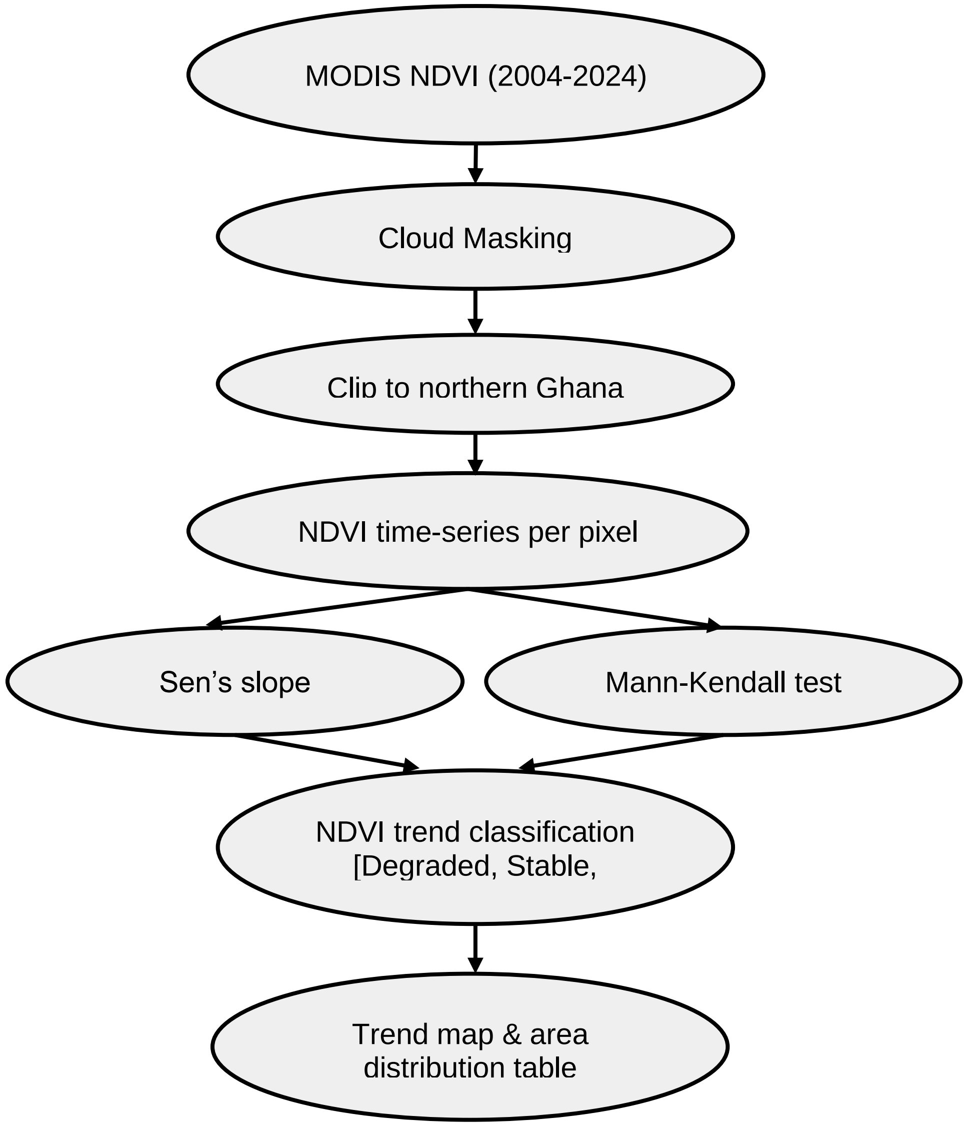

Figure 2: Data analysis workflow chart for objective 1

To identify the major drivers of vegetation degradation, a set of environmental and human pressure variables were extracted and processed using Google Earth Engine (GEE) at a spatial resolution of 500 meters. A boundary shapefile defining Northern Ghana was used to spatially constrain all datasets. The analysis focused on the growing season months (April to October) for the period 2004 to 2024.

Climate variables including precipitation, temperature, actual evapotranspiration (AET), solar radiation, and soil moisture were derived from the TerraClimate dataset

(IDAHO_EPSCOR/TERRACLIMATE). For each year, seasonal averages or totals were computed by aggregating monthly values within the growing season. For example, precipitation was summed over the growing season, while other variables such as temperature and AET were averaged.

In addition to climate variables, static layers were included: elevation from the SRTM digital elevation model (USGS/SRTMGL1_003), and three proxies of human activity—population density (WorldPop 2020), built-up volume (GHSL built volume), and nighttime light intensity (NOAA VIIRS 2012–2023 average). These three layers were normalized and combined into a single composite human pressure index by taking the average of their unit-scaled values. All variables were clipped to the study area and exported in GeoTIFF format for further statistical analysis in Python.

A multi-dimensional statistical framework—combining dimensionality reduction, classification, and regression analysis—was used, as summarized in Figure 3.

a. Principal Component Analysis (PCA)

PCA (principal component analysis) was applied to the seven variables (precipitation, temperature, soil moisture, actual evapotranspiration, solar radiation, slope, and human pressure composite index). PCA is frequently used as a mechanism for variable reduction through the identification of principal components (Jolliffe & Cadima, 2016). It transforms the original variables into smaller uncorrelated datasets (principal components) that account for maximum variance in the data. This simplification facilitates the identification of patterns that correlate with land degradation. Each principal component is associated with eigenvectors which can be used to obtain weights for LD indices.

The seven major components were extracted according to the seven variables that were utilized as input in the principal components tool in Python. The PCA procedure resulted in new raster files in which each raster represents a principal component. Each of the principal components is a linear combination of the original datasets and they reflect different patterns or information in the data. Also, each PC is represented by a set of eigenvectors, which are the proportions that each variable has in order to obtain PC1, PC2, PC3, etc. These take values in between ±1 and 0. The closer to ±1 they are, the higher contribution of the analyzed variables, and vice versa. The sign positive or negative indicates the direction in which a given variable in that PC is found along a one-dimensional vector. The PCA produced a set of uncorrelated components, and the first three principal components were retained for further analysis. The factor loadings of each variable on the retained components were analyzed to interpret the underlying environmental gradients. These components thus represented distinct natural and anthropogenic influences on NDVI trends.

b. Identification and Classification of Degradation Drivers

Using the outputs from the PCA and NDVI trend analysis, a spatial classification map was generated to identify the dominant drivers of degradation or restoration in each pixel. This was accomplished by integrating two layers:

1. NDVI trend direction, derived from Sen's slope estimates, and
2. Dominant principal components, indicating whether the pixel was primarily influenced by climate and anthropogenic factors or both.

