Original Research Article

Wildfires and Their Impact on Species Composition and Ecosystem Services in Ghana's Northern Savannah Ecoregions

ABSTRACT

Changes in fire regimes, climate change and land use practices threaten tree structural diversity and vegetation structure across spatial and temporal scales. Therefore, this study investigates the impacts of fire on the species dynamics, land cover changes and the vulnerability of trees ecosystem services. The research took place across the northern savanna ecoregions of Ghana, encompassing the Northern, Upper East, Upper West, Savannah, and North East regions. The study analyzed data collected between 2001 and 2022 using a combination of remotely sensed satellite data (MODIS NDVI, Sentinel-2 images) and field observation, involving collecting species data on 30 plots of land. A 30m x 30m plot was set across ten (10) communities, and tree heights and edaphic features were recorded for each plot. The results show a clear-cut reduction in forest cover and an increase in shrubby savannah and agroforestry types driven by recurring fires conversion to agriculture. The analysis revealed fire-prone areas, including the rangelands and vegetation areas close to the settlement areas, as those most frequently hit by fires. Species composition analysis reveals high numbers of fire-adapted species, including *Vitellaria paradoxa* and *Parkia biglobosa,* in fire-affected areas and low numbers where fire-sensitive species dominate. The study also provided insights into the vulnerabilities of significant ecosystem services and products, such as water bodies, forests and farmlands that are ferociously threatened by fire. The findings stipulate the need to implement more comprehensive and complicated approaches to fire management, integrating human activities and fire and ecosystem services preservation within savannah ecosystems.

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Keywords: Fire regimes, Ecosystem services, vegetation, Species composition, Remote sensing, Land use change

1. INTRODUCTION

Fire regimes, the frequency, intensity, and seasonality in which fires occur form a big part in shaping the savannah ecosystem's structure and composition. Trees and grasses coexist in dynamic balance within these ecoregions, with fire playing a major role in the ecological driving of tree structural diversity, vegetation dynamics, and, thus, general eco health. Savannahs are widely spread and cover about 20% of the Earth's surface; they are very sensitive to change regimes, which generally bring changes in biodiversity, carbon storage, and ecosystem services (Pausas & Keeley, Indeed, shifting fire regimes driven by climate change, land-use change, and agricultural development have strongly a vegetation structure and species composition in areas like Southern Africa, Argentina, and Australia. For instanc frequent and severe fires in the Argentine savannahs have reduced tree cover by 30% and shifted dominance from

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fire-sensitive trees to fire-tolerant ones (Crespo et al., 2023). In Australia, Bradstock et al. (2021) recorded that more severe fires have caused a 15% reduction in carbon storage and shifted toward homogenous, fire-resistant vegetation. The importance of region-specific assessments is underlined in these studies, forming the particular contribution of our research.

In Africa, fire mediates the structural diversity of trees. For example, regions experiencing an increased fire frequency in Southern and Eastern Africa have witnessed a 25% to 40% reduction in tree cover. This affects the status of biodiversity and ecosystem services related to soil fertility and water regulation. In West Africa, fire regimes of the savannah ecosystems are also being modified. Malgwi et al. (2023) showed that savannah ecosystems in Nigeria had a very high loss of tree cover due to increased fire regimes that have been highly promoted by human activities related to slash-and-burn agriculture and deforestation. Savannah ecosystems are fully fire-dependent and cover about 65% of the total land area within Ghana. In nature, wildfires represent an integral but nowadays more and more unpredictable disturbance factor in all the savannah ecoregions of Northern Ghana because of the complex interaction between natural and anthropogenic drivers: climate variability, land-use change, and policies on fire management. Fire long played the role of a natural process that balanced vegetation's woody and herbaceous components. However, recent changes in fire regimes raise questions regarding their implications for diversity in tree structure and vegetation dynamics.

It is an important step in understanding the impact of fire regimes on tree structural diversity and vegetation dynamics within ecosystem management and conservation efforts (Veenendaal et al., 2020). Fire regimes, aside from determining the survival and resilience of native tree species, will impact broader ecological functioning in these fire-prone systems. For instance, frequent fires can promote the dominance of fire-adapted species at the expense of fire-sensitive ones, affecting tree size distributions, canopy cover, and the overall structure of the savannah vegetation cover (Scholes et al., 2021). This process affects biodiversity conservation, habitat availability, and soil fertility to a considerable extent (Hoffmann et al., 2020).

Recent studies have pointed out that altered fire regimes significantly affect the tree structural diversity and vegetation dynamics in most savannah ecoregions of Ghana, and adaptive management strategies are paramount. For example, Boateng et al. (2021) show that over the last decade, there has been a 20% increase in the frequency of fires, which is highly associated with agricultural expansion, deforestation, and increasing settlement. This shift has resulted in domination by fire-tolerant species such as Terminalia avicennioides and Vitellaria paradoxa while the fire-sensitive species decline.

These variations threaten the structural diversity of the ecosystem and the services that emanate from them, including carbon sequestration, supporting biodiversity, and local livelihoods. For example, Siaw et al. (2022) identified fire suppression in agroforestry systems followed by 18% woody encroachment, reducing grassland biodiversity. Their finding showed that fire suppression disrupts the natural fire cycles critical for sustaining vegetation dynamics and that, in so doing, it has become the very cause of damage to land uses it was initially intended to protect; it points toward controlled burning as a means to rectify the balance between biodiversity conservation and agricultural needs. Anaba et al. (2023) cited this in a broader context to highlight that increased fire frequency and settlement growth have reduced carbon storage by 15%, changing the structural diversity of trees by weakening ecosystem resilience and compromising climatic regulation. This corresponds to global trends observed by Archibald and Hempson, 2022, who reported that climate change-driven increases in the intensity of fires are leading to a situation wherein fire-tolerant species are coming to dominate savannahs worldwide. Davies et al. (2023) established that fires in the dry season caused a 55% loss in aboveground biomass, with more significant effects on smaller trees and vegetation below 5 meters. Meanwhile, nuanced fire management strategies adopt fire frequency and seasonality to maintain heterogeneity in savannahs.

In addition, while the ecological role and function of fire in African savannahs have been considered within wider contexts, there still is a gap in understanding how fire regimes interact with tree structural diversity in specific environmental and socioeconomic conditions that characterise savannah ecoregions in Ghana (Yankson & Armah, 2023). Such changes in the frequency and impact of wildfires, particularly with growing human populations and increasing agricultural use of these lands, will pose new challenges for land management and biodiversity conservation (Antwi et al., 2021). In this respect, region-specific research is urgently needed to explore how fire regimes influence tree diversity, vegetation dynamics, and resilience of savannah ecosystems.

This study represents a concerted analysis of fire regimes and their impacts on tree structural diversity and vegetation dynamics in the savannahs of Northern Ghana. Integrating remote sensing data from the field-based ecological assessment offers fresh insights into the spatial and temporal patterns of fire-driven vegetation change and tree structural diversity, which covers how fire frequency, intensity, and seasonality drive differences in tree size classes and species composition. Recent advances in remote sensing technology and machine learning now provide unparalleled opportunities for monitoring and modelling fire events and their ecosystem consequences (Rajendiren & Suresh, 2023). Applying satellite-based remote sensing data like MODIS-NDVI has given better insight into how land use and fire regimes are interactive drivers of change in savannah vegetation structure and species composition (Hoffmann et al., 2012; Toko & Sinsin, 2011). These tools have become increasingly indispensable for assessing the long-term health of vegetation and understanding spatial patterns of land degradation and recovery in fire-prone landscapes (Archibald & Hempson, 2016).

The results of this study further underscore possible tradeoffs among fire suppression, land-use intensification, and critical ecosystem services conservation, which policymakers and practitioners badly need. The study's findings are placed within the context of broader fire ecology, and the study discusses what this potentially might mean for the management of savannahs in the wake of climate change and increasing human pressure.

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2. MATERIAL AND METHODS

2.1 Study area

This study was conducted in the entire northern savannah ecosystem zone of Ghana, specifically in the Upper West, Upper East, Northern, Savannah and North East regions and covers an area of approximately 65% of its total land area (Nsiah-Gyabaah, 1996). These savannahs are part of the larger Sudanian savannah belt stretching across West Africa and are broadly classified into two main types: the Guinea and the Sudan savannah. The Guinea savannah, also known as the Southern savannah woodland, occupies most of northern Ghana, extending from around 8°N latitude to about 10°N. A higher tree density and diversity than the Sudan savannah characterises this ecosystem. Common tree species in this zone include *Vitellaria paradoxa* (shea), *Parkia biglobosa* (dawadawa), *Adansonia digitata* (baobab), and various Combretum and Terminalia species (Ampadu-Agyei, 1988). The herbaceous layer is dominated by perennial grasses such as *Andropogon gayanus* and Hyparrhenia species. The Sudan savannah, found in the northernmost parts of Ghana above 10°N latitude, has a sparser tree cover and is dominated by drought-resistant species. Characteristic trees include Acacia species, *Balanites aegyptiaca*, and *Faidherbia albida*. The grass layer in this zone is often composed of shorter annual species, reflecting the more arid conditions.

