Wildfire Impacts on Species Composition, Land Use Dynamics, and Ecosystem Service Vulnerability in Northern Ghana's Savanna 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 investigated the impacts of fire on the species dynamics, land cover changes and the vulnerability of tree ecosystem servicesin the northern savanna regions 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. Species composition was assessed through vegetation inventories, and statistical models, including regression analysis and multivariate techniques, were applied to determine fire-induced changes in tree structural diversity and land use patterns on 30m x 30m plots of land (30 in total), across ten (10) communities. Land cover classification and change detection were performed using supervised classification in QGIS.The results showed a clear-cut reduction in forest cover and increased shrubby savannah and agroforestry types driven by recurring fires and agricultural land conversion. Fire-prone areas, particularly rangelands and vegetation zones near settlements, accounted for over 70% of recorded fires, making them the most frequently affected by wildfires. The dominance of fire-adapted species, such as *Vitellaria paradoxa (*14%) and *Parkiabiglobosa* (11%) of the total species recorded, was observed, whereas fire-sensitive species declined in areas with high fire frequency.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.

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 ecosystem health. Savannahs are widely spread and cover about 20% of the Earth's surface.They are very sensitive to changes in fire regimes, which generally bring changes in biodiversity, carbon storage, and ecosystem services(Pausas & Keeley, 2019). Indeed, shifting fire regimes driven by climate change, land-use change, and agricultural development have strongly affected vegetation structure and species composition in Southern Africa, Argentina, and Australia. For instance, more frequent and severe fires in the Argentine savannahs have reduced tree cover by 30% and shifted dominance from diverse, 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 tree cover loss 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.Wildfires in savannah regions in Ghana have both naturally and anthropogenically fueled sources. Sustained drought during the dry period, supplemented with strong Harmattan winds, creates combustible environments supporting rapid wildfire expansion (USDA Forest Service, n.d.). Fires, however, are mostly initiated through anthropogenically fueled sources. Traditional agricultural slash-and-burning, agricultural and settlement encroachment, burning for charcoal, and unregulated hunting have immensely fueled wildfire events (Asante et al., 2022). Policy loopholes and lack of proper management have, in turn, produced recurring and unregulated fires, contributing to augmented degradation of the environment and loss of ecosystem function (National Wildfire Management Policy, 2006)The Ghana National Fire Service Act (1997) provides legislative support for fire management and suppression. However, poor community mobilization and compliance with legislation have continued to hinder the effective suppression of wildfires.

 In nature, wildfires represent an integral but increasingly 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 has long played the role of a natural process that balances 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 findings 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 broader 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.

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), *Parkiabiglobosa* (dawadawa), *Adansoniadigitata* (baobab), and various Combretum and Terminalia species (Ampadu-Agyei, 1988). The herbaceous layer is dominated by perennial grasses such as *Andropogongayanus* 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, *Balanitesaegyptiaca*, and *Faidherbiaalbida*. The grass layer in this zone is often composed of shorter annual species, reflecting the more arid conditions.
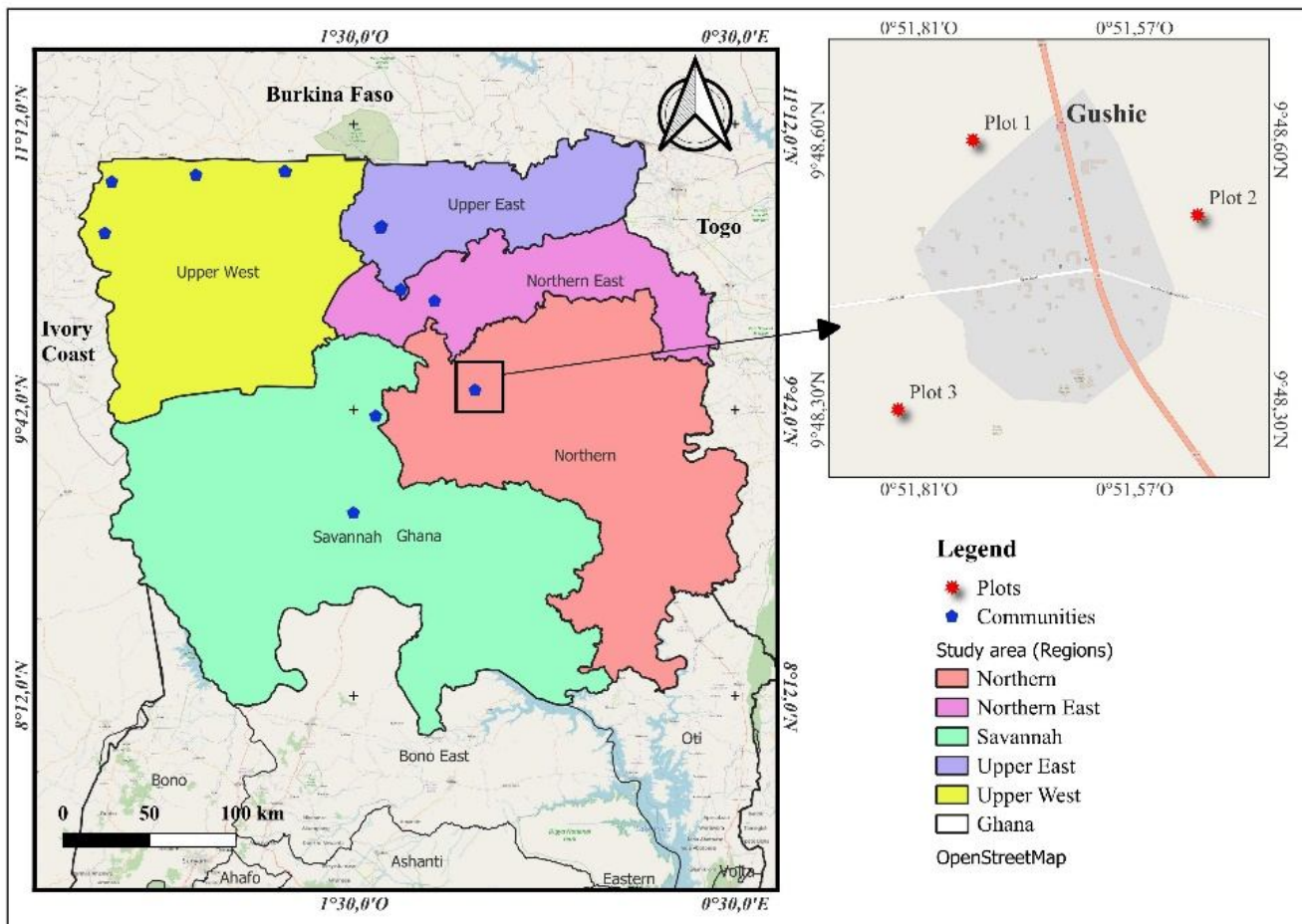

Figure 1: Study area location: Northern savannah ecological zone with the five regions captured and a Google image showing how three plots are identified in each of the communities