Pixels were classified into six categories based on the combination of NDVI trend direction and dominant PCA-derived drivers (Chen et al., 2023):

- Climate-Driven Degradation (CDD)
- Human-Driven Degradation (HDD)
- Both-Driven Degradation (BDD)
- Climate-Driven Restoration (CDR)
- Human-Driven Restoration (HDR)
- Both-Driven Restoration (BDR)

To assess the spatial dominance and distribution of each driver type across the landscape, a quantitative summary of the area coverage (in square kilometers and percentage) was calculated for each restoration and degradation class (Kang et al., 2021).

c. NDVI Residual Analysis

To further identify vegetation changes not explained by climate and topographic variables Mumtaz et al. (2023), a multiple linear regression model was developed using the retained principal components (PCs) as predictors of observed NDVI values. The residuals—calculated as the difference between the observed NDVI and the NDVI values predicted by the PCA-based regression model—were computed for each pixel (Geerken & Ilaiwi, 2004). The equation is given by

$$NDVI_{\,residual} = NDVI_{observed} - NDVI_{predicted\ (from\ PC1\ –\ PC3)}$$

The residual outputs were mapped spatially to identify areas where vegetation change was not adequately explained by environmental factors. Negative residuals indicated unexplained degradation, while positive residuals reflected unexpected vegetation improvement. This residual analysis indicated areas of concern for further research by indicating differences between the observed and predicted vegetation dynamics. Find some articles and add those references

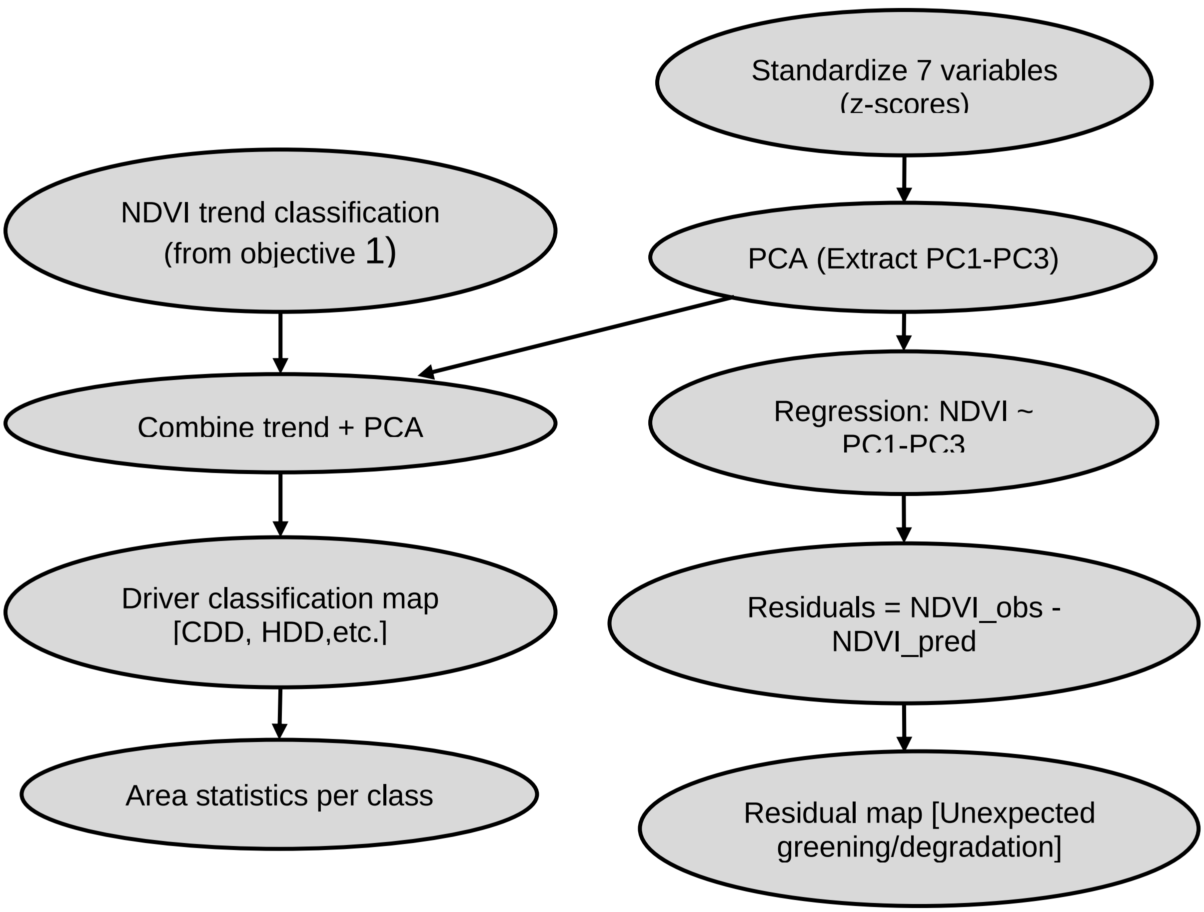

Figure 3: Data analysis workflow chart for objective 2

The study utilized pixel-based NDVI trend analysis and a multivariate analysis to determine drivers of vegetative degradation in Northern Ghana. The use of the Sen's Slope estimator and Mann-Kendall test to calculate the long-term NDVI trends and thus categorize if the area is stable, being degraded, or undergoing restoration. In order to identify which were the main environmental gradients and to reduce the existing complexity, PCA analyses on climate, topography, and anthropogenic variables were used to explore potential factors underlying such an effect. These components of the PCA were combined with the trend of the NDVI to develop a further set of remote sensing-based maps related to the spatial patterns of climate control, human activity, and a combination of both degradation and restoration. Lastly, residual trend analysis was applied to extract vegetation dynamics not accounted for by environmental variables and reveal additional information about local, or non-climatic, driving factors.