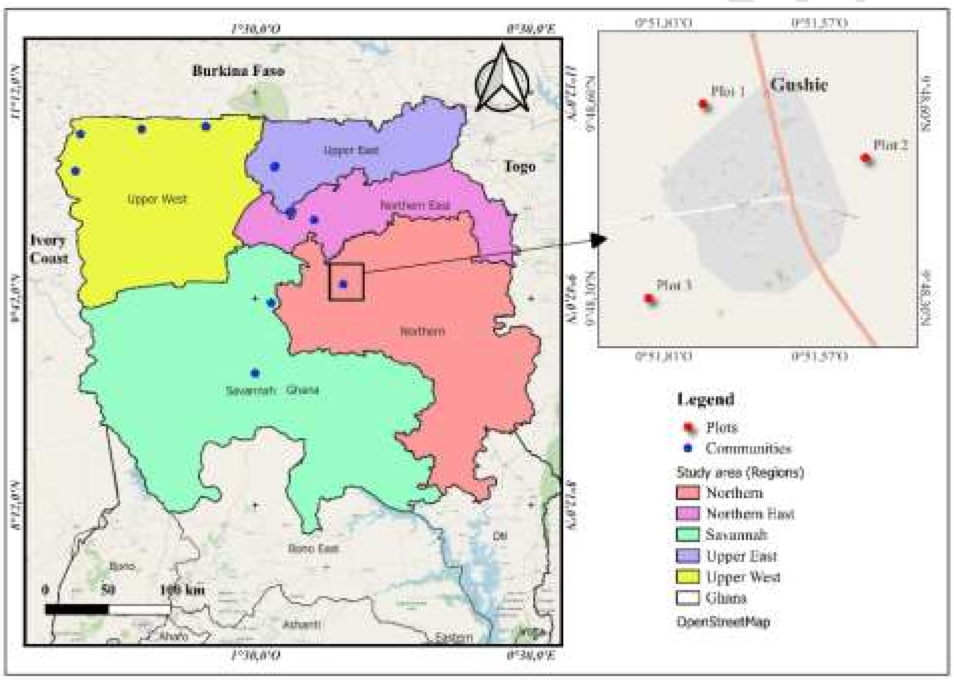

Figure 1: Study area location: Northern savannah ecological zone with the five regions captured and a Google image showing how three plots are identified in each of the communities

The study area's topography is undulating, coupled with some hills and isolated highlands over flat plains with an elevation of 150 to 300 meters above sea level (Smith et al., 2021). The drainage is dominated by seasonal rivers and streams drained into major river basins such as the White Volta, Black Volta, and Oti Rivers. Most of these rivers have flow regimes characterised by high flow during the rainy season and dry up or reduce to pools during the dry seasons, causing temporary water shortages (Kombat et al., 2023). The dominant socio-economic activities in the Northern Savannah ecoregion include agriculture, rearing, and agroforestry systems. Farming primarily involves cultivating subsistence crops of millet, maize, sorghum, groundnuts, and yam and small-scale cash crop production of shea nuts and cotton. Besides farming, livestock herding, especially cattle, goats, and sheep, is widespread and supplements the few livelihoods available. The area comprises ethnic groups, such as the Mole-Dagbane, Waala, Dagara, and Gurune, governed by traditional solid leadership structures. Festivals, farm rituals, and communal activities all play their role in reinforcing social cohesion (Owusu et al., 2022). Traditional agroforestry systems are a common means of managing natural resources, while many communities engage in activities related to fuelwood collection, charcoal making, and hunting. However, the region has several problems accompanying it, including poverty, lack of infrastructure, and vulnerability to climate variability, all of which impact the livelihood and cultural activities of the people.

Climate plays a crucial role in shaping these savannah ecosystems. Ghana's northern savannahs are characterised by a single rainy season, typically lasting from May to October, followed by a prolonged dry season. Annual rainfall ranges from about 1000-1300 mm in the Guinea savannah to 600-900 mm in the Sudan savannah (Kwadwo Owusu & Waylen, 2009). This rainfall pattern, combined with high temperatures and frequent fires, is instrumental in maintaining the savannah physiognomy. The Harmattan winds, which occur from December to early February, have a considerable effect on the temperatures in the region, which may vary between 14°C at night and 40°C during the day (Asante & Siaw, 2019)These dry conditions and the strong Harmattan winds facilitate vegetation burning. Early dry season burns are usually done between November and January, whereas late season burning begins in February and ends in March.

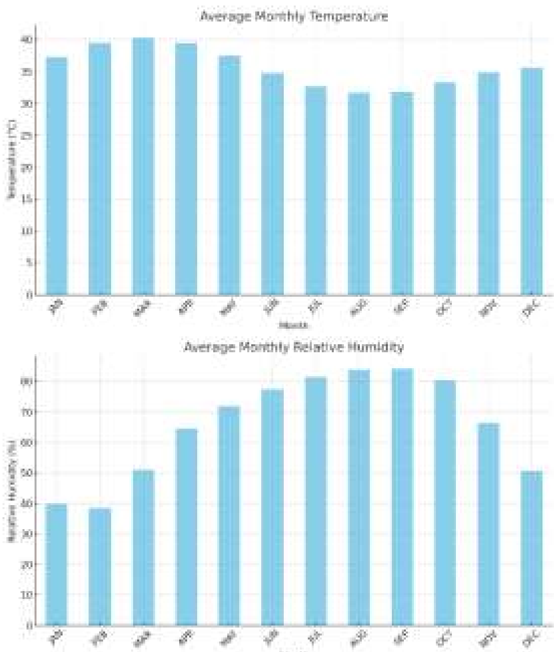

Figure 2: Average monthly temperature and humidity values of the study area from 1992 to 2022. Source of data: https://modis.gsfc.nasa.gov/data/

2.2. DATA COLLECTION AND PROCESSING

2.2.1 MODIS NDVI image description and processing

For the assessment of large-scale vegetation cover changes, MOD13Q1 (MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid) NDVI data from the NASA Earth Observing System Data and Information System (EOSDIS) platform (available at: https://earthexplorer.usgs.gov/), was used. The MOD13Q1 product provides bi-weekly composite images at a spatial resolution of 250 meters. The 250-meter spatial resolution allowed for a detailed analysis of vegetation cover changes at regional and local scales, while the 16-day temporal resolution facilitated tracking of seasonal and interannual variability in vegetation cover between 2001 and 2022. MODIS NDVI data were selected according to cloud covering percentage of less than 10% and data availability in the dry season to reduce cloud effects, vegetation phenology and differences in soil moisture (Wu et al., 2021). Also, thirty (30) GPS ground truth points (UTM Zone 30N, WGS 84 at 3 m level of accuracy) were obtained from sample points of the identified land cover classes (forest (F), shrubby/woody

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savannah (SWS), Agroforestry/park/field lands (AF), waterbodies (WB), and human settlement (HS) during field visits across the study area. These GPS points were also used to validate the satellite-based vegetation indices.

Preprocessing of MODIS NDVI Image

The original sinusoidal MODIS data projection was reprojected to the WGS 1984 coordinate system, as it is the current standard used by most geographic information systems or GIS datasets. Since MODIS data intrinsically have pixels affected by clouds, cloud masking was developed from the QA layers that come with such data (Dwyer & Schmidt, 2006). This ensured that only pixels free of clouds were retained for computation in NDVI. To refine data quality, atmospheric correction techniques, such as the 6S atmospheric correction model, were applied to reduce distortions due to aerosol and water vapour. This step increases the reliability of NDVI values. Later on, data clipping was done to focus on specific study areas, such as the Northern region, Upper West, Upper East, Savannah, and North East region. This type of spatial subsetting reduced the volume of the data and kept the analysis concentrated on the relevant geographic areas. In the case of computing NDVI, the precalculated values are obtained using a formula from the red (visible) and near-infrared (NIR) reflectance bands (Equation 1):

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$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

The NDVI values ranged from -1 to 1, with higher values indicating healthy and dense forest vegetation, while lower values corresponded to sparse vegetation, urban areas, water bodies, and bare land. NDVI values were followed by LULC classification, where vegetation cover was differentiated into various classes based on the NDVI values and other contextual information. These categories included Forest in dark green, Shrubby/Woody Savannah in light green, Agroforestry Parks/Fields/Fallow Land in yellow-green, Water Bodies in blue, and Human Settlements in orange. Generally, areas with forests had a high NDVI due to the high density of vegetation. At the same time, shrubby/woody savannah and agroforestry showed moderate NDVI values due to poor vegetation coverage. Non-vegetated surfaces like water bodies and human settlements did not tend to return high NDVI values.