152

153 The study area's topography is undulating, coupled with some hills and isolated highlands
154 over flat plains with an elevation of 150 to 300 meters above sea level (Smith et al., 2021).
155 The drainage is dominated by seasonal rivers and streams drained into major river basins
156 such as the White Volta, Black Volta, and Oti Rivers. Most of these rivers have flow regimes
157 characterised by high flow during the rainy season and dry up or reduce to pools during the
158 dry seasons, causing temporary water shortages (Kombat et al., 2023). The dominant
159 socio-economic activities in the Northern Savannah ecoregion include agriculture, rearing,
160 and agroforestry systems. Farming primarily involves cultivating subsistence crops of millet,
161 maize, sorghum, groundnuts, and yam and small-scale cash crop production of shea nuts
162 and cotton. Besides farming, livestock herding, especially cattle, goats, and sheep,
163 is widespread and supplements the few livelihoods available. The area comprises ethnic
164 groups, such as the Mole-Dagbane, Waala, Dagara, and Gurune, governed by traditional
165 solid leadership structures. Festivals, farm rituals, and communal activities all play their role
166 in reinforcing social cohesion (Owusu et al., 2022). Traditional agroforestry systems are a
167 common means of managing natural resources, while many communities engage in
168 activities related to fuelwood collection, charcoal making, and hunting. However, the region
169 has several problems accompanying it, including poverty, lack of infrastructure, and
170 vulnerability to climate variability, all of which impact the livelihood and cultural activities of
171 the people.
172 Climate plays a crucial role in shaping these savannah ecosystems. Ghana's northern
173 savannahs are characterised by a single rainy season, typically lasting from May to October,
174 followed by a prolonged dry season. Annual rainfall ranges from about 1000-1300 mm in the
175 Guinea savannah to 600-900 mm in the Sudan savannah (Kwadwo Owusu & Waylen,
176 2009). This rainfall pattern, combined with high temperatures and frequent fires, is
177 instrumental in maintaining the savannah physiognomy. The Harmattan winds, which occur
178 from December to early February, have a considerable effect on the temperatures in the
179 region, which may vary between 14°C at night and 40°C during the day (W. Asante & Siaw,
180 2019)These dry conditions and the strong Harmattan winds facilitate vegetation burning.
181 Early dry season burns are usually done between November and January, whereas late
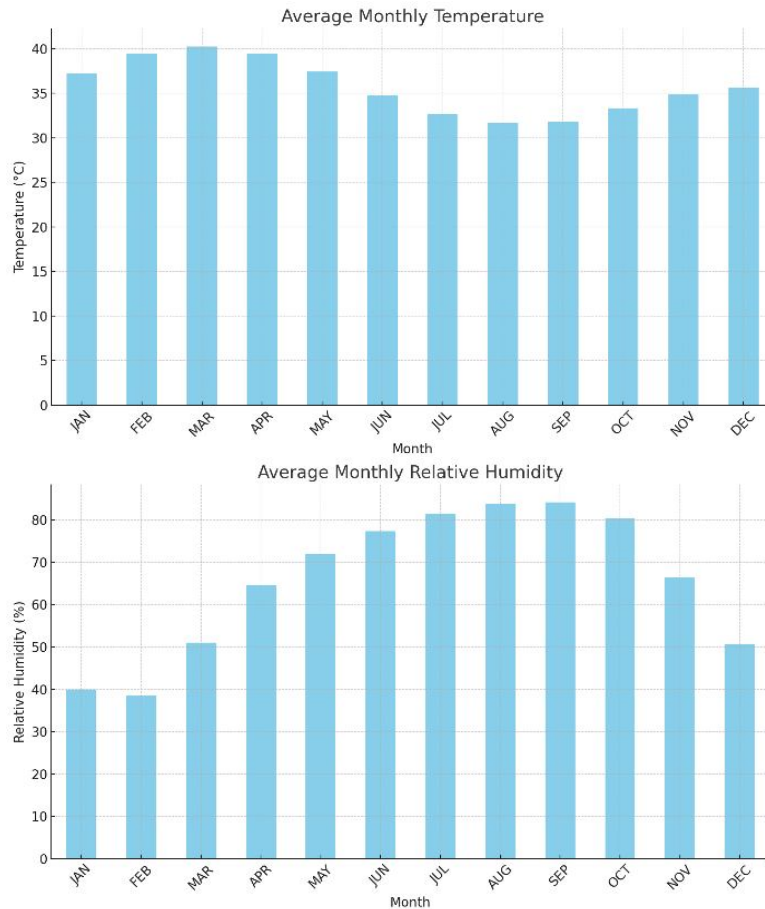182 season burning begins in February and ends in March.
183

184

185
186 *Figure 2: Average monthly temperature and humidity values of the study area from 1992 to*
187 *2022. Source of data: https://modis.gsfc.nasa.gov/data/*
188

2.2. DATA COLLECTION AND PROCESSING
2.2.1 MODIS NDVI image description and processing

191

192 For the assessment of large-scale vegetation cover changes, MOD13Q1 (MODIS/Terra
193 Vegetation Indices 16-Day L3 Global 250m SIN Grid) NDVI data from the NASA Earth
194 Observing System Data and Information System (EOSDIS) platform (available at:
195 https://earthexplorer.usgs.gov/), was used. The MOD13Q1 product provided bi-weekly
196 composite images at a spatial resolution of 250 meters. The 250-meter spatial resolution
197 allowed for a detailed analysis of vegetation cover changes at regional and local scales,
198 while the 16-day temporal resolution facilitated tracking of seasonal and interannual
199 variability in vegetation cover between 2001 and 2022. MODIS NDVI data were selected
200 according to cloud covering percentage of less than 10% and data availability in the dry
201 season to reduce cloud effects, vegetation phenology and differences in soil moisture (Wu et
202 al., 2021). Also, thirty (30) GPS ground truth points (UTM Zone 30N, WGS 84 at 3 m level of
203 accuracy) were obtained from sample points of the identified land cover classes (forest (F),
204 shrubby/woody savannah (SWS), Agroforestry/park/field lands (AF), waterbodies (WB), and
205 human settlement (HS) during field visits across the study area. These GPS points were also
206 used to validate the satellite-based vegetation indices.
207

208 **Preprocessing of MODIS NDVI Image**

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

222 $NDVI = \frac{NIR-RED}{NIR+RED}$ (1)

223 The NDVI values ranged from -1 to 1, with higher values indicating healthy and dense forest
224 vegetation, while lower values corresponded to sparse vegetation, urban areas, water
225 bodies, and bare land. NDVI values were followed by LULC classification, where vegetation
226 cover was differentiated into various classes based on the NDVI values and other contextual
227 information. These categories included Forest in dark green, Shrubby/Woody Savannah in
228 light green, Agroforestry Parks/Fields/Fallow Land in yellow-green, Water Bodies in blue,
229 and Human Settlements in orange. Generally, areas with forests had a high NDVI due to the
230 high density of vegetation. At the same time, shrubby/woody savannah and agroforestry
231 showed moderate NDVI values due to poor vegetation coverage. Non-vegetated surfaces
232 like water bodies and human settlements did not tend to return high NDVI values.
233
234 **Testing of the Classified Images**
235 Images were validated using the accuracy metrics, which included Overall Accuracy (OA),
236 Kappa Statistic (KS), and the Confusion Matrix (CM), to analyse and confirm their statistical
237 accuracy. The statistical classification testing generated confusion matrices for every
238 classified image using the sklearn library (from sci-kit in Python) to create confusion
239 matrices. The overall accuracy (OA) was obtained by comparing the ratio of accurately
240 classified pixels to the number of reference points of the entire image (Kamusoko, 2022).
241 This metric gave a rough estimate of the degree of fit of the classified output data to the
242 reference data and was computed from the following equation;
243

244 $Overall\ Accuracy = \frac{Total\ Correct\ Classifications}{Total\ Number\ of\ Reference\ Points} \times 100$

245 Producer's Accuracy was then calculated to determine how well each class in the actual field
246 was classified in the image. It quantified the omission error that arises when a certain land
247 cover type is classified into the wrong class (Kamusoko, 2022).
248

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

249
250
251 User's Accuracy was computed to measure the likelihood of the pixel being correctly
252 classified to the intended land cover class in the reference data (Kamusoko, 2022;Prasad,
253 2020). It is a measure of commission error whereby a pixel is either misclassified in an
254 image or computed incorrectly in a matrix.
255

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

256 In addition, the Kappa Coefficient was computed to quantify the degree of agreement
257 between classified data and reference data besides the chance variable. The Kappa
258 coefficient varies from 0 to 1, where values closer to 1 indicate a higher level of compliance
259 between the classification and actual ground truth (Prasad, 2020)
260
261

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

262 Where:
263 *Po* is the observed accuracy (same as overall accuracy),and *Pe* is the expected accuracy by
264 chance.
265
266 **2.2.2. Land use and land cover classification**
267 For the study area, shape files were used to extract data on the various land covers: forest,
268 shrubby/woody savannah, agroforestry lands, water, and human settlements for 2001, 2006,
269 2011, 2016, and 2022. The Semi-Automatic Classification Plugin (SCP) in QGIS was used to
270 classify each pixel accurately before change detection, and the results were then exported to
271 Excel for further analysis (Congedo, 2016). The SCP 'Land Cover Change' algorithm
272 produced the transition matrices that described the changes in different land cover types,
273 thereby pointing out the deforestation rate and how the agricultural lands have been
274 expanding. The SCP "Classification Report" algorithm created Excel reports of the LULC
275 class areas for each period to determine the change rate. The average annual rate of land
276 cover change was calculated using the formula:
277

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

278 This was used to calculate changes in forest cover, shrubby savannah, agroforestry lands,
279 and human settlements.
280
281 **2.2.3. Statistical Methods**
282 To assess changes over time, linear regression models were applied to each land cover
283 type. The slope of the regression line represents the rate of change per year, while the R-
284 squared value indicated the proportion of variance explained by the model.
285
286 **2.3. Hotspot analysis of fire impact on vegetation using Sentinel-2 and MODIS**
287 **NDVI**
288 A fire hot spot map was generated from a Sentinel-2 satellite image, and the vegetation
289 types were extracted using NDVI indices. MODIS data for 2000-2021 was utilised to obtain
290 historical fire occurrences as input for the study. The district capitals were georeferenced by
291 overlaying layers derived from the administrative boundaries data layers. Supervised
292 classification was done using satellite data to identify forests, water bodies, and agroforestry
293 parklands. To increase classification accuracy, preprocessing steps were employed through
294 atmospheric correction and cloud masking. The classification results obtained were validated
295 using accuracy assessment techniques as described above. The spatial layers were
296 appended using the QGIS open-source GIS, which was used to assess further
297 the distribution of fire points with the land cover type and human settlement. An appropriate
298 coordinate system and projection, WGS84, enhanced the spatial reference and accuracy.
299
300 **2.4 Species Composition and Phytogeographic Analysis**
301 Vegetation measurements at the site included a structured and systematic vegetation
302 inventory on 30 plots, where species composition and vegetation structure were
303 documented. The species were categorised according to their fire tolerance and origin from

304 three eco-geographical zones, including Guineo-Congolese and Sudanian. This
305 classification provided a very rich analysis of how various species may be affected by a level
306 of fire and anthropogenic impact.