Chapter 3: Results

The main results—including spatial maps of NDVI trends categorized into degradation and restoration classes, PCA loadings and component scores representing dominant gradients of climatic and anthropogenic variables, and residual maps highlighting unexplained vegetation change—are presented in this chapter. Summaries of quantitative data, such as area proportions per class, rates of change over time, and contributions of drivers, are presented in figures and tables.

3.1 Spatial Distribution of Vegetation Degradation

The temporal trends in vegetation were examined by mapping the mean annual NDVI from 2004 to 2024 across northern Ghana. This time series showed significant inter-annual variation, with mean annual NDVI between 0.430 and 0.469 (Figure 4). The most notable peak in greenness was observed in 2009, followed by a decrease from 2015 to 2016. A linear regression applied to the resulting NDVI time series showed a slight decreasing slope (slope ≈ -0.0003), suggesting a slow, continuous reduction in vegetation productivity over the 20-year period.

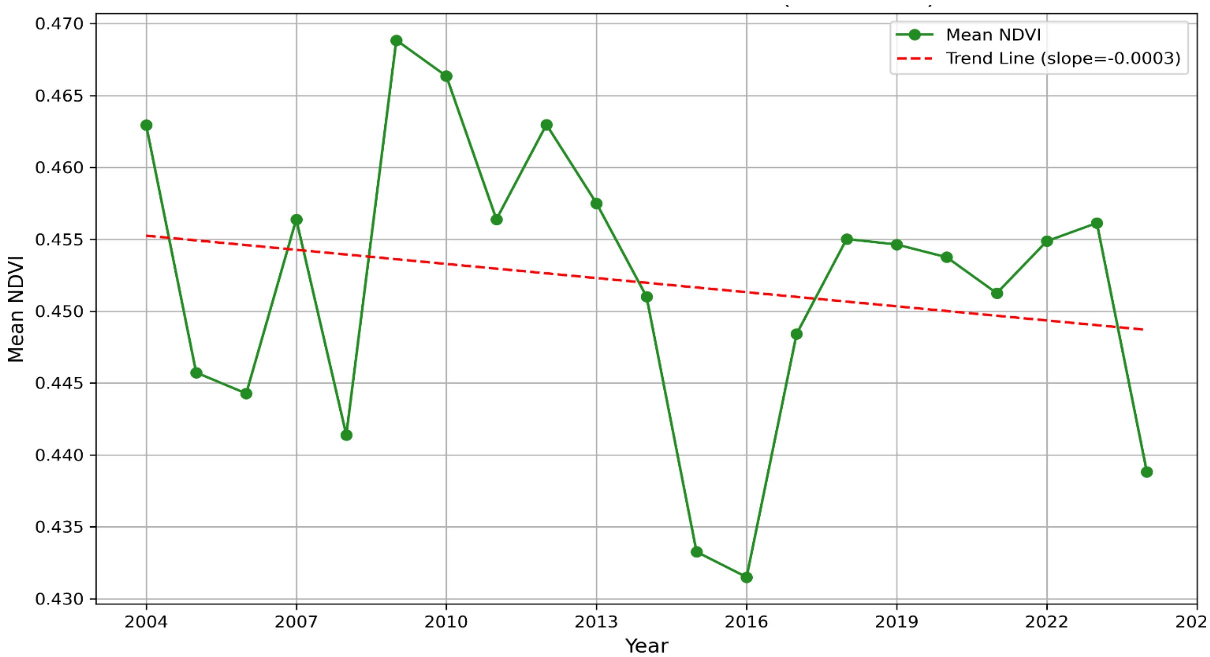

Figure 4: Annual mean NDVI time series (2004–2024) across Northern Ghana with linear trend line.

Based on the Sen's slope estimator, pixels were classified into five categories. The outcome is shown in Figure 5 as a map highlighting moderately and severely degraded zones as well as areas exhibiting moderate and strong vegetation recovery across northern Ghana.

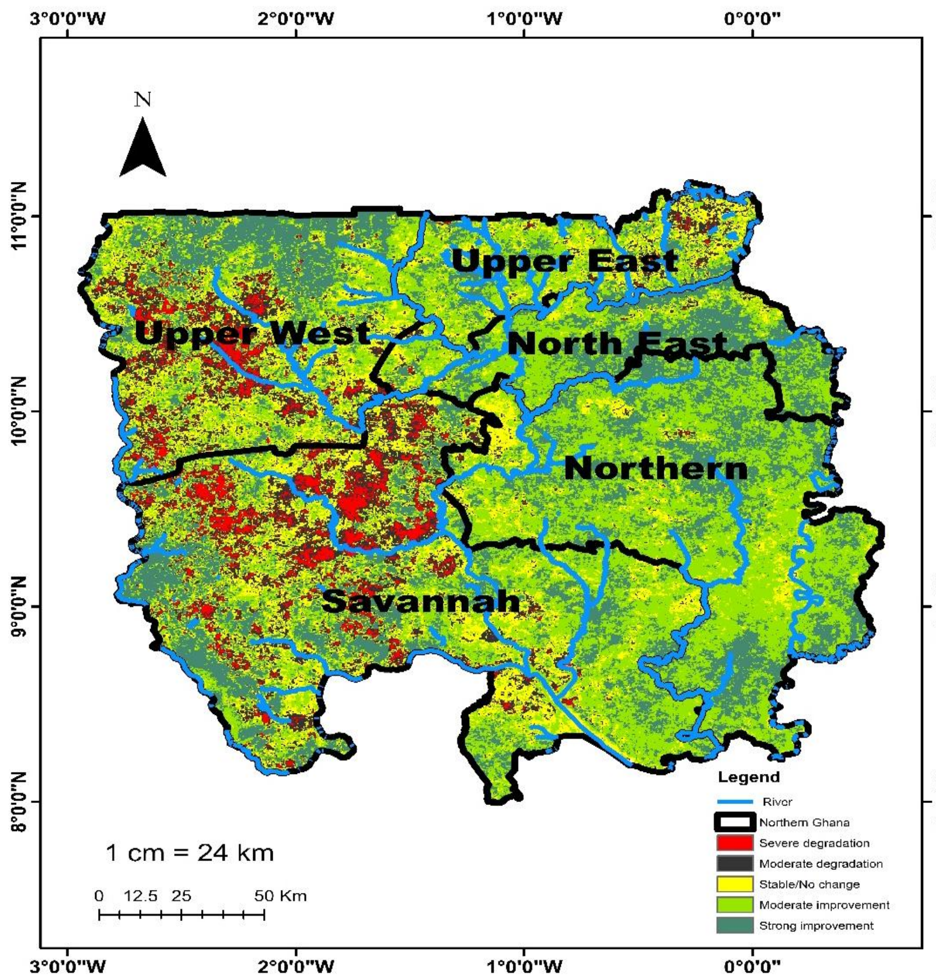

Figure 5: NDVI-based vegetation degradation hotspot distribution for Northern Ghana from 2004-2024