Testing of the Classified Images

Images were validated using the accuracy metrics, which included Overall Accuracy (OA), Kappa Statistic (KS), and the Confusion Matrix (CM), to analyse and confirm their statistical accuracy. The statistical classification testing generated confusion matrices for every classified image using the sklearn library (from sci-kit in Python) to create confusion matrices. The overall accuracy (OA) was obtained by comparing the ratio of accurately classified pixels to the number of reference points of the entire image (Kamusoko, 2022). This metric gave a rough estimate of the degree of fit of the classified output data to the reference data and was computed from the following equation;

$$Overall\ Accuracy = \frac{Total\ Correct\ Classifications}{Total\ Number\ of\ Reference\ Points} \times 100$$

Producer's Accuracy was then calculated to determine how well each class in the actual field was classified in the image. It quantified the omission error that arises when a certain land cover type is classified into the wrong class (Kamusoko, 2022).

$$Producer's\ Accuracy = \frac{Correctly\ Classified\ in\ Row}{Total\ in\ Row} \times 100$$

User's Accuracy was computed to measure the likelihood of the pixel being correctly classified to the intended land cover class in the reference data (Kamusoko, 2022;Prasad, 2020). It is a measure of commission error whereby a pixel is either misclassified in an image or computed incorrectly in a matrix.

$$User's\ Accuracy = \frac{Correctly\ Classified\ in\ Column}{Total\ in\ Column} \times 100$$

In addition, the Kappa Coefficient was computed to quantify the degree of agreement between classified data and reference data besides the chance variable. The Kappa coefficient varies from 0 to 1, where values closer to 1 indicate a higher level of compliance between the classification and actual ground truth (Prasad, 2020)

$$Kappa = \frac{Po - Pe}{1 - Pe}$$

Where:
Po is the observed accuracy (same as overall accuracy), and *Pe* is the expected accuracy by chance.

2.2.2. Land use and land cover classification

For the study area, shape files were used to extract data on the various land covers: forest, shrubby/woody savannah, agroforestry lands, water, and human settlements for 2001, 2006, 2011, 2016, and 2022. The Semi-Automatic Classification Plugin (SCP) in QGIS was used to classify each pixel accurately before change detection, and the results were then exported to Excel for further analysis (Congedo, 2016). The SCP 'Land Cover Change' algorithm produced the transition matrices that described the changes in different land cover types, thereby pointing out the deforestation rate and how the agricultural lands have been expanding. The SCP "Classification Report" algorithm created Excel reports of the LULC class areas for each period to determine the change rate. The average annual rate of land cover change was calculated using the formula:

$$\frac{Area\ at\ final\ year - Area\ at\ initial\ year}{Area\ at\ initial\ year} \times \frac{1}{number\ of\ years} \times 100$$

This was used to calculate changes in forest cover, shrubby savannah, agroforestry lands, and human settlements.

2.2.3. Statistical Methods

Linear regression models were applied to each land cover type to assess changes over time. The slope of the regression line represents the rate of change per year, while the R-squared value indicates the proportion of variance explained by the model.

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2.3. Hotspot analysis of fire impact on vegetation using Sentinel-2 and MODIS NDVI

A fire hot spot map was generated from a Sentinel-2 satellite image, and the vegetation types were extracted using NDVI indices. MODIS data for 2000-2021 was utilised to obtain historical fire occurrences as input for the study. The district capitals were georeferenced by overlaying layers derived from the administrative boundaries data layers. Supervised classification was done using satellite data to identify forests, water bodies, and agroforestry parklands. To increase classification accuracy, preprocessing steps were employed through atmospheric correction and cloud masking. The classification results obtained were validated using accuracy assessment techniques as described above. The spatial layers were appended using the QGIS open-source GIS, which was used to assess further the distribution of fire points with the land cover type and human settlement. An appropriate coordinate system and projection, WGS84, enhanced the spatial reference and accuracy.

2.4 Species Composition and Phytogeographic Analysis

Vegetation measurements at the site included a structured and systematic vegetation inventory on 30 plots, where species composition and vegetation structure were documented. The species were categorised according to their fire tolerance and origin from three eco-geographical zones, including Guineo-Congolese and Sudanian. This classification provided a very rich analysis of how various species may be affected by a level of fire and anthropogenic impact.

Tree height for tall trees was measured using a clinometer, while for smaller trees, it was a simple tape measure. Measurement was taken from the ground, which is the base of every tree, to its topmost branch. Measurements were conducted at random points within selected plots across the study area to capture the variability in tree height. The height data estimates the mean and variation of tree height among species and compares tree height of fire-tolerant and fire-sensitive species. Similarly, a simple tape measured the circumference of the tree at DBH (1.3 meters, or approximately 4.5 feet) above ground. Circumference was divided by π (3.1416) to calculate diameter.
A Detrended Correspondence Analysis (DCA) and Canonical Component analysis (CCA) was conducted to assess the plant community structure further. This multivariate statistical method was used to determine the gradients concerning fire intensity and the influence of human disturbance. The DCA analysis helped recognise the relations between plant communities and identify fire-tolerant and fire-sensitive plant species within the disturbance gradients. This approach helped to understand how fire and human activities affect vegetation, especially in fire-dominated ecosystems like the Northern Savannah Ecological Zone.

2.5. Fire effects on savannah ecosystems

An ecosystem impact/vulnerability map was developed to determine the vulnerability of the study area to the loss of ecosystems due to wildfire. The map was created using Sentinel-2 images because they offer a much higher spatial resolution, are multispectral, and have a high repeat frequency. The images used in this study were selected based on a cloud cover percentage below 10% to reduce cloud interference and vegetation changes. Table 1 summarises the general features of Sentinel-2 imagery, such as spatial and spectral resolutions, temporal revisit frequency, and large scene width, which allowed focusing on details of fire impact zones and performing time series analysis of post-fire ecosystem rehabilitation. The imagery was classified using supervised classification techniques with QGIS to develop the hotspot map.

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Table 1: Summary of Key Features - Sentinel-2 Imagery

Feature	Details
Spatial Resolution	10 m (RGB and NIR), 20 m (Red Edge, SWIR), 60 m (Water Vapor)
Spectral Resolution	13 spectral bands (VNIR and SWIR)

Temporal Revisit Frequency	5 days (Sentinel-2A and 2B combined), 10 days (single satellite)
Scene Size	100 km x 100 km
Radiometric Resolution	12-bit
Processing Levels	Level-1C (TOA), Level-2A (BOA)

2.5.1 Preprocessing and processing of Sentinel-2 satellite image

Sentinel-2 imagery for fire vulnerability assessment involves several steps to pre-process and process the data correctly to ensure data quality and accuracy. The data was derived from the European Space Agency's Copernicus program, which offers high-resolution multispectral data for vegetation health, mapping of the land cover classification, and identifying wildfire risks. The data was downloaded with band resolutions of 10m, 20m, or 60m (Phiri et al., 2020).

For analysis, the imagery was preprocessed using the Sen2Cor processor to perform atmospheric correction. This correction converts level-1C (top of atmosphere reflectance) data into level-2A (bottom of atmosphere reflectance), eliminating interferences from aerosols and water vapour in the atmosphere. The obtained images were processed to exclude cloud-covered pixels using the Scene Classification Layer (SCL). After atmospheric correction and cloud masking, the images were resampled to maintain consistency, using the 10-meter resolution for wildfire analyses (Phiri et al., 2020). The data was then clipped to the area of study in Northern Ghana. Clipping reduces the processing space to only necessary places, making it efficient and accurate. For this assessment, two(2) important indices were calculated to assess vegetation health and moisture levels: *Normalized Difference Vegetation Index (NDVI) in equation (1) above and Normalized Difference Water Index (NDWI):*

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

NDWI is calculated using the Near-Infrared (Band 8) and Short-Wave Infrared (Band 11 or 12) bands to estimate vegetation moisture content. Lower NDWI values suggest dry conditions, making an area more susceptible to wildfire.