307 Tree height for tall trees was measured using a clinometer, while for smaller trees, it was a
308 simple tape measure. Measurement was taken from the ground, which is the base of every
309 tree, to its topmost branch. Measurements were conducted at random points within selected
310 plots across the study area to capture the variability in tree height. The height data estimates
311 the mean and variation of tree height among species and compares tree height of fire-
312 tolerant and fire-sensitive species. Similarly, a simple tape measured the circumference of
313 the tree at DBH (1.3 meters, or approximately 4.5 feet) above ground. Circumference was
314 divided by π (3.1416) to calculate diameter.
315 A Detrended Correspondence Analysis (DCA) and Canonical Component analysis (CCA)
316 was conducted to assess the plant community structure further. This multivariate statistical
317 method was used to determine the gradients concerning fire intensity and the influence of
318 human disturbance. The DCA analysis helped recognise the relations between plant
319 communities and identify fire-tolerant and fire-sensitive plant species within the disturbance
320 gradients. This approach helped to understand how fire and human activities affect
321 vegetation, especially in fire-dominated ecosystems like the Northern Savannah Ecological
322 Zone.
323
324 **2.5. Fire effects on savannah ecosystems**
325 An ecosystem impact/vulnerability map was developed to determine the vulnerability of the
326 study area to the loss of ecosystems due to wildfire. The map was created using Sentinel-2
327 images because they offer a much higher spatial resolution, are multispectral, and have
328 a high repeat frequency. The images used in this study were selected based on a cloud
329 cover percentage below 10% to reduce cloud interference and vegetation changes. Table 1
330 summarised the general features of Sentinel-2 imagery, such as spatial and spectral
331 resolutions, temporal revisit frequency, and large scene width, which allowed focusing on
332 details of fire impact zones and performing time series analysis of post-fire ecosystem
333 rehabilitation. The imagery was classified using supervised classification techniques with
334 QGIS to develop the hotspot map.
335 *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)

336
337 **2.5.1 Preprocessing and processing of Sentinel-2 satellite image**
338 Sentinel-2 imagery for fire vulnerability assessment involved several steps in pre-processing
339 and processing the data correctly to ensure data quality and accuracy. The data was derived
340 from the European Space Agency's Copernicus programme, which offers high-resolution
341 multispectral data for vegetation health, mapping of the land cover classification, and
342 identifying wildfire risks. The data was downloaded with band resolutions of 10m, 20m, or
343 60m (Phiri et al., 2020).
344 For analysis, the imagery was preprocessed using the Sen2Cor processor to perform
345 atmospheric correction. This correction converts level-1C (top of atmosphere reflectance)

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

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

356 NDWI is calculated using the Near-Infrared (Band 8) and Short-Wave Infrared (Band 11 or
357 12) bands to estimate vegetation moisture content. Lower NDWI values suggest dry
358 conditions, making an area more susceptible to wildfire.
359 The technique used in assessing wildfire vulnerability entails calculating vegetation indices
360 and classifying the land use and land cover (LULC). This categorises the landscape into
361 various vulnerability classes dependent on parameters like vegetation type and density, soil
362 moisture and wildfire risk level. Zones were represented by green for forest reserves to
363 signify low vulnerability and red for high vulnerability areas. Environmental variables,
364 including fire frequency (derived from the MODIS data of 2001-2021) and species richness
365 (from the field), are combined to measure ecosystem resilience. Population density and land
366 use intensity are also mapped from census, remote sensing, and GIS data layers. The
367 georeferenced variables are read into GIS software, normalised, and scaled to assign higher
368 vulnerability scores to regions with greater fire risk and susceptibility to ecosystem
369 degradation.
370
371 **3. RESULTS:**
372
373 **Land Use Classification and Accuracy Assessment**
374 Five land use classes were identified: Forest(F), Shrubby/Woody Savannah(SWS),
375 Agroforestry Parks/Fields/Fallow Land (APF), Water Bodies(WB), and Human Settlement
376 (HS). The confusion matrix (Figure 3) and accuracy metrics (Table 2) The result shows that
377 the performance of each land cover type was excellent. Each class, like Human Settlement,
378 Shrubby/Woody Savannah, Agroforestry, Forest, and Water Bodies, was classified ideally,
379 as shown by the diagonal elements in the confusion matrix with no misclassifications and no
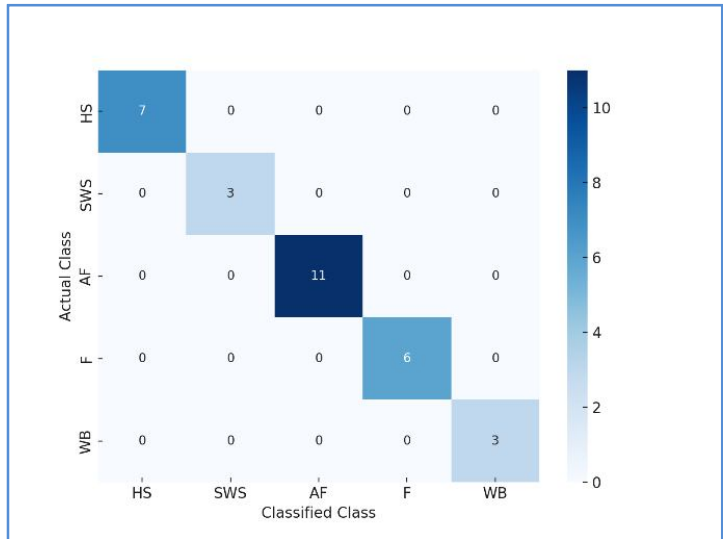380 confusion between the different land cover types.

381
382 *Figure 3: Confusion Matrix for Land Cover Classification*
383 Specific to classification models, two accurate measurements that can be used are
384 Producer's Accuracy (PA) and User's Accuracy (UA). Producer's Accuracy determines the
385 density of each land cover type in a classified image. At the same time, the User's Accuracy
386 quantifies the probability of an area belonging to a given class being classified. Since there
387 were no false classifications in the above matrix, PA and UA would be 100, indicating that
388 the model achieved optimal performance for all land cover types.
389 However, to provide additional information about the model's accuracy and reliability, the
390 accuracy metrics were computed and presented in (Table 2) below;
391
392 *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

393
394 (Table 2) Shows outstanding performance in the additional land cover classification model
395 metrics. The accuracy shows that the classification model was correctly classified in every
396 land cover class. The Producer's Accuracy (PA) was perfect for each class, indicating that all
397 actual samples were correctly classified. Similarly, the User's Accuracy (UA) for all land
398 cover classes is shown to belong to their appropriate categories. The Kappa Coefficient also
399 shows perfect agreement between actual and classified data and results that are better than
400 would be expected by chance. These metrics validate the high reliability and precision of the
401 classification model.
402

Land use and land cover dynamics in the study area

(Figures 4,5.6,7,8) 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.
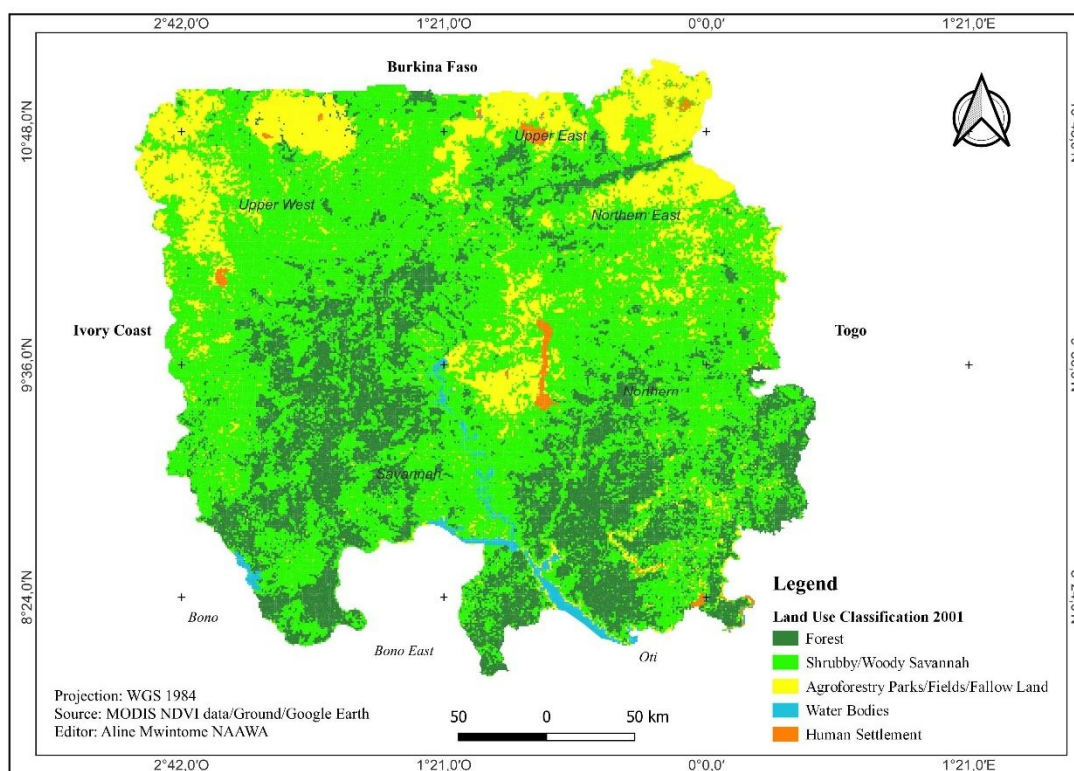
Figure 4: Land Cover Classification Map for 2001 Using MODIS NDVI Data.