Essentially, between 2004 and 2024, 11.17% of the region's vegetation cover showed significant change. The areas that experienced degradation amount to 5.64%, while 5.53% experienced recovery. Vegetation degradation was most notable in the Upper West and Savannah regions, where declining vegetation (negative NDVI trends) was more widespread than recovery (positive NDVI trends). Vegetation recovery was, however, observed in all five regions.

The area distribution of vegetation degradation and restoration classes derived from the Sen's Slope trends is summarized in Table 2 below.

Table 2: Area Distribution of Vegetation Degradation and Restoration Classes Derived from Sen's Slope Trends (2004–2024) in Northern Ghana

Class	Pixel count	Area (km^2)	Percent area (%)
Moderate Degradation	1065587	266396.75	48.08
No change	620659	155164.75	28.00
Moderate Restoration	480172	120043.00	21.67
Severe Degradation	26493	6623.25	1.20
Strong Restoration	23423	5855.75	1.06

Table 3: Classification of NDVI Trend Significance Based on Mann-Kendall Test

Score	Significant level (p value)	Confidence level	Pixel count	Percent area (%)
3	0.01 to 0.05	95% confidence level	21938	5.64%
2	0.05 to 0.1	90% confidence level	21529	5.53%
1	0.1 to 1.0	<90% No Sig. trend	345688	88.83%

3.2 Principal Component Analysis

The PCA produced new raster datasets, with each raster representing a principal component. Each component was composed of eigenvectors indicating how each original variable contributed to the respective PCs (i.e., PC1, PC2, and PC3) (Mann, 1945). These eigenvector values ranged from ±1 to 0, where values closer to ±1 indicated greater contribution and those closer to 0 indicated weaker influence. The sign (positive or negative) represents the direction of influence of each variable on a given component axis (Table 2).

The PCA results indicated that PC1 alone accounted for 46.82% of the total variance, followed by PC2 with 20.53%, PC3 with 14.28%, PC4 with 13.60%, and PC5 with 2.65%. The cumulative eigenvalues indicated that the first three components collectively account for 81.63% of the variance.

Table 4: Principal Component Analysis

Variables	PC1	PC2	PC3	PC4	PC5
Precipitation	-0.42658	-0.39029	-0.00241	-0.37577	-0.36144
Temperature	-0.13965	-0.79280	-0.01438	0.10326	-0.06848
Elevation	0.43514	-0.19392	0.00854	-0.52407	0.46483
Solar radiation	0.47850	-0.17774	0.00672	-0.40144	-0.12294
Soil moisture	-0.00178	-0.01935	0.99951	0.02376	0.00193
Population	-0.34070	0.38413	0.02553	-0.63125	-0.24213
AET	0.51394	0.04487	0.00099	0.11526	-0.75820

Metrics	PC1	PC2	PC3	PC4	PC5
Eigenvalues	3.27724	1.43715	0.99990	0.94915	0.18535
% Eigenvalues	46.81757	20.53064	14.28422	13.55918	2.64791
Accumulative of Eigenvalues (%)	46.81757	67.34822	81.63244	95.19162	97.83953

3.3 Distribution of Drivers of Vegetation Degradation Based on Dominant PCA Components

Following the PCA results and trend classification, a spatial classification was performed to assign each pixel to one of the climatic or anthropogenic drivers of degradation or restoration. This approach was based on the assumption that the first few PCs represented interpretable environmental and anthropogenic gradients and that the dominant component at each location indicated the primary driver of degradation. This allowed for the differentiation between climate-driven degradation, human-driven degradation, and degradation driven by both. Similarly, zones exhibiting restoration were classified using the same logic.

Pixels showing a significant negative NDVI trend (Sen's slope < -0.0005) were designated as degradation zones, while positive trends (> 0.0005) were classified as restoration zones. The corresponding PCA-driven driver categories were then assigned to each zone accordingly (Table 3 and Figure 6).

Table 5: Spatial distribution of drivers of land degradation and restoration in Northern Ghana

NDVI trend (Sen's slope)	Trend of factor	Mean PC1	Mean PC2	Mean PC3	Percentage (%)
< -0.0005	CDD	1.752867	0.128350	0.008028	33.48
< -0.0005	BDD	-2.066466	1.070389	0.123435	3.17
< -0.0005	HDD	-0.671270	-0.062733	0.008943	27.90
≥ 0.0005	CDR	-1.225996	0.111611	-0.002221	9.25
≥ 0.0005	BDR	-2.591710	1.253908	-0.015725	2.81
≥ 0.0005	HDR	-0.769682	-1.587409	0.011243	14.85
-0.0005 to 0.0005	Stable	-505.075287	-505.018524	-504.924042	8.54

CDD is climate-driven degradation, HDD is human-driven degradation, BDD is degradation driven by both climate and human activities, CDR is climate-driven restoration, HDR is human-driven restoration, and BDR is restoration driven by both climate and human activities.