The technique used in assessing wildfire vulnerability entails calculating vegetation indices and classifying the land use and land cover (LULC). This categorises the landscape into various vulnerability classes dependent on parameters like vegetation type and density, soil moisture and wildfire risk level. Zones were represented by green for forest reserves to signify low vulnerability and red for high vulnerability areas. Environmental variables, including fire frequency (derived from the MODIS data of 2001-2021) and species richness (from the field), are combined to measure ecosystem resilience. Population density and land use intensity are also mapped from census, remote sensing, and GIS data layers. The georeferenced variables are read into GIS software, normalised, and scaled to assign higher vulnerability scores to regions with greater fire risk and susceptibility to ecosystem degradation.

3. RESULTS AND DISCUSSION

Land Use Classification and Accuracy Assessment

Five land use classes were identified: Forest(F), Shrubby/Woody Savannah(SWS), Agroforestry Parks/Fields/Fallow Land (APF), Water Bodies(WB), and Human Settlement (HS). The confusion matrix (Figure 3) and accuracy metrics (Table 2) The result shows that the performance of each land cover type was excellent. Each class, like Human Settlement, Shrubby/Woody Savannah, Agroforestry, Forest, and Water Bodies, was classified ideally, as shown by the diagonal elements in the confusion matrix with no misclassifications and no confusion between the different land cover types.

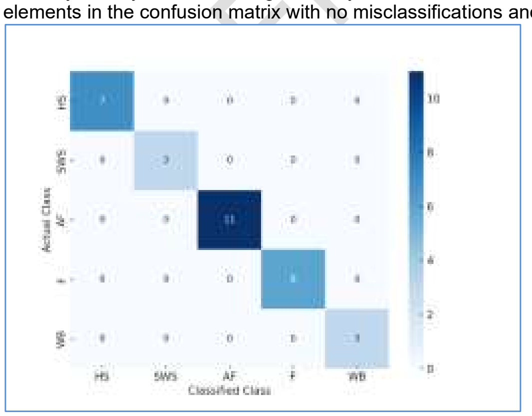

Figure 3: Confusion Matrix for Land Cover Classification

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Specific to classification models, two accurate measurements that can be used are Producer's Accuracy (PA) and User's Accuracy (UA). Producer's Accuracy determines the density of each land cover type in a classified image. At the same time, the User's Accuracy quantifies the probability of an area belonging to a given class being classified. Since there are no false classifications in the above matrix, PA and UA would be 100, indicating that the model achieved optimal performance for all land cover types.

However, to provide additional information about the model's accuracy and reliability, the accuracy metrics were computed and presented in (Table 2) below;

Table 2: Accuracy Assessment for Land Cover Classification

C	Overall Accuracy (%)	Producer's Accuracy (PA)	User's Accuracy (UA)	Kappa Coefficient
HS	100	1	1	1
SWS	100	1	1	1
AF	100	1	1	1
F	100	1	1	1
WB	100	1	1	1

(Table 2) Shows outstanding performance in the additional land cover classification model metrics. The accuracy shows that the classification model was correctly classified in every land cover class. The Producer's Accuracy (PA) was perfect for each class, indicating that all actual samples were correctly classified. Similarly, the User's Accuracy (UA) for all land cover classes is shown to belong to their appropriate categories. The Kappa Coefficient also shows perfect agreement between actual and classified data and results that are better than would be expected by chance. These metrics validate the high reliability and precision of the classification model.

Land use and land cover dynamics in the study area

(Figure 4) reveals the distribution of LULC for 2001, 2006, 2011, 2016, and 2021 in northern Ghana. The details revealed certain discernible fluctuations throughout the years. The change in forest cover decreased steadily between 2001 and 2022. By 2022, there was a significant reduction, possibly due to deforestation, land conversion, or fire incidents. On the other hand, shrubby savannah increased consistently at the expense of the forest areas. This vegetation type dominated much of the landscape in 2022, indicating widespread degradation and conversion resulting from human activities and climate change. Agroforestry surface areas have increased over time. This reflects an intensification of agriculture and increased pressure on land for food production. However, water bodies in the entire period do not show any appreciable change, with only minor changes in the levels of the major rivers and reservoirs. The level of small water bodies could change due to conditions such as drought or flood. Human settlements show a conspicuous increase between 2001 and 2022 because of increases in urbanisation and population.

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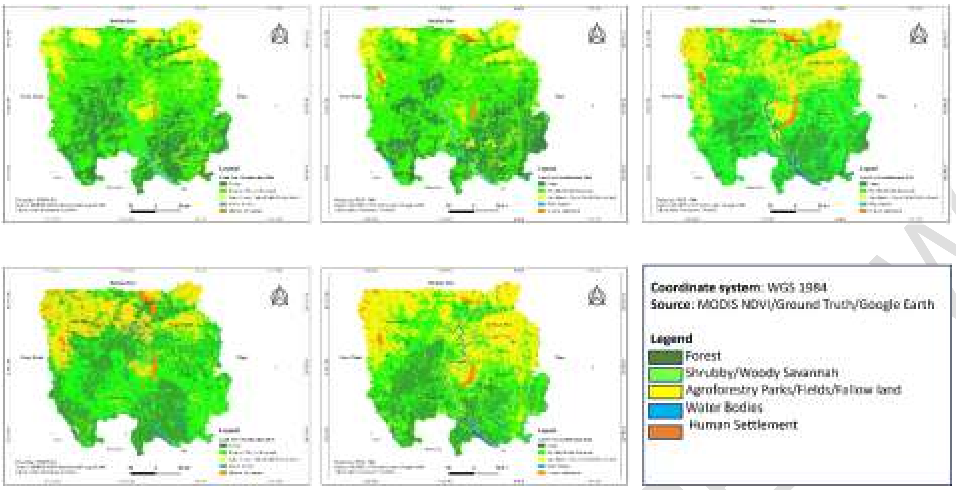

Figure 4: Land Cover Classification Maps for 2001, 2006, 2011, 2016 and 2021 Using MODIS NDVI Data.

(Table 3) below are the changes in land cover from 2001 to 2022 across five major LULC classes: Forest, Shrubby/Woody Savannah, Agroforestry parks/Fields/Fallow lands, Water Bodies, and Human Settlement. It was observed that a loss of 10.86% in forest cover and a reduction of 38.82% in Shrubby/Woody Savannah were observed. Agroforestry parks/Fields/Fallow lands increased by a factor of 145.17% owing to increased agricultural as well as agroforestry activities. Water Bodies increased by 170.76%, probably because of changes in environmental conditions and land-use policies relevant to water bodies' conservation, whether artificial or natural. Human settlements increased significantly, with a strength of 177.12%, reflecting the region's rapid population growth and urbanisation. These findings demonstrate the dynamic nature of land-use change in Northern Ghana, which has an important bearing on ecosystem services, biodiversity, and natural resource management. The high rise in agroforestry and settlement areas might reflect the socio-economic pressures and shifting priorities of land use, while the loss of forest and savannah causes environmental concern.

Table 3: Changes in land cover types (Forest, Shrubby/Woody Savannah, Agroforestry parks/Fields/Fallow lands, Water Bodies, and Human Settlement) from 2001 to 2022

Land cover	**2001**	**2006**	**2011**	**2016**	**2022**	**Percentage Change (2001-2022)**
Forest	23718.33	23988.55	17648.43	30699.47	21141.42	-10.8647
Shrubby/Woody Savannah	57225.12	55633.51	47348.64	40049.35	35009.2	-38.822
Agroforestry parks/Fields/Fallow lands	15121.92	15750.15	28676.64	23293.56	37074.08	145.1679
WaterBodies	995.365	1092.645	1843.686	1961.839	2695.078	170.7628
Human Settlement	643.9349	1239.463	2186.646	1699.988	1784.454	177.1171

Assessing Land cover Changes over time

The regression analysis (Table 4) results reveal some characteristics of the trends in land cover change over the 21 years. Shrubby/Woody Savannah decreased considerably with a negative slope of -1152.6 and an R-square value of 0.97, showing a solid decreasing trend. In contrast, Agroforestry parks/Fields/Fallow lands had a positive trend with a slope of

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998.3 and an R-square of 0.79. At the same time, water bodies have also consistently increased from 82.4 square kilometres to 0.95 R-square. These changes demonstrate trends that reflect the continued land-use change impelled by agricultural expansion, deforestation, and the growth of urban areas.