421
422   *Figure 5: Land Cover Classification Map for 2006 Using MODIS NDVI Data.*
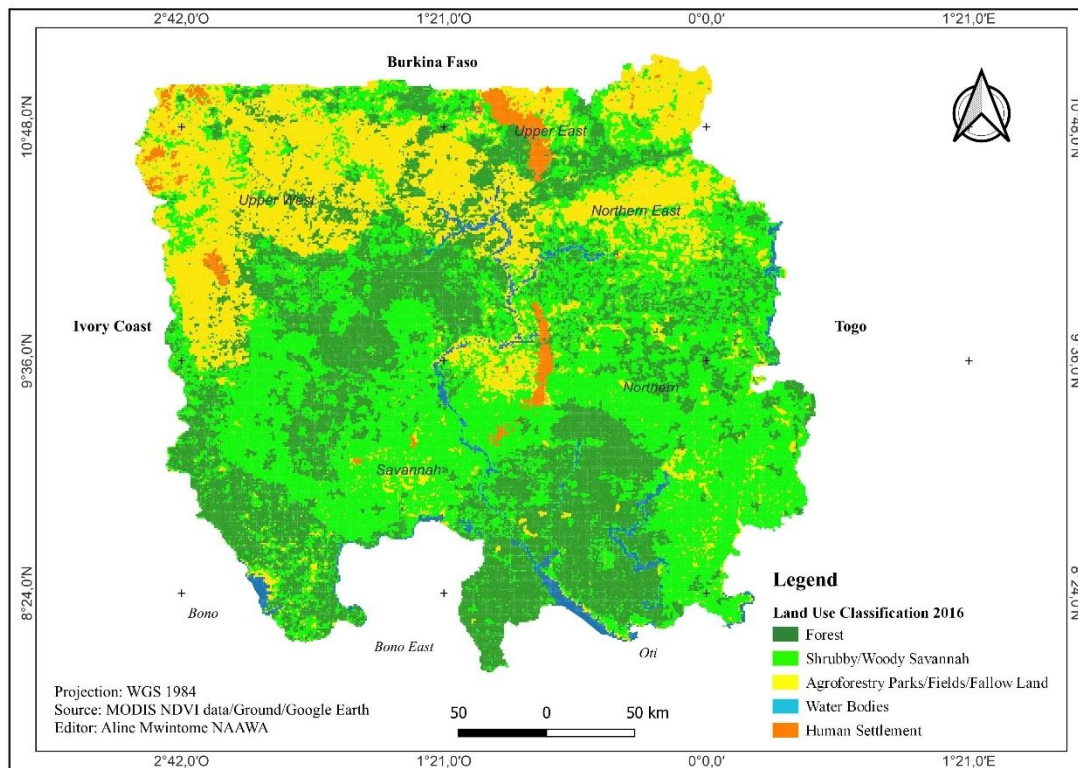
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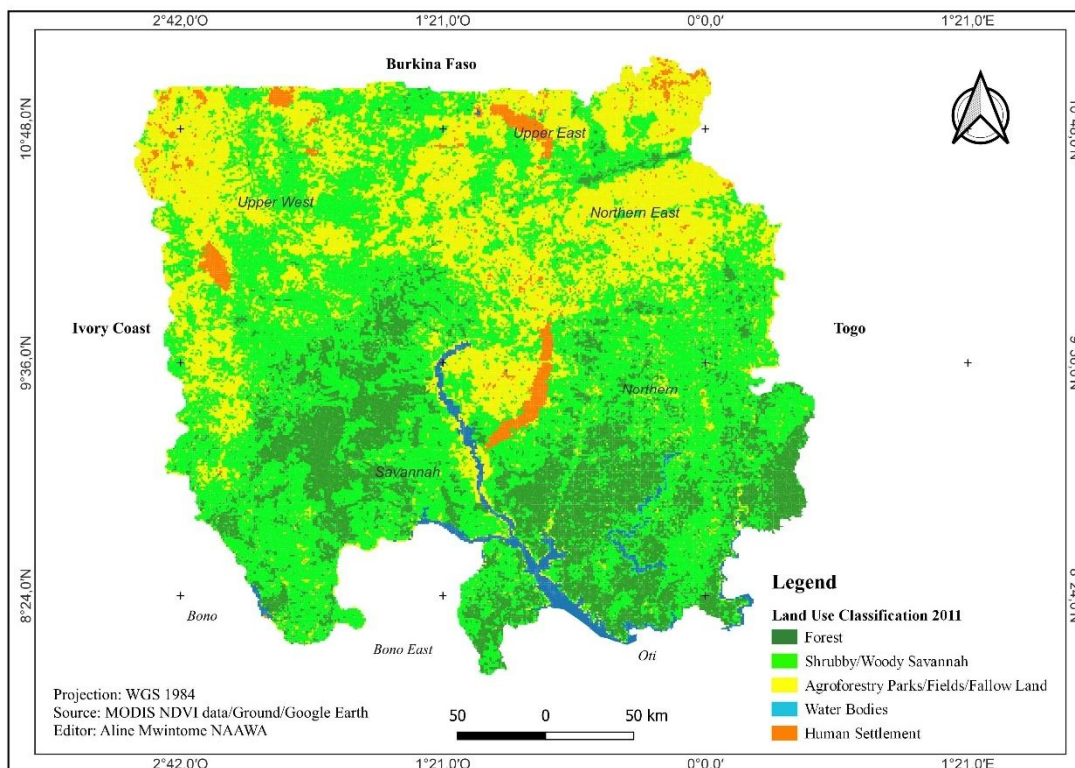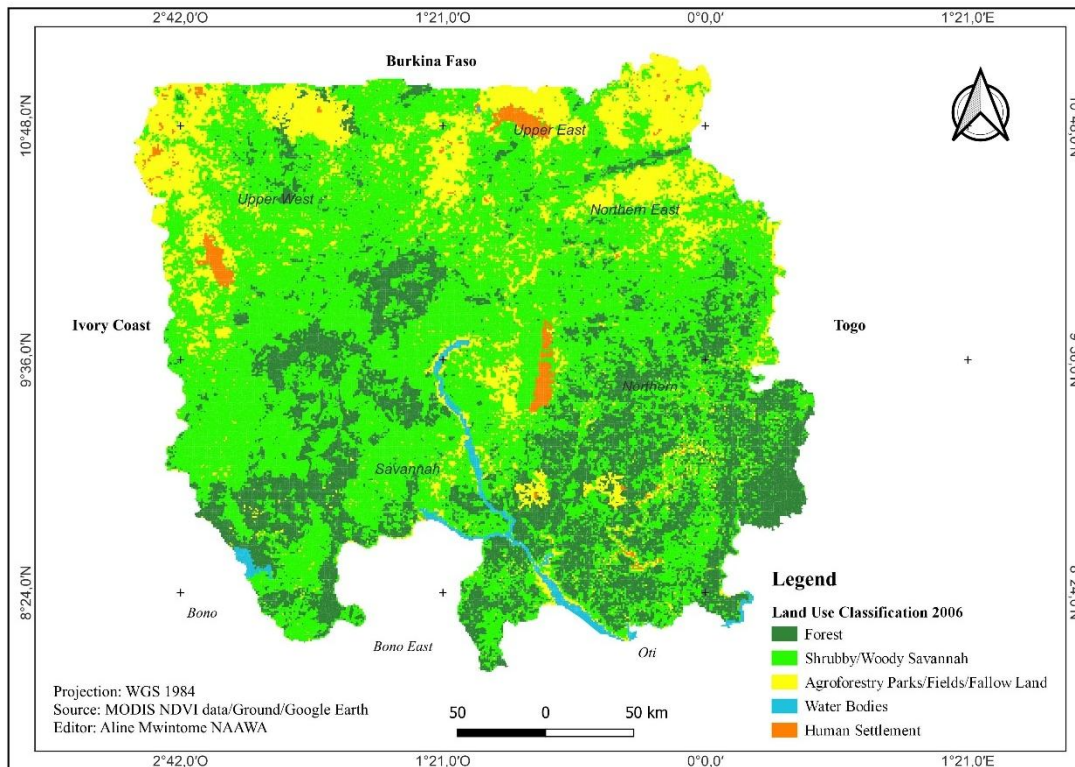
426 *Figure 6: Land Cover Classification Map for 2011 Using MODIS NDVI Data.*