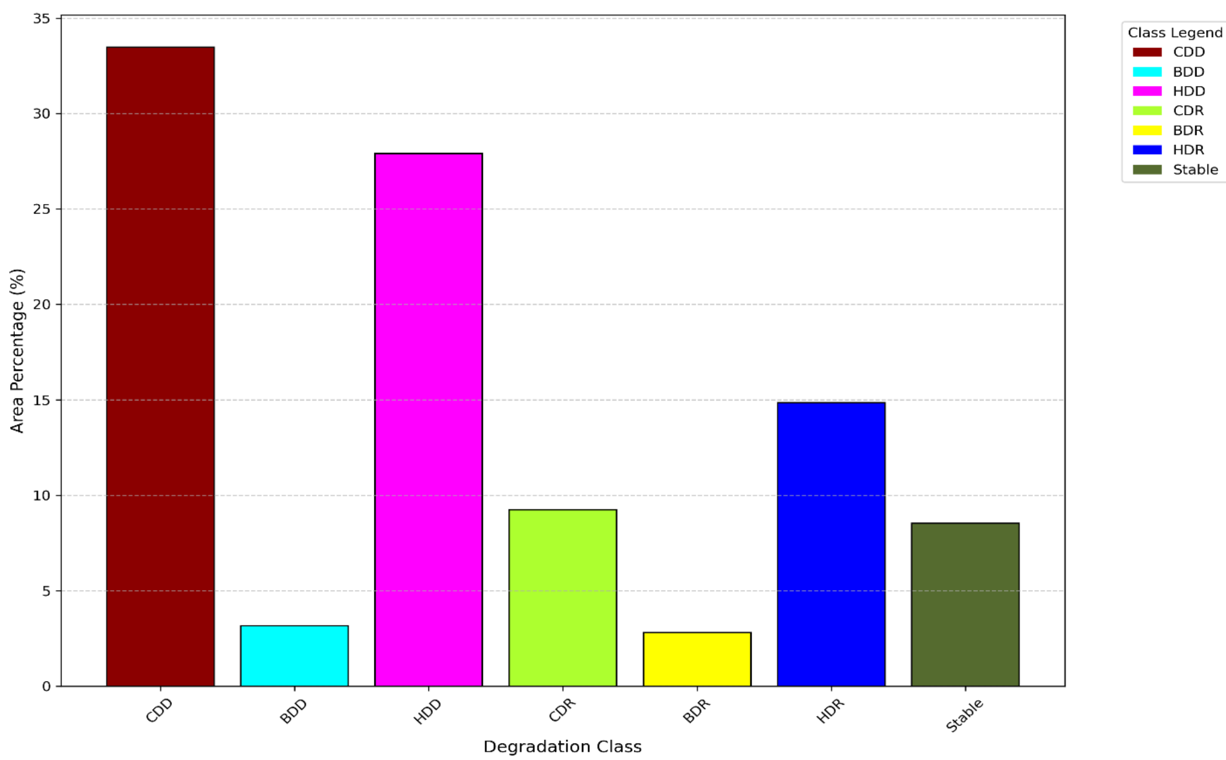

Figure 6: Percentage area under each NDVI degradation and restoration driving factors based on NDVI-PCA classification.

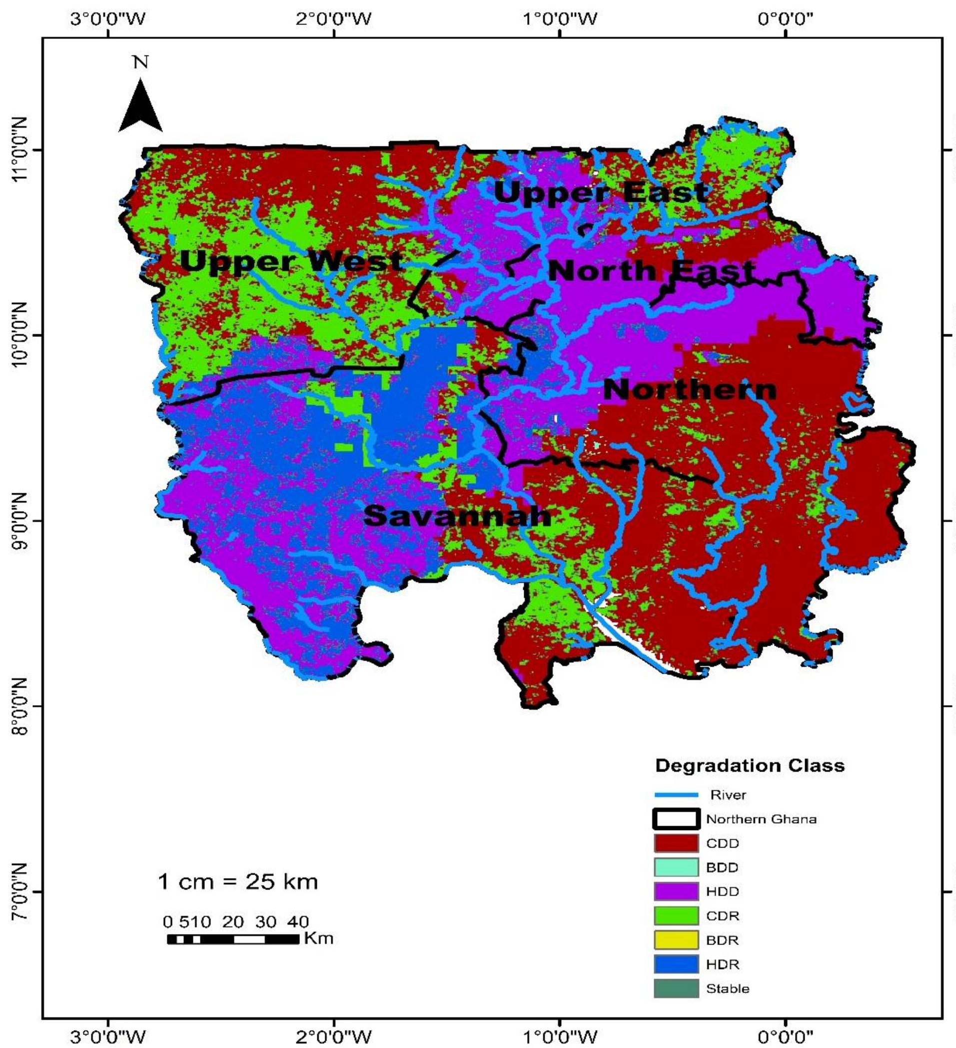

Figure 7: Spatial distribution of driving factors of vegetation degradation and restoration in Northern Ghana.