Table 4: Regression analysis of land cover types

Land Cover Type	**Slope**	**Intercept**	**R-squared**
Forest	20.26453	-17316.8	0.00121
Shrubby/Woody Savannah	-1152.6	2365161	0.968933
Agroforestry parks/Fields/Fallow lands	998.2626	-1983722	0.793284
WaterBodies	82.42414	-164054	0.946757
Human Settlement	51.62988	-102327	0.518379

Fire Hotspot and Vegetation Dynamics

(Figure 5) shows the fire occurrences in the northern Ghana savannah zone, with high concentrations of fire points mainly in areas classified as rangeland (***orange***) and vegetation (***green***). Fire points clustered in these locations suggest that wildfires are one of the significant land-use issues in the study area. The hotspot also reveals that crop and vegetative lands are prone to fire, possibly driven by agricultural activities, dry conditions, or traditional land-clearing practices. The noticeable fire points around human settlements also suggest the proximity of fire events to human-populated areas. The built-up areas are mainly concentrated around the district capitals and are less affected than the rural rangelands and vegetative areas. Forest cover showed very few fire points, indicating that these zones are either less prone to wildfires or better managed regarding fire control. However, fire points near forest areas could threaten biodiversity and forest resources. Similarly, water bodies show restrained fire points, probably because wet conditions minimize the chances of fire outbreaks.

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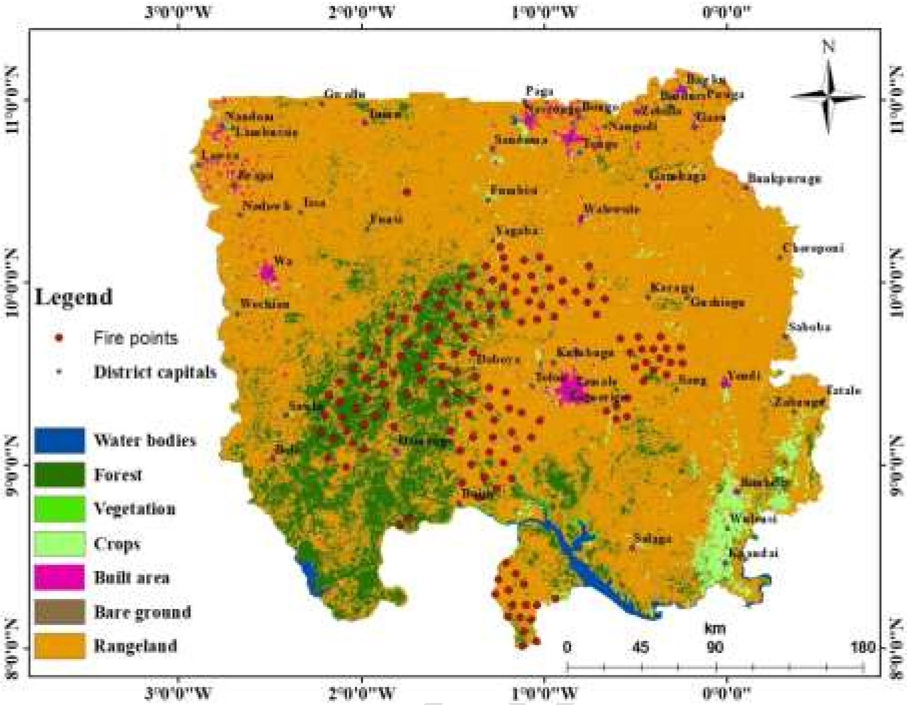

Figure 5: Fire Points(Hotspot) and Land Cover Distribution in Northern Ghana

Species Composition and Phytogeographic Analysis

(Figures 6, 7 and 8) present the Species Composition and Phytogeographic Analysis, which gives valuable information on the floristic structure and ecological adaptation of species in the study area. A total of 123 species from 102 genera and 38 families were recorded, with the highest family, Fabaceae, constituting about 23% of the total number of species recorded. Fabaceae dominance is derived from a competitive advantage over others, as it is nitrogen-fixing, solving the problem of poor soil nutrient conditions characterised by savannahs. Key species, including *Vitellaria paradoxa*, *Parkia biglobosa*, *Anogeissus leiocarpus*, and *Diospyros mespiliformis*, dominated the spectrum, with Vitellaria paradoxa constituting the highest relative frequency at 14%. These species have thick bark and a deep rooting system, and they can resprout, ensuring a better adaptation to the frequent fire events that have characterised the landscape.

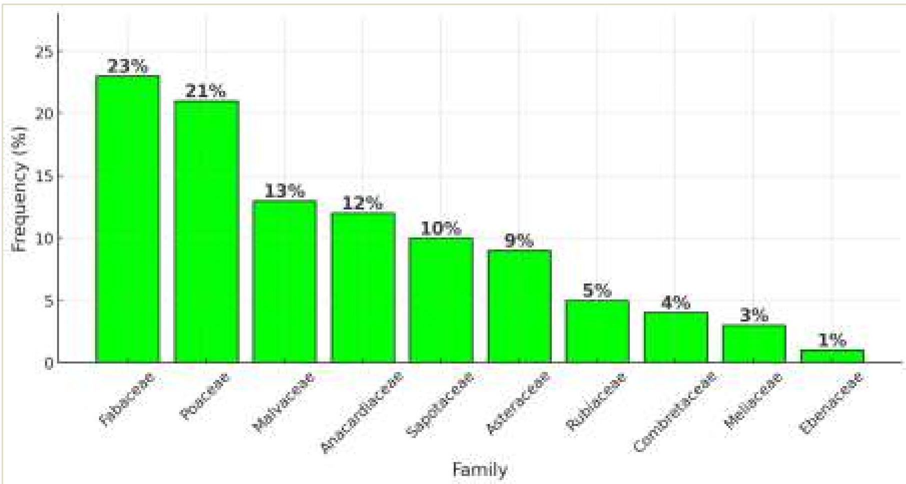

Figure 6: Frequency Distribution of Plant families

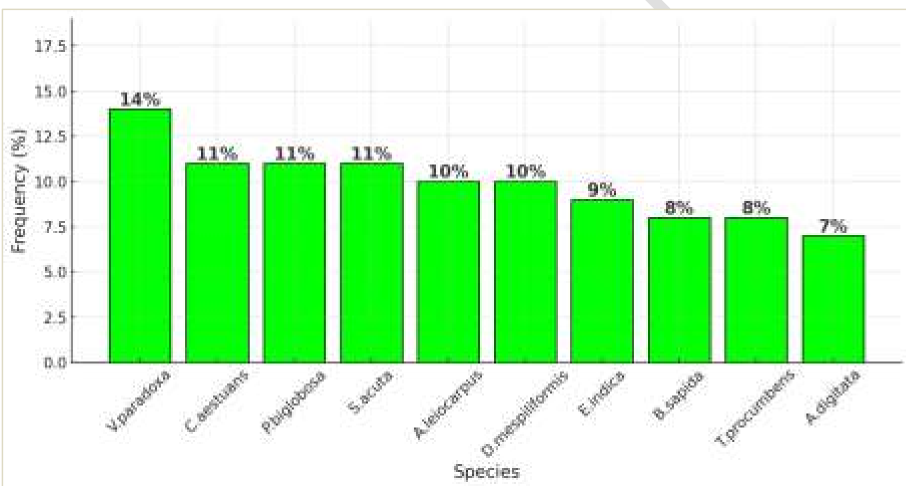

Figure 7: Frequency Distribution of Plant Species

(Figure 8) Compares the frequency percentage of various phytogeographic types between burned and non-burned areas. It illustrates the domination of vegetation by species of Guineo-Congolese/Sudanese-Zambezi (GC-SZ) and Sudanese-Zambezi (SZ) regions, accounting for 41.64% and 29.91%, respectively, of the raw spectra. Species belonging to these regions are adapted to the transitional savannah environment, where fire plays an important role in the maintenance of the structure of the ecosystem. Species belonging to the Guinean-Congolese(GC) region generally occur in more humid forests and are less represented due to their sensitivity to fire. Introduced species(I) were moderately represented and showed evidence of fire. Other types, such as Guineo-Congolese (GC), Afro-Tropical (AT), and Sudano-Guinean (SG), are poorly represented. The data gives insight into how different vegetation types respond to fire disturbance.
Occurrence

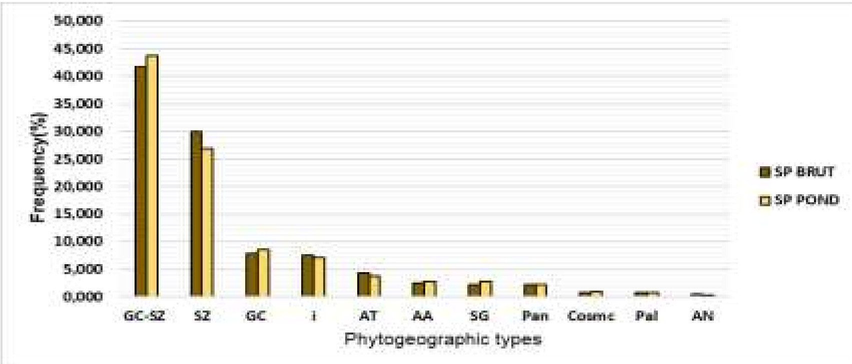

Figure 8: Distribution of Phytogeographic Types in Burned (SP BRUT) and Non-Burned (SP POND) Areas