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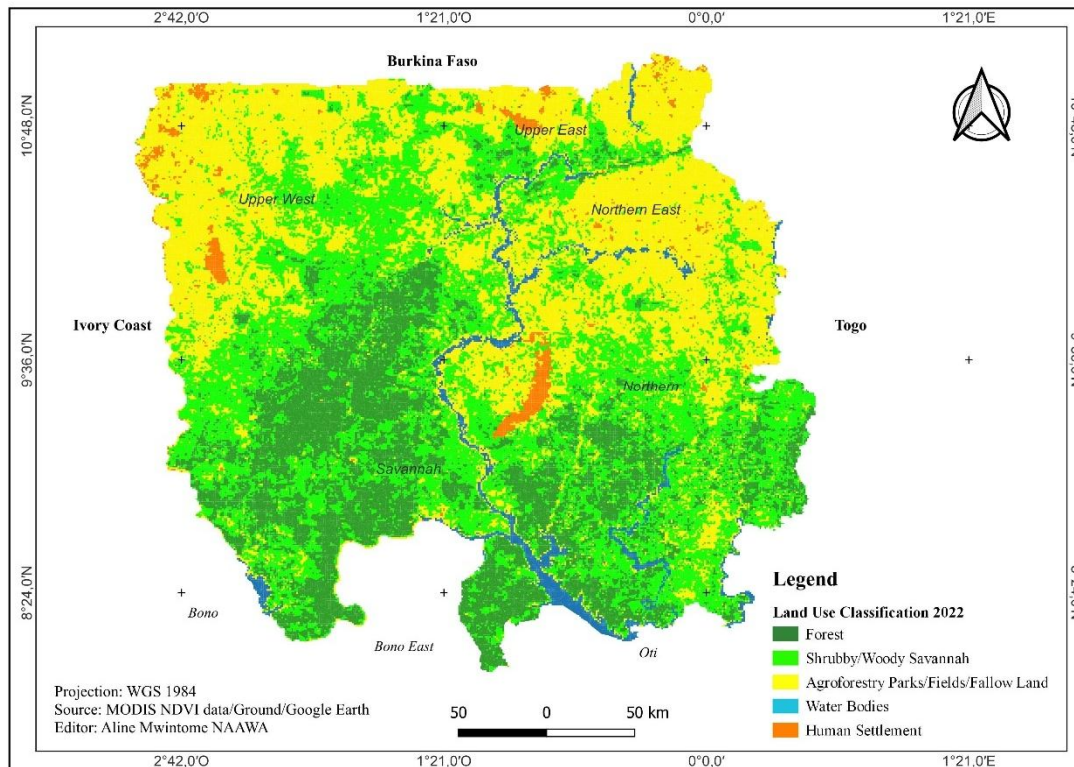430 *Figure 7: Land Cover Classification Map for 2016 Using MODIS NDVI Data*

Figure 8: Land Cover Classification Map for 2022 Using MODIS NDVI Data

The changes in land cover from 2001 to 2022 (Table 3) below are across five major LULC classes: Forest, Shrubby/Woody Savannah, Agroforestry parks/Fields/Fallow lands, Water Bodies, and Human Settlement.

From 2001 to 2022, 10.86% of forest cover declined due to deforestation, agricultural land expansion, and frequent fires. However, a single spike was observed in 2016.Shrubby savannahs have continuously declined at a rate of 38.82% over the study period. Agroforestry lands have increased immensely, with a 145.17% expansion between 2001 and 2022. Water bodies have increased by 170.76% over the study period, whereas human settlements have expanded substantially, recording a 177.12% increase from 2001 to 2022.

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 revealed 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 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 were 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.
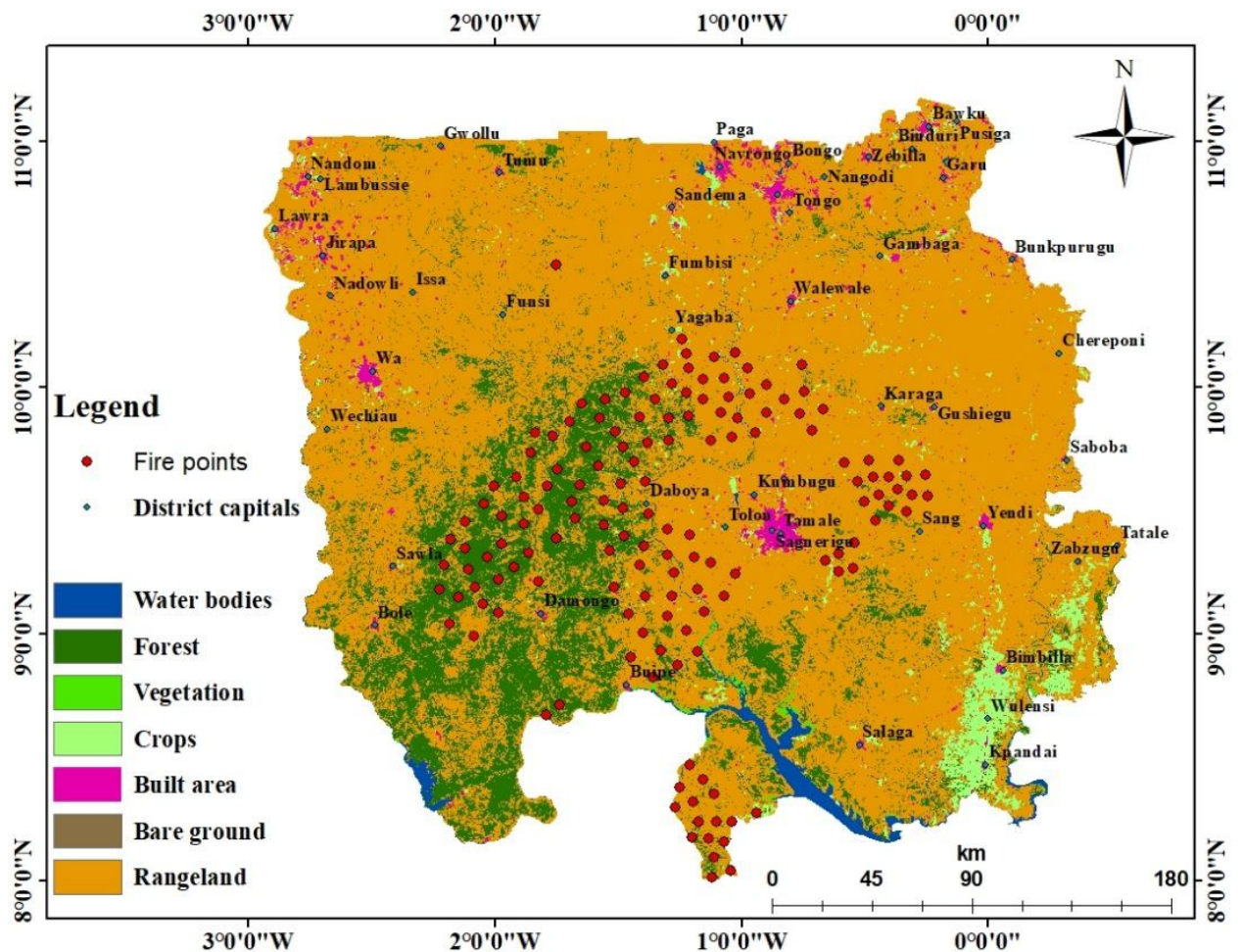
Figure 9: Fire Points(Hotspot) and Land Cover Distribution in Northern Ghana