3.4 NDVI Residual Analysis to Identify Unexplained Degradation

The residuals represent areas where vegetation change deviated from expectations based on known climate and environmental factors and were interpreted as potential indicators of local human influence or other unaccounted-for drivers of degradation. Figure (3) shows the spatial distribution of NDVI residuals derived from the PCA-based multiple regression model.

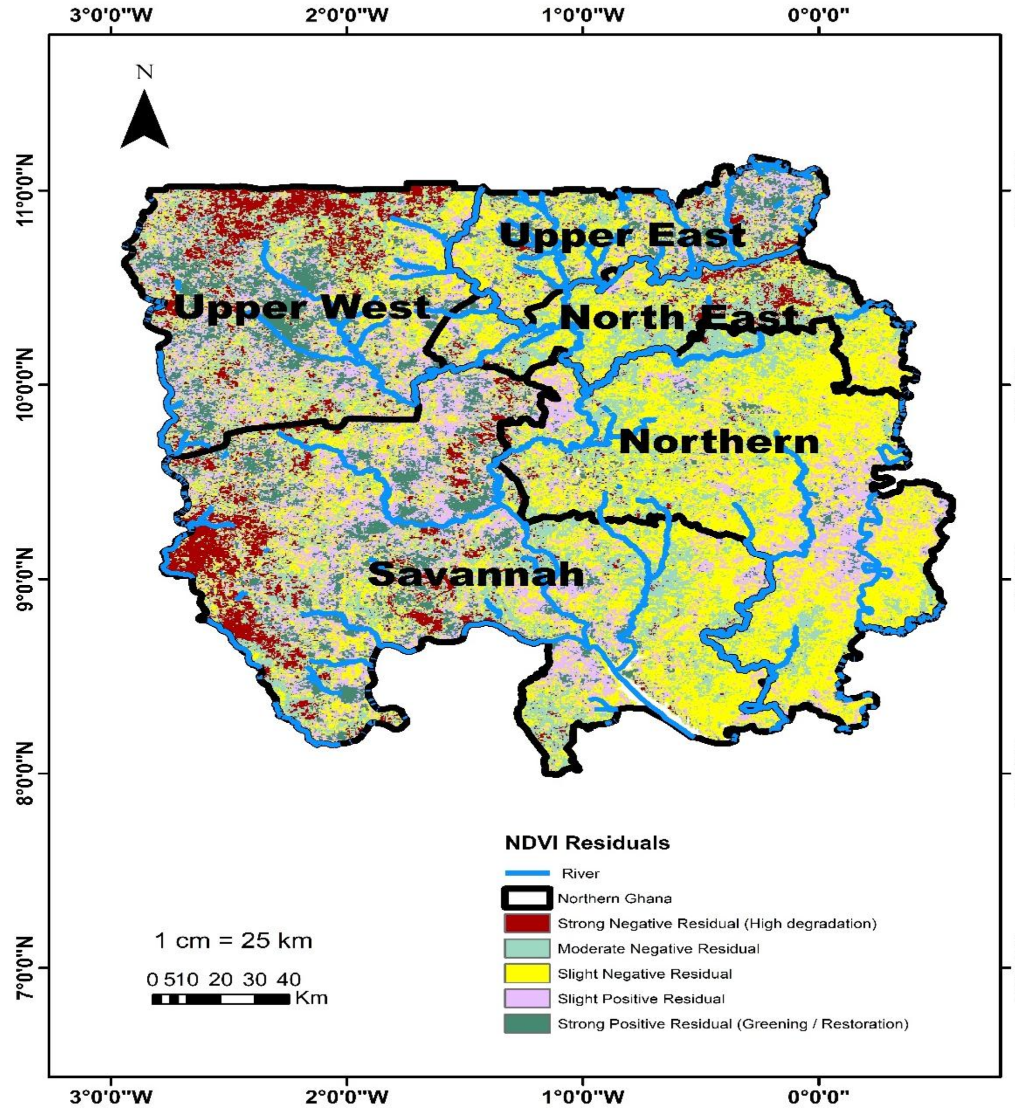

Figure 8: Spatial distribution of NDVI residuals across Northern Ghana

In an effort to gain a better understanding of vegetation shifts that did not seem to be completely accounted for by climatic and human variables, NDVI residuals by class of degradation and restoration were examined using a boxplot (Figure 8). The residuals are the observed NDVI trends subtracting the trends predicted by the PCA components PC1-PC3. Negative values indicate sites with higher levels of deterioration than predicted by environmental drivers, while positive ones reflect higher levels of recovery than predicted by climate and topography.