Detrended Correspondence Analysis (DCA)

In this context, DCA in (Figure 9) provided insight into species distribution patterns along fire intensity and human disturbance gradients. The DCA identified three major plant groups, G1 (open forest), G2 (mosaic shrubby/tree savannah and dry forest), and G3 (wooded/tree savannah), indicative of different levels of exposure to fire and deforestation. Open Forest Group occurred primarily in sites with relatively low fire frequencies and is dominated by these fire-sensitive species that thrive in undisturbed environments. A second group, representing a Mosaic of Shrubby/Tree Savannah and Dry Forest, occupied the areas exposed to moderate fire disturbances. The species of this group combined fire tolerance features with adaptations typical of transitional ecosystems in between forest and savannah. Finally, the areas of Wooded/Tree Savannahs were dominated by highly fire-tolerant species. Such species are represented mainly by resprouting or fire-resistant species, primarily adapted to regeneration after fire events. The DCA analysis strongly outlined ecological diversity among species, highly influenced by their resilience and adaptation to fire disturbance and human activities.

The Canonical Correspondence Analysis (CCA) in Figure 10 examined the interaction of species distribution, fire regimes, and environmental factors such as elevation, proximity to water bodies, and soil types. This CCA showed significant correlations between the fire occurrence and these environmental variables, giving more profound insights into how fire shapes plant communities. While the higher elevations tended to have fewer fires, probably because of their inaccessibility and denser natural vegetation, the frequency of fires was more significant in the lower elevations where human activity is concentrated, prompted by agricultural pursuits and the expansion of settlements. Water bodies, especially riverine environments with moist soils, acted as natural firebreaks, buffering fire spread. However, the expansion of agriculture into the riparian zones reduced this buffering effect and allowed the fires to penetrate previously fire-protected areas. The soil type was also a determining factor in the fire response; sandy soils were more fire-prone, supporting fire-adapted species, and clay-loamy soils sustained fewer fires, sustaining the less fire-tolerant species.

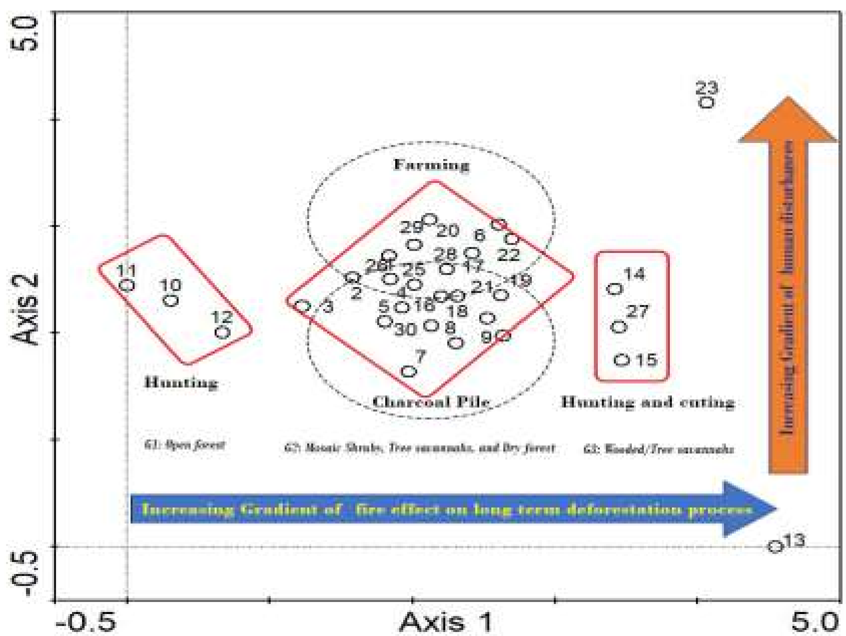

Figure 9: Detrended Correspondence Analysis (DCA) of Plant Communities and Disturbance

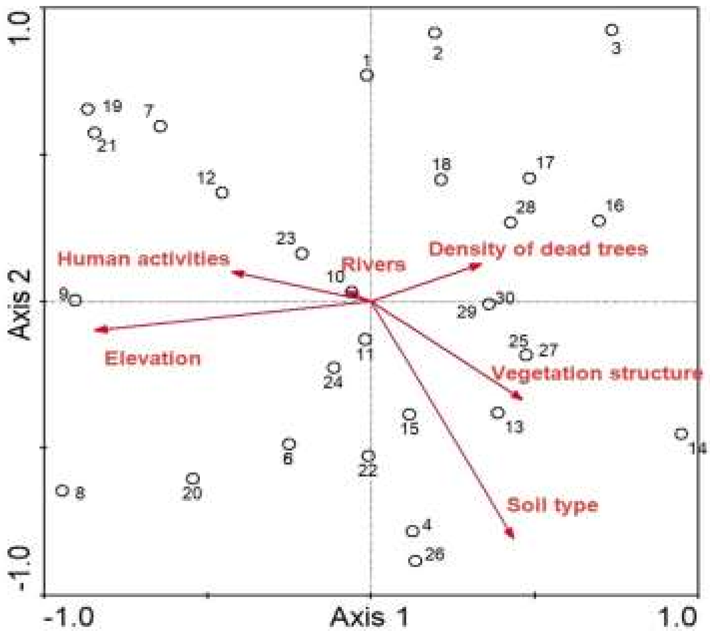

Figure 10: Canonical Correspondence Analysis (CCA) of Environmental Variables and Species Distribution

Vulnerability of Northern Ghana Savannah Ecosystems

(Figure 11) below shows how water bodies are exposed to wildfires as a primary ecosystem service. The spatial analysis of wildfire occurrences shows vast variations in fire activities relative to the proximity to water bodies. Waterbodies' proximity was categorised using a gradient showing an increase in distance away from both major and minor rivers. Areas closer to water bodies (darker blue) show fewer fire occurrences, while areas farther away (lighter blue) indicate a high number of fires. This pattern directly correlates with the exposure of water bodies to fires; the farther away from water bodies, the more exposed.

According to the vulnerability map(Figure 12), very high-vulnerability areas are visualised as red and have a severe environmental threat, mainly connected with alternative ecosystems, such as water supply and agricultural productivity. Where high vulnerability is concentrated near large forest preserves and major rivers, it presupposes these ecosystems' critical role in service provisioning. The orange areas (high vulnerability) face higher risks associated with several factors, including human activities and natural conditions, such as proximity to fire-prone zones and water bodies. The yellow represents a moderate vulnerability and faces moderate risks to ecosystem services, particularly farmlands and forests. While the exposure in these zones to the risk of wildfires and environmental degradation could be high, resilience and adaptive capacity might still be developed, thus dampening the overall impact. Low vulnerability areas (purple) tend to be less affected by fire incidences or environmental degradation, suggesting stronger ecosystem resilience or reduced human pressures.