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*, *Parkiabiglobosa*, *Anogeissusleiocarpus*, 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.
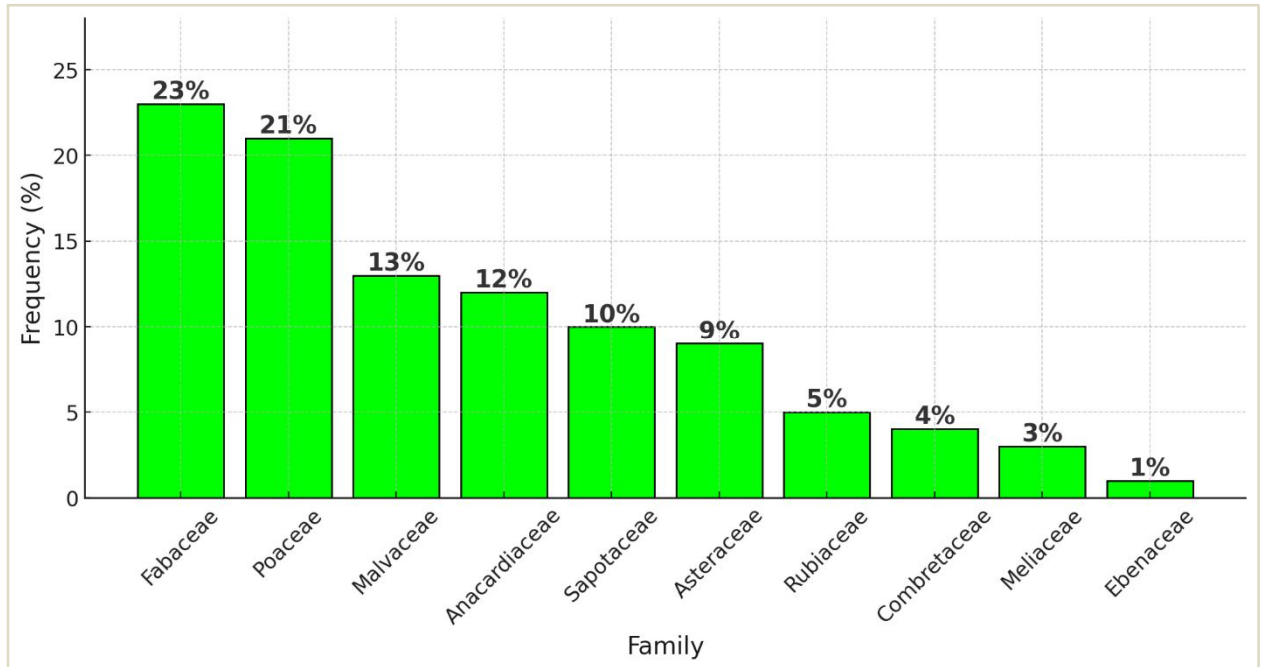
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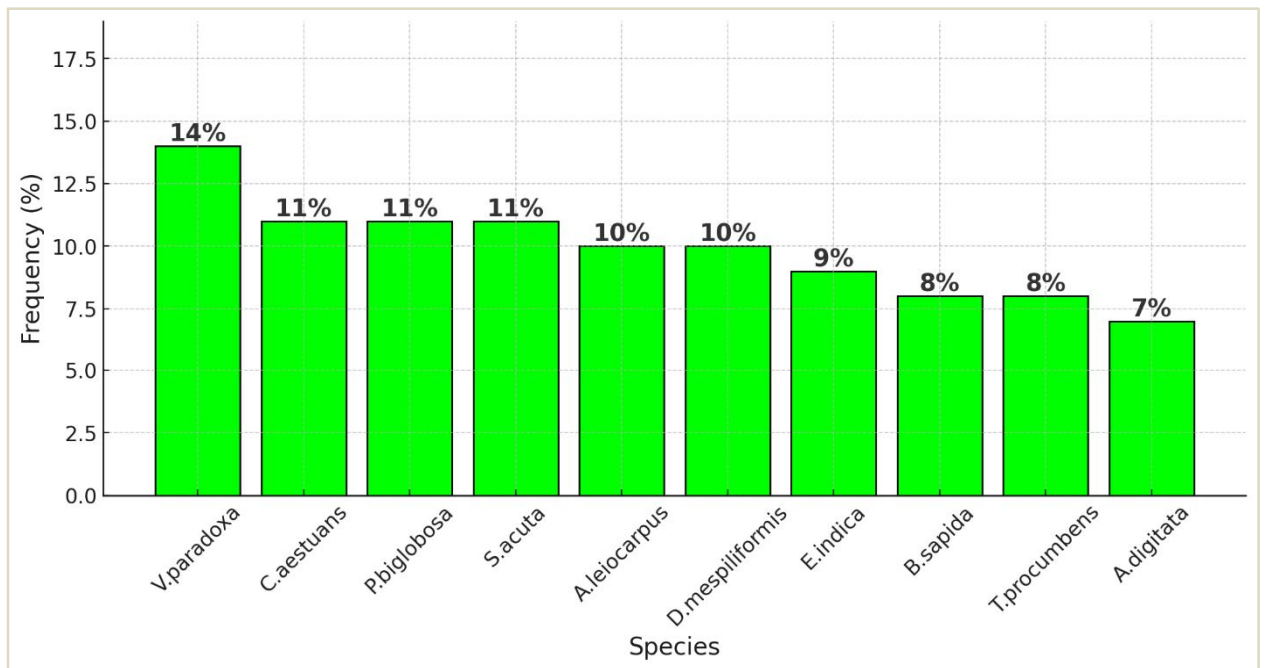494 *Figure 10: Frequency Distribution of Plant families*
495

496
497
498 *Figure 11: Frequency Distribution of Plant Species*
499
500 (Figure 8) Compares the frequency percentage of various phytogeographic types between
501 burned and non-burned areas. It illustrates the domination of vegetation by species of
502 Guineo-Congolese/Sudanese-Zambezi (GC-SZ) and Sudanese-Zambezi (SZ) regions,
503 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.
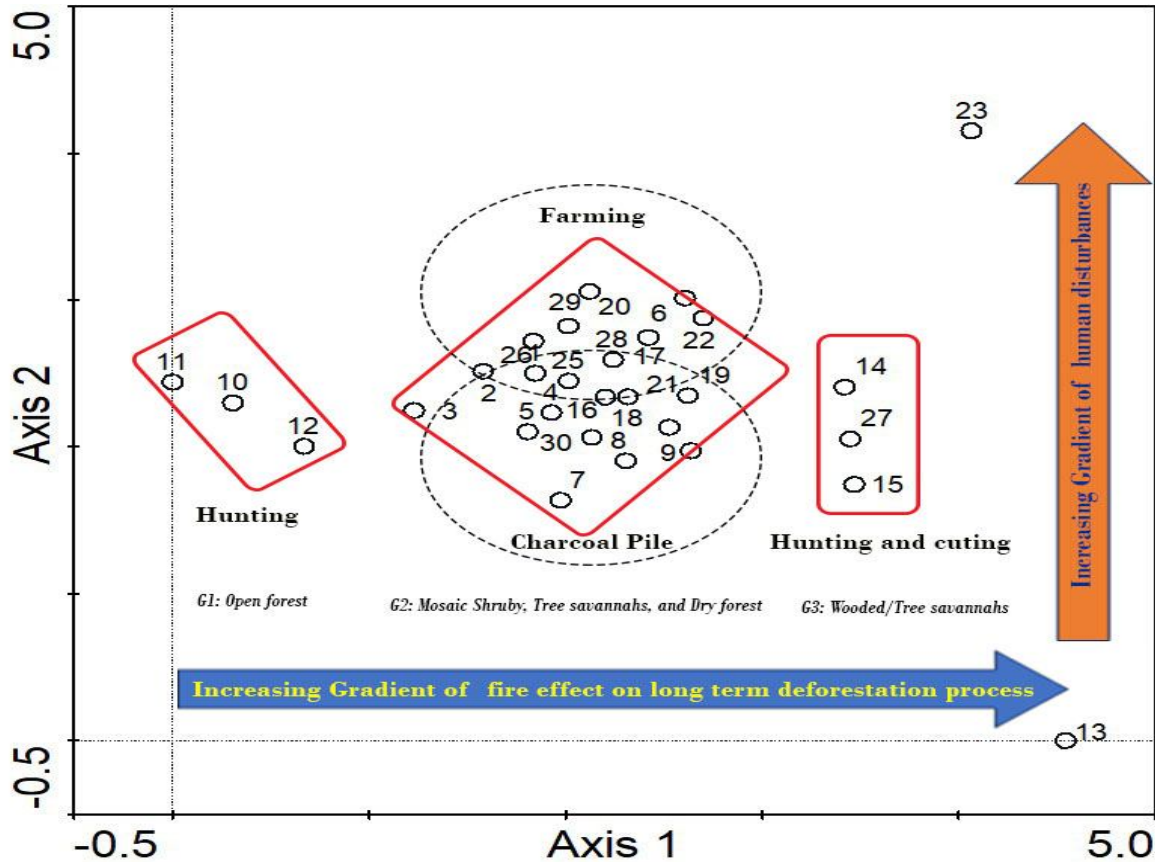
Occurrence
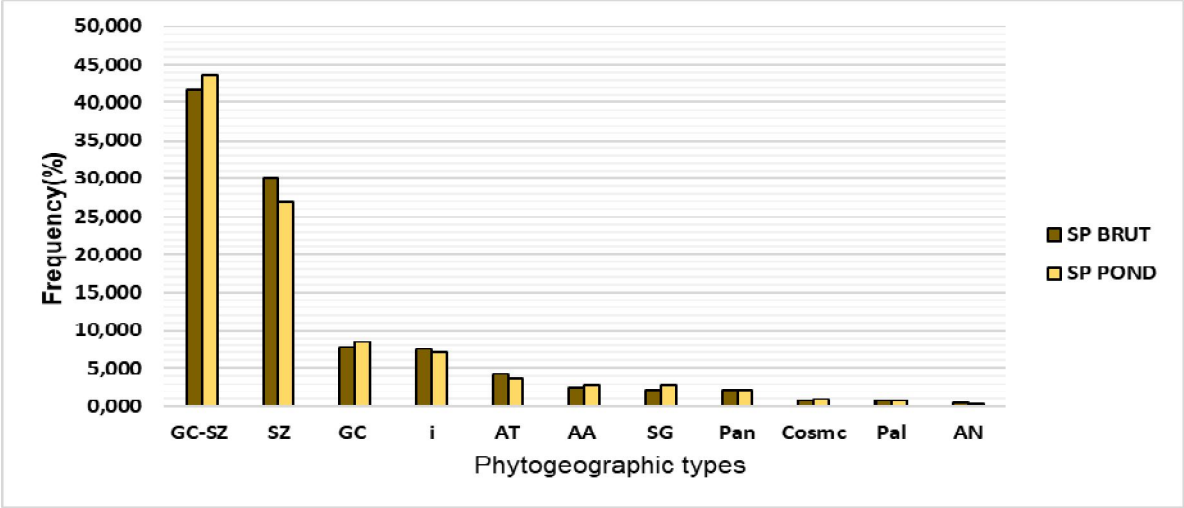
Figure 12: Distribution of Phytogeographic Types in Burned (SP BRUT) and Non-Burned (SP POND) Areas
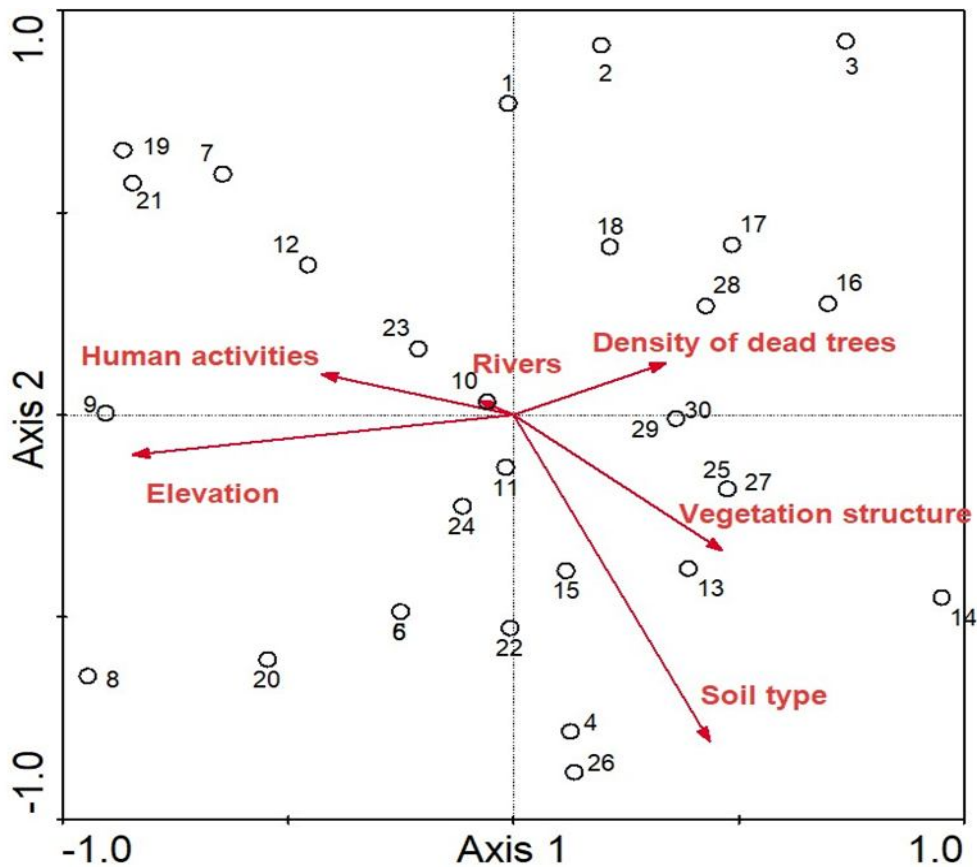
Detrended Correspondence Analysis (DCA)