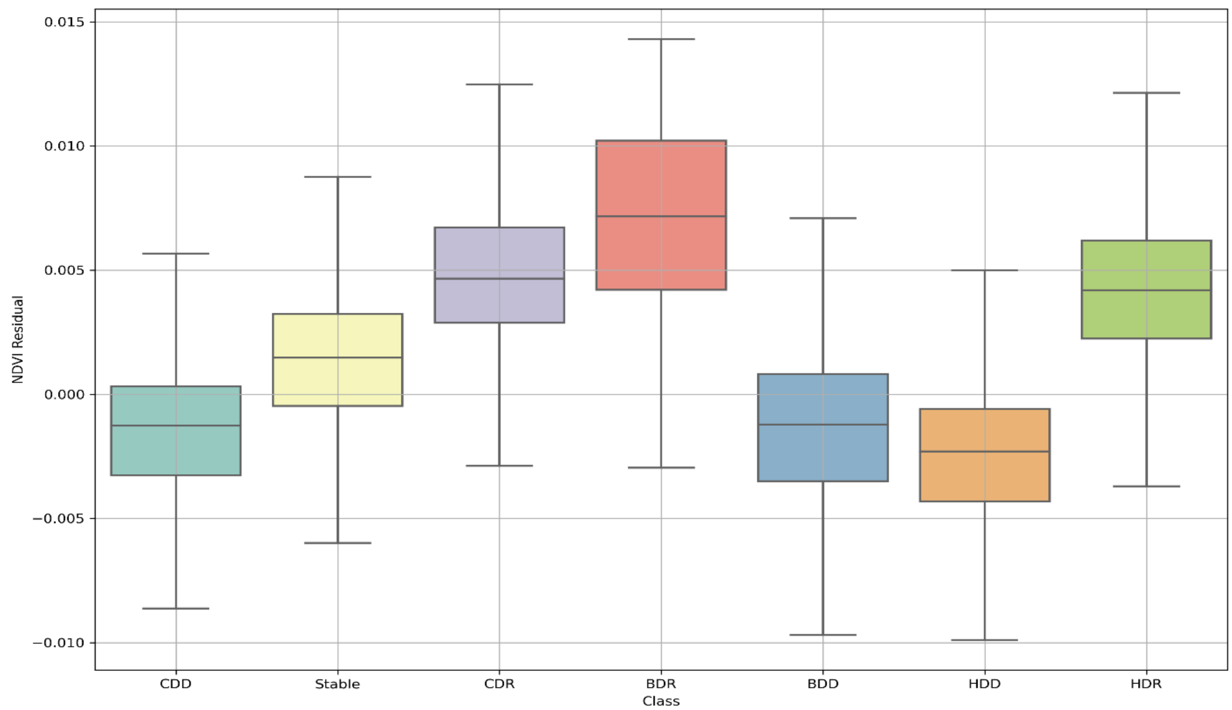

Figure 9: A boxplot showing the distribution of NDVI residuals across degradation and restoration classes.

The findings of this study represent patterns of NDVI trends as an indicator of vegetation degradation, as well as the relationships between NDVI trends and climatic and anthropogenic drivers. Although these results are important for deepening the understanding of spatial patterns of degradation at the landscape level across Northern Ghana, it is worth noting that NDVI-based research offers only a partial view of land degradation. Other dimensions, such as soil degradation and hydrological changes, fall beyond the scope of this study. Conclusions drawn from this study should therefore be understood within the context of vegetation assessments.

The findings also reveal the heterogeneity of vegetation dynamics across Northern Ghana, highlighting distinct degradation hotspots associated with rainfall deficits and population density. Moreover, the residual analysis reveals pockets of unexpected greening in certain locations. These findings set the stage for an in-depth discussion in Chapter 4, where methodological implications and practical relevance of the findings will be explored.

Chapter 4: Discussions

This chapter discusses the key findings of the study in relation to the research questions outlined at the beginning. It evaluates the strengths and limitations of combining NDVI trend analysis with principal component analysis and residual modeling to assess vegetation degradation and its drivers. The chapter also discusses the identified ecological and socio-economic drivers of vegetation change, compares the results with findings from other relevant studies, and reflects on the effectiveness of the methods used. It concludes with management implications and recommendations for future research.

4.1 Vegetation Degradation Trends across Northern Ghana

The study revealed that 11.17% of vegetation cover in Northern Ghana experienced significant change between 2004 and 2024. Out of this, 5.64% was degraded, and 5.53% showed signs of restoration.

Degradation trends were most prominent in the Upper West and Savannah regions, where negative NDVI slopes indicated sustained vegetation loss. These patterns confirm earlier assessments, including Ibrahim et al. (2015) and Yiran et al. (2012), who also reported localized degradation hotspots in northern Ghana. The UNCCD 2017 report similarly identified large parts of the region as vulnerable to desertification, particularly in semi-arid belts.

On the other hand, vegetation recovery was observed across all five regions, although more scattered and often occurring alongside degradation. Prior studies provide supporting evidence: Braimoh & Vlek (2004) reported increased precipitation as a driver of greening in the Volta Basin savannas. Zoungrana and Dimobé (2023) found notable greening in the Sudanian Savanna, while Maillard et al. (2025) linked NDVI increases to post-fire vegetation resurgence in northern Africa, including Ghana.

These findings collectively suggest that land degradation in northern Ghana is both spatially heterogeneous and driven by multiple interacting factors, with some areas exhibiting degradation under climatic stress and others showing resilience or recovery possibly aided by local land management or rainfall patterns.

4.2 NDVI Time Series Analysis

Temporal analysis of mean annual NDVI from 2004 to 2024 in northern Ghana revealed significant year-to-year variation, with the highest vegetation greenness occurring in 2009. This observation is most likely linked to the 2009 West African monsoon and subsequent flooding across the Volta and Niger basins, which increased soil moisture and produced a strong greening signal. A notable declining trend followed around 2015-2016. The sudden decrease in NDVI between 2015 and 2016 may be linked to one of the strongest El Niño events, which altered rainfall patterns across West Africa. As a result, northern Ghana experienced delayed rains, a shortened growing season, and significant vegetation stress (FAO, 2016). These climatic imbalances, combined with ongoing land-use activities, likely contributed to the worsening degradation trends during this period.

The observed NDVI decline, indicating a gradual drop in vegetation productivity over 20 years, aligns with the degradation patterns identified in the Sen's slope and residual trend analyses. The overall decline in NDVI supports other evidence of trends in the region, suggesting a combined impact of climatic stress and human pressure on vegetation health (Ibrahim et al., 2015). The timing of the decline, especially the drop after 2013, further supports the classification of certain areas as degradation hotspots, whether driven by climate or human activities.

4.3 Climatic and Anthropogenic Drivers of Vegetation Degradation

As described in table 2 above, the largest contributor to PC1 was actual evapotranspiration (AET), with secondary contributions from solar radiation and elevation in addition to a substantial contribution from precipitation. This suggests that PC1 mostly reflects variation in woody vegetation condition due to climate's water and energy supply. Since PC1 did not account for 100% of the variation, PC2 was maintained, representing 21% of the variability and being defined by temperature and population pressure, both of which highlight thermal and anthropogenic influences. PC3, accounting for nearly 14% of explained variance, was largely determined by soil moisture, further highlighting the importance of moisture availability for vegetation dynamics. PC4 was affected by solar radiation, temperature, and soil moisture, and PC5 was composed mainly of elevation. The first three components, PC1, PC2, and PC3, were retained for interpretation and classification since they cumulatively explained more than 80% of the total variance and thus captured the primary factors behind vegetation degradation in the entire region.