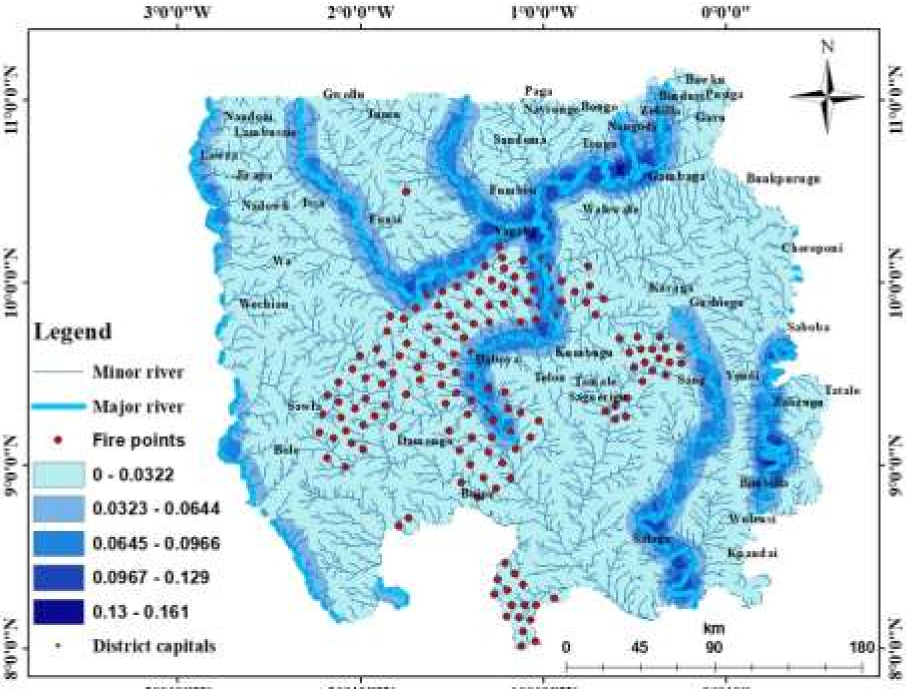

Figure 11: The distribution of fire points within the river network

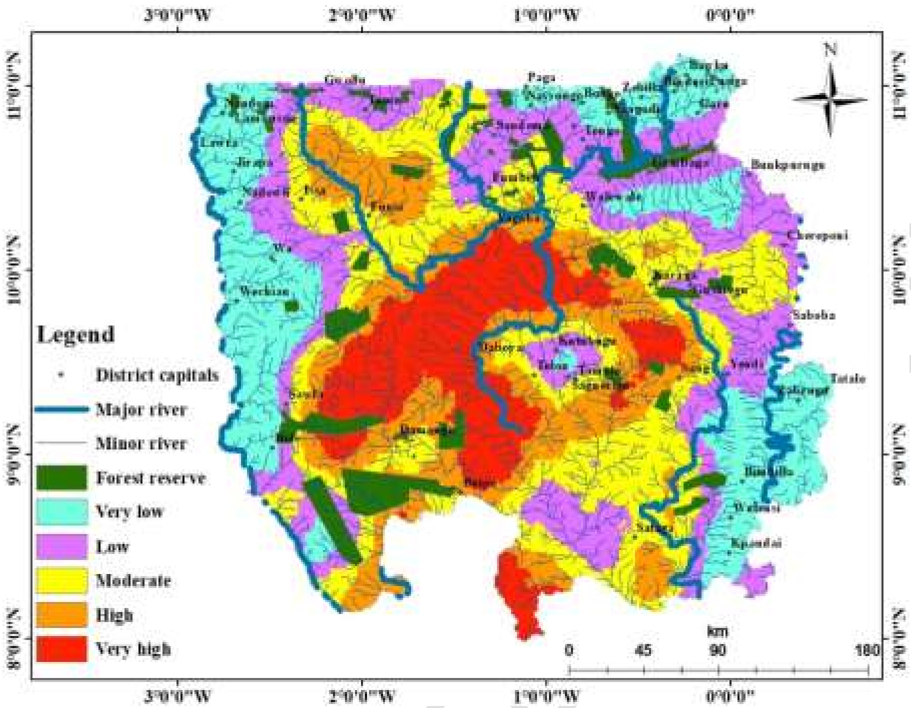

Figure 12: Wildfire Susceptibility Map of Northern Ghana: Depicting the varying levels of fire risk across the region, categorized from very low to very high susceptibility, with major rivers, minor rivers, and forest reserves marked for reference."

Discussion

Accuracy of Remote Sensing and Classification Techniques in land classification and Vegetation Change dynamics
This study's high accuracy of the MODIS NDVI-based land classification is central to understanding vegetation change in the northern savannah of Ghana. In confirmation of the robustness of the MODIS NDVI method, the Confusion Matrix ensured that all five land cover classifications, namely, Forest (F), Shrubby/Woody Savannah (SWS), Agroforestry Parks (AF), Water Bodies (WB), and Human Settlements (HS), were classified with 100% accuracy. Indeed, according to (Lu & Weng, 2007)), high-resolution remote sensing significantly advances classification accuracy in complex ecosystems. The Overall Accuracy(OA) is 100%, and the Kappa Coefficient equals 1.0, which testifies that the model was efficient and reliable in recognising land cover types and minimising random classification errors, as supported by (Congalton & Green, 2008). The metrics also allow precision in land cover transitions essential to fire management and land use sustainability, particularly in fire-prone areas where change is driven by wildfires and human activities, as observed by (Backer et al., 2004).
Besides, the Producer's Accuracy (PA) and User's Accuracy (UA) were perfect for all the land cover types, demonstrating the model's high performance in precisely representing and capturing the land cover classes. The ability of the model to distinguish between Shrubby/Woody Savannah and Agroforestry Parks is fundamental for understanding the effects of fire, even though the NDVI values are similar, as stated by (Pettorelli et al., 2005). The study observed changes in land cover classes between 2001 and 2022, with a reduction in forest cover, indicating the impact of wildfires and human activities. These findings confirm Hoffmann et al. (2012), who noted that remote sensing is an ideal methodology for monitoring vegetation change in fire-impacted areas. It further iterates that remote sensing effectively identifies fire-prone areas to inform fire management strategies. The accuracy of such classifications is vital for urban planning wildfire vulnerability and risk mitigation in areas with increasing human settlements (Roy et al., 2008; Giglio & Roy, 2020). Overall, the study demonstrates the reliability of MODIS NDVI for monitoring vegetation changes and supports its application in fire management and land use planning to conserve savannah ecosystems in Northern Ghana.

Land Use and Land Cover (LULC) Changes

Some of the transitions observed between land cover classes in the northern savannah of Ghana are the outright decline in forest cover and the increase in shrubby/woody savannah and agroforestry areas. Significantly, this study recorded a reduction in the forest cover from 2001 to 2022 due to recurring wildfires and increased human activities leading to the expansion of agricultural lands and settlements. The trend of forest decline agrees with other works, such as (Kalfas et al., 2024), who also reported that fire and land use changes negatively affect similar environmental forest ecosystems. An increase in shrubby/woody savannah and agroforestry classes represents a change in vegetation structure with relevant implications for biodiversity and ecosystem services. Shrubby savannahs, due to repeated fires and deteriorated lands, typically support fewer species than forests. This shift might reduce species that rely on dense forest habitats for their existence, further threatening the region's biodiversity. (Petermann & Buzhdygan, 2021) observed similar patterns, with fire-dominated grassland ecosystems leading to much-simplified vegetation structures with reduced biodiversity. Further, the shift from forest to shrubby savannah has implications for other ecosystem services, such as carbon sequestration. Forests are essential in sequestering CO_2, which causes global warming and climate change. When forest composition is reduced, the region's potential for carbon storage is significantly reduced. (Pettorelli et al., 2005) note that high-density fire events and changes in land cover, particularly in dense forests, lead to carbon emissions and increased climate change effects.

In contrast, the increase in the agroforestry areas is evidence of increased agricultural activities, possibly encouraged by increased demand for food and challenging economic situations. Besides that, improved soil fertility and sources of income for villagers could be some positive impacts caused by agroforestry systems. Nevertheless, these developments also mean increased tension on land resources, accelerating soil degradation and a drop in long-term agricultural productivity. Studies by Yaro (2008) indicate that agricultural land expansion at unsustainable levels in savannah ecosystems may cause soil fertility loss and threaten future agricultural output and food security. The observed land transitions indicate trade-offs between the changes in land use and ecosystem services. This reduction in forest cover will inadvertently reduce water regulation and biodiversity conservation. At the same time, the increase in agroforestry areas could improve agricultural productivity in the short term but at the cost of ecosystem resilience in the longer term. Boateng (2017) states that a proper balance between land use demands and the preservation of ecosystem services is crucial for environmental sustainability and agricultural productivity. Changes in land cover indicate that fire management and land use planning should go hand in hand to protect the remaining forests and support sustainable agricultural practices. This agroforestry area can continue supporting biodiversity and agricultural productivity with minimum negative impacts on ecosystem services through a balanced agriculture expansion and conservation approach.

Fire Hotspots and Vegetation Dynamics:

Spatial distribution showed that fire occurrences in the northern savannahs of Ghana were highly concentrated in rangeland and vegetation areas, especially around human settlement areas. This trend is highly related to land use activities like livestock grazing, agriculture, and land clearing. Similar findings by (Croker et al., 2023) highlight that these two practices, grazing and traditional farming methods, contribute significantly to fire occurrences in the savannah ecosystem. Fire is a land management tool used in rangelands. However, under repeated fires, vegetation degrades and may convert dense forests to shrubby savannahs or grasslands with biodiversity losses and carbon sequestration (Bond & Keeley, 2005). Agricultural expansion and urbanisation in most areas have led to highly concentrated fire activity around human settlements. Land clearing for farms and buildings increases the tendency for fires to occur, forming a clustered distribution pattern around human settlement areas as Laris, (2002) states. Climate conditions such as the extensive dry season and Harmattan winds also tend to enhance fire activity, as observed by Owusu and Waylen, (2013). Dry seasons increase the flammability of vegetation and promote incidents of fire. Fire incidents occurring closer to water bodies are also ecologically relevant, as water bodies tend to create natural firebreaks and are typically unaffected. According to (Swaine, 1992), the encroachment of agriculture into riparian zones can compromise this natural buffer and allow fires to spread into previously protected areas. Fewer fire incidents around significant water bodies were recorded due in part to moisture content; however, human activities can alter this protective dynamic.