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,

542 the expansion of agriculture into the riparian zones reduced this buffering effect and allowed
543 the fires to penetrate previously fire-protected areas. The soil type was also a determining
544 factor in the fire response; sandy soils were more fire-prone, supporting fire-adapted
545 species, and clay-loamy soils sustained fewer fires, sustaining the less fire-tolerant species.
546

547
548 *Figure 13: Detrended Correspondence Analysis (DCA) of Plant Communities and*
549 *Disturbance*

Figure 14: Canonical Correspondence Analysis (CCA) of Environmental Variables and Species Distribution

**Fire Occurrence and Susceptibility in Relation to Water Bodies Northern Ghana**

The spatial distribution of wildfire occurrences and vulnerability in Northern Ghana reveals a high level of congruence between high-fire areas and important river networks.

(Figure 15) showed how water bodies are exposed to wildfires as a primary ecosystem service,most noticeably in regions with high human activity in terms of settlements and agricultural activity. Areas closer to water bodies (darker blue) show fewer fire occurrences, while areas farther away (lighter blue) indicate a high number of fires.This observation suggests that fires are not randomly distributed but rather strongly associated with land use near water bodies

A look at Figure (16) revealedthat 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. While rivers are generally perceived as natural firebreaks, this spatial trend indicates that riparian areas may, in fact, contribute to fire dynamics rather than prevent them. The flammability of riparian vegetation, particularly during the dry season, plays a key role in this phenomenon. Riverbanks often support dense

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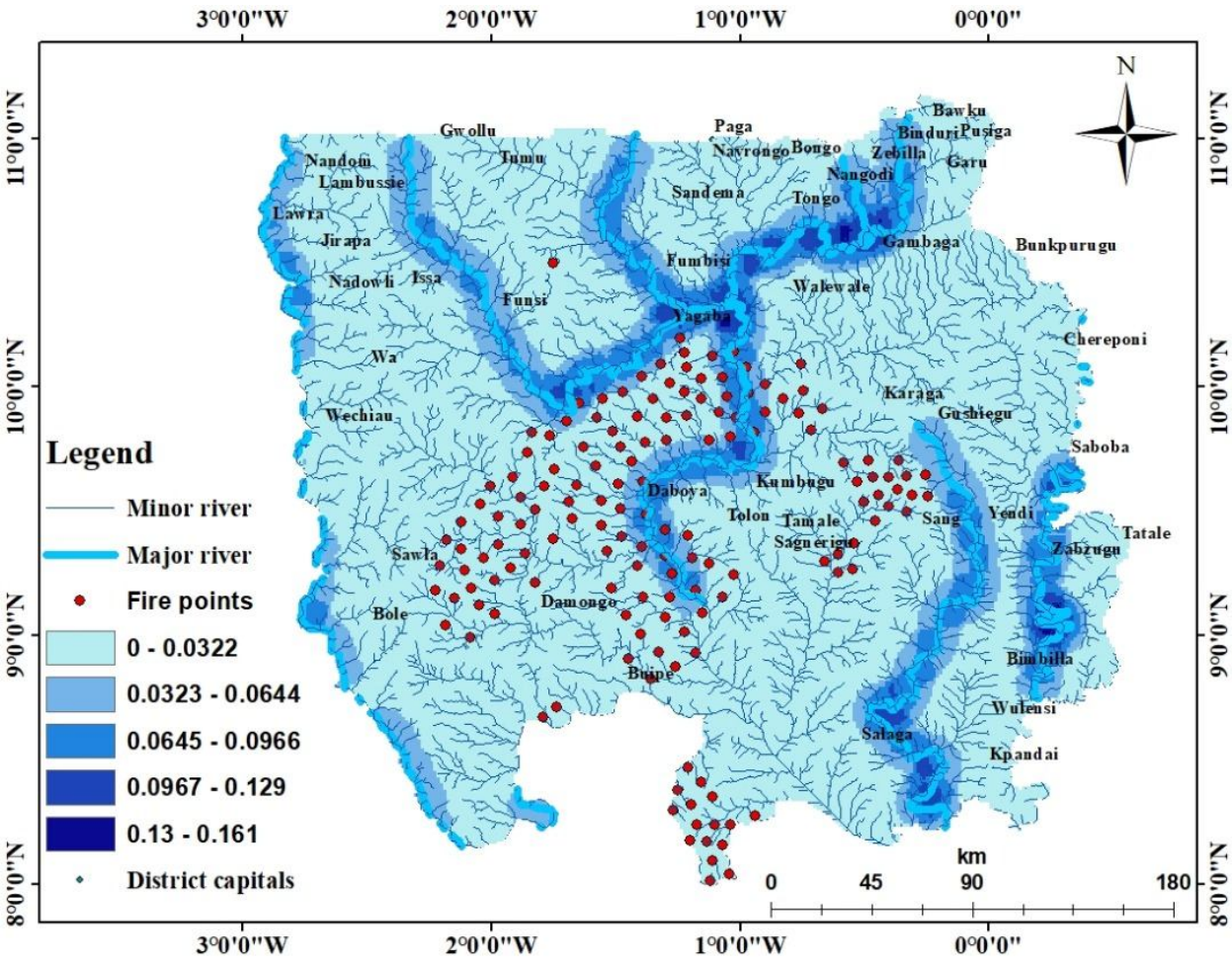
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575
576   *Figure 15: The distribution of fire points within the river network*
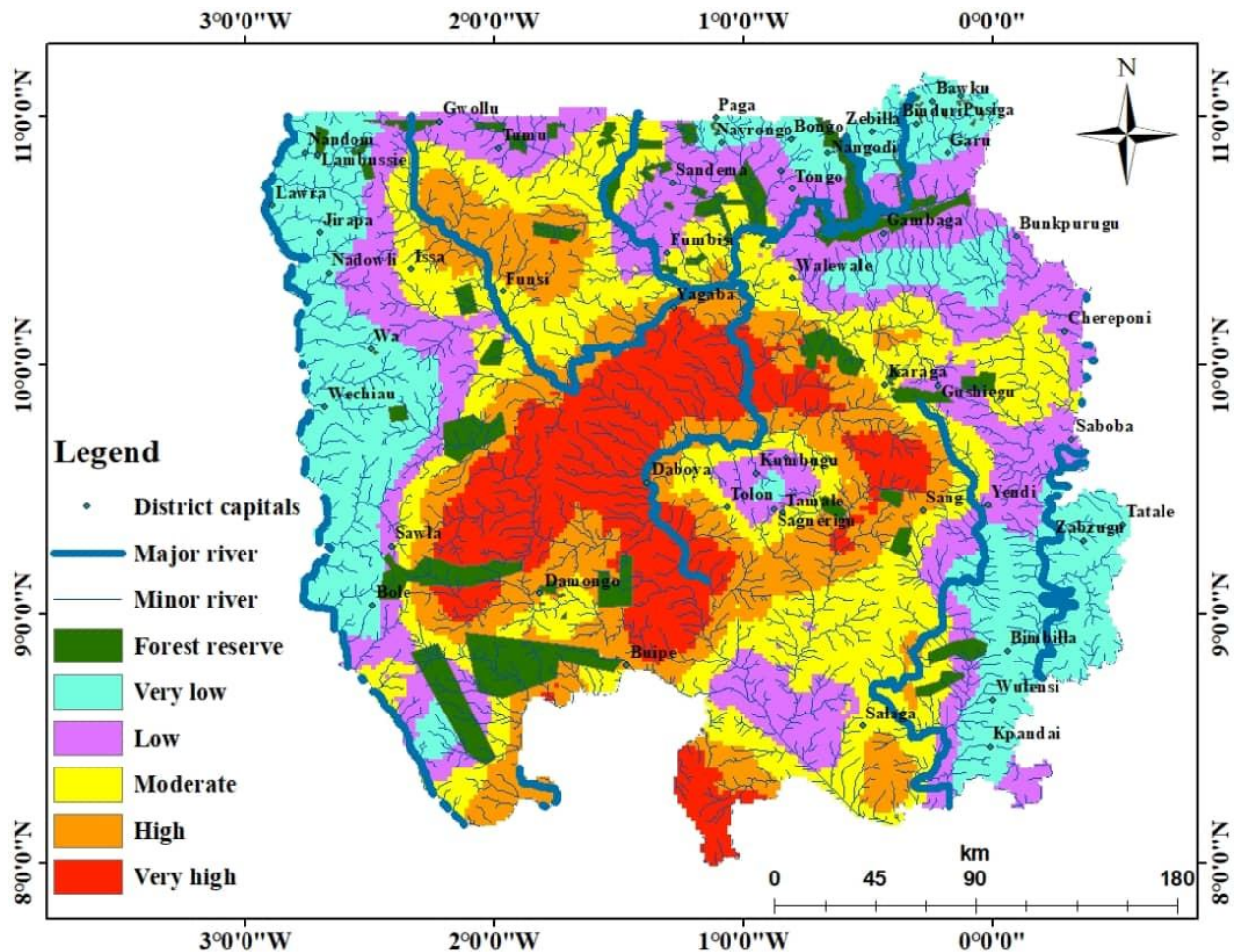
Figure 16: Wildfire Susceptibility Map of Northern Ghana: Depicting the varying levels of fire risk across the region, categorized from very low to very high susceptibility, with major rivers, minor rivers, and forest reserves marked for reference."