Spatial distribution of the degradation types, according to the dominant component scores from PCA and positive and negative NDVI trends, shows a total of 33.48% of climate-driven degradation (CDD), 27.90% of human-driven degradation (HDD), and 3.17% of both-driven degradation (BDD). This shows that climate, through evapotranspiration or radiation deficits, is the main driver of reduced vegetation in Northern Ghana. But they also occur as a result of anthropogenic pressures due to land-use change, overgrazing, and farming expansion, particularly in more populated or intensively managed areas. This affirms the findings of past studies by Cherif et al., 2023, and Descroix et al., 2009, that identified population pressure and climatic water stress as the leading degradation factors in the Sahel and Sudano-Sahelian zones.

Overall, the PCA supports that climatic stressors, most prominently the absence of rainfall, high rates of evapotranspiration, and low soil moisture, are consistently the primary causes of vegetation decline in Northern Ghana. While the human footprint does show clearly some impact, it also seems not to be spatially continuous or not so explicitly or directly correlated, and the need for more spatially explicit or process-oriented assessments for the footprint is still needed to fully address its impacts.

4.4 Insights from NDVI Residual Analysis

Climate-driven degradation (CDD) and human-driven degradation (HDD) exhibited almost exclusively negative residuals, indicating that in those transition zones, vegetation loss could not be explained solely by the climatic and human pressures that were retained in the model. This suggests the possible impact of local or un-modeled processes like land management, soil erosion, or climate disasters. Likewise, BDD exhibited a marginally negative distribution, further supporting the notion that compound stress increases the likelihood of unexplained degradation. Negative residuals that are strongly negative in some human-driven degraded and both-driven degraded areas support the hypothesis that local human pressure remains undetected by the composite index of human pressure. This is in line with the findings of Wessels et al. 2007 and Evans & Geerken 2004, who, also in residual analyses, found unaccounted-for anthropogenic degrading trends.

On the other hand, restoration classes climate-driven restoration (CDR), both-driven restoration (BDR), and human-driven restoration (HDR) presented overall positive residuals. This suggests that the vegetation conditions in those areas improved more than anticipated, possibly due to effective adaptation measures, local-community-driven restoration efforts, or resilience of local ecosystems. This is particularly relevant as the BDR class also had the highest values of median residuals, indicating the presence of synergistic positive interactions between climate and human interventions in these regions. The stable zone also exhibits a slightly positive median residual. This implies that while these areas do not show a strong upward or downward trend over time, the observed NDVI is generally higher than the PCA model predicts. This could result from stable but favorable local conditions (e.g., fertile soils, minor irrigation, or unmeasured local variables), leading to a consistent greenness level that exceeds modeled expectations.

In general, this residuals analysis gives an additional view to the PCA and trend-based classifications by focusing on areas where vegetation change was not in line with what would be expected in relation to other variables. These differences provide useful information on potential additional biophysical or socioeconomic drivers to explore, as well as geographic areas where restoration might be more successful.

4.5 Methodological Reflections and Limitations

This combination of methods proved effective in capturing multiple aspects of degradation; however, several limitations should be considered:

1. **NDVI limitations:** NDVI measures vegetation greenness but does not account for changes in biodiversity, occurrence of invasive species, or changes in soil quality.
2. **Temporal resolution:** While MODIS imagery provides long-term coverage, it may miss ephemeral but important disturbances.
3. **Simplified driver representation:** PCA reduces data complexity with the possibility to miss complex interactions among degradation drivers. The human pressure index may also generalize different anthropogenic influences.
4. **Residual interpretation:** While negative residuals generally point to anthropogenic degradation, other factors such as microclimate variation or soil conditions may also contribute.

Notwithstanding these limitations, the NDVI-PCA-residual method remains a valuable approach for regional-scale land degradation analysis.

Chapter 5: Conclusion and Perspective

This thesis analyzed land degradation in northern Ghana through the lens of vegetation trend over a period of 20 years (2004-2024), utilizing remotely sensed NDVI data alongside climatic with anthropogenic factors. Analysis of residual NDVI trends, Sen's slope estimator and Mann–Kendall trend detection, and principal component analysis (PCA) to reduce the number of dimensions and help attribute drivers of degradation made up a hybrid analysis. It was found that, regionally, degradation far exceeds restoration, but there was also large spatial variation. The most prevalent type of degradation was climate-driven degradation (CDD) in 33.48% of the area, followed by human-driven degradation (HDD) in 27.90%. A few exhibited signs of recovery, suggesting some level of restoration, although this was not the general pattern. The residuals of NDVI analysis also highlighted the influence of localized anthropogenic pressure, pointing to places in which the observed vegetation loss could not be accounted for simply by environmental conditions.

The findings support the hypothesis that the loss of vegetation in Northern Ghana is not a consistent or homogenous process but the result of a combination of climatic variability and anthropogenic drivers. The combined approach applied here successfully highlighted degradation hot spots and drivers and is a useful tool for informing land management and restoration planning.

The implications of the findings here are significant for policy and management as well as future research:

Policy Implications: By being able to identify areas of degradation and their main driving factors at a spatial scale, this study will further help the targeted implementation of the Land Degradation Neutrality (LDN) agenda in Ghana. For example, CDD zones would involve the promotion of drought-resistant crops and water-saving culture, while in HDD zones this can imply more rigid land regulation and sustainable agricultural practices.

Operational monitoring systems: The PCA-RESTREND approach could be adopted into national and regional land monitoring systems to allow operational real-time or at least seasonal updates of the condition of the land. This is relatively easy to accomplish with high computation power such as Google Earth Engine (GEE).

Involvement of stakeholders: Focus on land management by communities, particularly in degraded areas within the human landscape. Combining local knowledge with remote sensing information could also increase sustainability and a sense of ownership of the restoration efforts.

Future Research Directions:

- Use high-resolution land cover/land use change data to allow for more granular detection of degradation.
- Incorporate more socio-economic variables such as poverty, land tenure, and education as part of the characterization of human pressure.
- Use machine learning approaches (e.g., random forests, CNNs) to understand complex nonlinear interactions between degradation drivers.

Overall, this work adds to a developing framework for monitoring land degradation in sub-Saharan Africa by providing an approach that is scalable and based in empirical data to help discern and address vegetation decline in sensitive dryland ecosystems.

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