Fire impacts on vegetation recovery and degradation are complex. While regenerative fire is essential in fire-prone ecosystems like the northern savannah, frequent anthropogenic fires prevent full vegetation recovery and create conditions for long-term degradation. Hoffmann et al. (2012) noted that fire frequency changes species composition by favouring fire-tolerant species at the expense of fire-sensitive ones. Over the last two decades, the frequent fire disturbances in rangeland have increasingly led to forest loss in the study area, following the global trends of reduced ecosystem resilience to frequent fire disturbances (Pettorelli et al., 2005).

Fire and Vegetation Dynamics: Species Composition, Ecological Gradients, and Environmental Factors

The phytogeographic analysis and the species composition in the northern savannah indicate that fire-tolerant species, such as Vitellaria paradoxa (shea), Parkia biglobosa (dawadawa), and Diospyros mespiliformis proliferate under fire-prone conditions due to their adaptive attributes of thick bark, deep roots, and resultant sprouting. These species thrive in the savannah fire regime, exacerbated by natural causes and human land clearing and agriculture activities. In support, (2005) noted that fire-adapted species possess specific characteristics that allow them to survive frequent disturbances caused

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by fire in savannahs. This is due to their ecological adaptations, which give them an advantage over fire-sensitive species. Hoffmann et al. (2012) mentioned that eliminating the fire-sensitive species from fire-prone landscapes results in the floristic composition shift in this savannah.

The Detrended Correspondence Analysis (DCA) identified three main vegetation groups along the fire and deforestation gradients: the Open Forest Group, the Mosaic of Shrubby/Tree Savannah and Dry Forest, and the Wooded/Tree Savannahs. The Open Forest Group includes fire-sensitive pioneer species that happen to survive in low frequencies of fires but have been declining with the rise and increasing frequency of fires. As explained by Pettorelli et al. (2005), fire-sensitive species are usually confined to fire-protected areas. The Mosaic of Shrubby/Tree Savannah and Dry Forest is a transitional ecosystem with coexisting fire-tolerant and fire-sensitive species. However, the domination of fire-tolerant species increases with increasing disturbance due to fires. Wooded/Tree Savannahs were dominated by fire-tolerant species that can withstand frequent and intense fires, and their domination increased with increasing fire intensity. According to Bond and Keeley, (2005), fire regulates the relative dominance between woody and herbaceous vegetation in savannahs.

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Canonical Correspondence Analysis (CCA) revealed that environmental variables like elevation, distance to water, and soil type are significant in explaining fire regimes within the northern savannahs, which agrees with global observations. For example, Pettorelli et al. (2005) assess that fire frequencies tend to be lower at high elevations because of reduced human activities and sometimes microclimatic conditions. Human activities and expansion of agriculture in lower elevations and riparian zones thus foster fire risk in fire-prone regions such as California and Australia. Another essential factor influencing fire frequency concerns soil type: the sandier the soils, the quicker they dry out, and hence, the more frequent the fires occur in Australia and parts of Southern Africa (Bradstock et al., 2012). This interaction between fire intensity, human disturbances, and these other environmental factors improves the performance of fire-tolerant species at the expense of fire-sensitive species. This more general pattern has implications for biodiversity and ecosystem services. In summary, these patterns underscore how fire management strategies must be tailored analogously to account for human and environmental drivers of fire risk. These patterns underscore the need for tailored fire management strategies that account for both human and environmental drivers of fires.

Fire-Induced Vulnerability of Ecosystems in Ghana's Northern Savannah zone

From the spatial relation between wildfires and water bodies in the savannah ecosystems of Northern Ghana, an inverse correlation may be seen in that areas closer to water bodies have fewer incidences of fire. Water bodies can be considered a natural firebreak, which limits the number of wildfire occurrences within their surroundings with reduced intensity of the wildfires. This also calls for the conservation of water bodies, as they serve a vital function in mitigating fire risks and protecting the surrounding ecosystem. Other studies have identified that not only rivers and lakes provide a natural barrier against wildfire but have again raised calls for these bodies of water to be treated in a conservation effort with intensified fire mitigation. (Caroni et al., 2024; Kraaij et al., 2013).

The vulnerability map identifies the classes of the area by wildfire exposure. It shows that the areas of very high vulnerability, such as forest preserves and major rivers, have extreme threats to key ecosystems, including water supply and agricultural productivity. Wildfires can seriously degrade ecosystems by reducing water quality and affecting vegetation dynamics and biodiversity. Because of the proximity to fire-prone zones, high-vulnerability areas usually associated with human activities like agriculture are highly vulnerable. Land-use change increases wildfire vulnerability and enhances ecosystem degradation, similar to what is recorded in other analyses of fire-prone ecosystems.

Moderate-vulnerability areas represent potential for resilience since these zones are less exposed to the most severe wildfire risks and thus may have greater capacity to recover and adapt. In this regard, implementing adaptive management practices, such as community-based fire management and sustainable land-use strategies, may reduce vulnerability in these regions. Local knowledge in rural savannahs globally has been critical in implementing effective fire mitigation, thereby improving resilience with community fire management. Other ways include implementing more fire-resistant agroforestry systems to reduce the incidence of wildfire spread and maintaining ecosystem functionality for productive agriculture.

These maps further indicate that areas with high human activities, like agricultural expansion and settlement growth, tend to be highly prone to wildfires. These human-induced pressures, added to natural fire-prone conditions, exacerbate fire risks and degradation of ecosystem services. Indeed, a study by (Jolly et al., 2015)Bowman et al. (2021) has shown that agricultural practices like slash-and-burn techniques greatly heighten fire incidences and further degrade ecosystems. In sum, integrated land-use planning and adopting fire management strategies will be highly important in addressing combined pressures that reduce wildfire risks, hence protecting ecosystem services in Northern Ghana.

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These findings highlight the need for area-targeted fire management strategies that give prominence to highly vulnerable areas with critical roles in ecosystem service provision. Policies for conservation should be directed at promoting a natural firebreak role for water bodies and practising firebreak systems in high-risk zones near forests and rivers. According to Staver et al. (2022), when complemented by community-based fire management practices, early fire detection technologies at a smaller scale could result in fewer fire incidences that would contribute to more sensitive ecosystems. Moreover, sustainable agriculture and land-use planning could reduce the risk of human-induced wildfires in the most vulnerable areas, thereby increasing ecosystem resilience.

4. CONCLUSION

This study has highlighted how fire regimes influence land cover change, species composition, and ecosystem services vulnerability in the northern part of Savannah, Ghana. The result points to a decreased forest cover with an expanding shrubby savannah and agroforestry system driven primarily by recurring fire incidents and human activities like agricultural expansion and land clearing. Fire-prone zones were identified in rangelands and near settlements, where traditional practices for land clearing with livestock grazing and a dry season climate support frequent fire outbreaks. Analysis of species composition also indicated that fire-tolerant species, such as *Vitellaria paradoxa* (shea) and *Parkia biglobosa* (dawadawa), dominate the savannahs. In contrast, fire-sensitive species are threatened and can lead to decreased biodiversity and an altered vegetation structure. The vulnerability assessment analysis indicated that critical ecosystem services, such as water bodies, forests, and farmlands, are increasingly subjected to fire-induced degradation. Water bodies, which serve as fire breaks, have been compromised due to increased human activities encroaching upon riparian zones. The forests and farmlands are vulnerable, with frequent fires reducing soil fertility and vegetation recovery. The findings indicate that immediate action is required to address these concerns through targeted management strategies.
Remote sensing technologies such as the MODIS NDVI and Sentinel-2 imagery must be increased to enhance vegetation change, fire patterns, and ecosystem health monitoring. Integrating these tools with ground-based observations will aid in identifying fire hotspots and assessing the impact of fire on vegetation dynamics and ecosystem services over time. Continuous use of remote sensing is fundamental to providing timely and efficient fire management. The involvement of local communities in Sustainable land-use planning can balance agricultural expansion with the conservation of forests and other vital ecosystems. This will encourage agroforestry practice that combines agricultural productivity with environmental conservation, thereby reducing pressures on remaining forested areas and improving the resilience of ecosystems to fire and other disturbances.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declares that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during the writing or editing of manuscripts. The paper used Grammarly to improve upon the grammar.

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