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).

599 Besides, the Producer's Accuracy (PA) and User's Accuracy (UA) were perfect for all the
600 land cover types, demonstrating the model's high performance in precisely representing and
601 capturing the land cover classes. The ability of the model to distinguish between
602 Shrubby/Woody Savannah and Agroforestry Parks is fundamental for understanding the
603 effects of fire, even though the NDVI values are similar, as stated by (Pettorelli et al., 2005).
604 The study observed changes in land cover classes between 2001 and 2022, with a reduction
605 in forest cover, indicating the impact of wildfires and human activities. These findings confirm
606 Hoffmann et al. (2012), who noted that remote sensing is an ideal methodology for
607 monitoring vegetation change in fire-impacted areas. It further iterates that remote sensing
608 effectively identifies fire-prone areas to inform fire management strategies. The accuracy of
609 such classifications is vital for urban planning wildfire vulnerability and risk mitigation in
610 areas with increasing human settlements (Roy et al., 2008; Giglio & Roy, 2020). Overall, the
611 studydemonstrates the reliability of MODIS NDVI for monitoring vegetation changes and
612 supports its application in fire management and land use planning to conserve savannah
613 ecosystems in Northern Ghana.
614
615 **Land Use and Land Cover (LULC) Changes**
616 Some of the transitions observed between land cover classes in the northern savannah of
617 Ghana are the outright decline in forest cover and the increase in shrubby/woody savannah
618 and agroforestry areas. Significantly, this study recorded a reduction in the forest cover from
619 2001 to 2022 due to recurring wildfires and increased human activities leading to the
620 expansion of agricultural lands and settlements. The trend of forest decline agrees with other
621 works, such as (Kalfas et al., 2024), who also reported that fire and land use changes
622 negatively affect similar environmental forest ecosystems. An increase in shrubby/woody
623 savannah and agroforestry classes represents a change in vegetation structure with relevant
624 implications for biodiversity and ecosystem services. Shrubby savannahs, due to repeated
625 fires and deteriorated lands, typically support fewer species than forests. This shift might
626 reduce species that rely on dense forest habitats for their existence, further threatening the
627 region's biodiversity. Petermann and Buzhdygan (2021) observed similar patterns, with fire-
628 dominated grassland ecosystems leading to much-simplified vegetation structures with
629 reduced biodiversity. Further, the shift from forest to shrubby savannah has implications for
630 other ecosystem services, such as carbon sequestration. Forests are essential in
631 sequestering CO_2, which causes global warming and climate change. When forest
632 composition is reduced, the region's potential for carbon storage is significantly reduced.
633 Pettorelli et al. (2005) noted that high-density fire events and changes in land cover,
634 particularly in dense forests, lead to carbon emissions and increased climate change effects.
635 In contrast, the increase in the agroforestry areas is evidence of increased agricultural
636 activities, possibly encouraged by increased demand for food and challenging economic
637 situations. Besides that, improved soil fertility and sources of income for villagers could be
638 some positive impacts caused by agroforestry systems. Nevertheless, these developments
639 also mean increased tension on land resources, accelerating soil degradation and a drop in
640 long-term agricultural productivity. Studies by Yaro (2008) indicated that agricultural land
641 expansion at unsustainable levels in savannah ecosystems may cause soil fertility loss and
642 threaten future agricultural output and food security. The observed land transitions indicate
643 trade-offs between the changes in land use and ecosystem services. This reduction in forest
644 cover will inadvertently reduce water regulation and biodiversity conservation. At the same
645 time, the increase in agroforestry areas could improve agricultural productivity in the short
646 term but at the cost of ecosystem resilience in the longer term. Boateng (2017) stated that a
647 proper balance between land use demands and the preservation of ecosystem services is
648 crucial for environmental sustainability and agricultural productivity. Changes in land cover
649 indicate that fire management and land use planning should go hand in hand to protect the
650 remaining forests and support sustainable agricultural practices. This agroforestry area can
651 continue supporting biodiversity and agricultural productivity with minimum negative impacts

652 on ecosystem services through a balanced agriculture expansion and conservation
653 approach.
654
655 **Fire Hotspots and Vegetation Dynamics**:
656 Spatial distribution showed that fire occurrences in the northern savannahs of Ghana were
657 highly concentrated in rangeland and vegetation areas, especially around human settlement
658 areas. This trend is highly related to land use activities like livestock grazing, agriculture, and
659 land clearing. Similar findings by (Croker et al., 2023) highlight that these two practices,
660 grazing and traditional farming methods, contribute significantly to fire occurrences in the
661 savannah ecosystem. Fire is a land management tool used in rangelands. However, under
662 repeated fires, vegetation degrades and may convert dense forests to shrubby savannahs or
663 grasslands with biodiversity losses and carbon sequestration (Bond & Keeley, 2005).
664 Agricultural expansion and urbanisation in most areas have led to highly concentrated fire
665 activity around human settlements. Land clearing for farms and buildings increases the
666 tendency for fires to occur, forming a clustered distribution pattern around human settlement
667 areas as Laris, (2002) states. Climate conditions such as the extensive dry season and
668 Harmattan winds also tend to enhance fire activity, as observed by Owusu and Waylen,
669 (2013). Dry seasons increase the flammability of vegetation and promote incidents of fire.
670 Fire incidents occurring closer to water bodies are also ecologically relevant, as water bodies
671 tend to create natural firebreaks and are typically unaffected. According to (Swaine, 1992),
672 the encroachment of agriculture into riparian zones can compromise this natural buffer and
673 allow fires to spread into previously protected areas. Fewer fire incidents around significant
674 water bodies were recorded due in part to moisture content; however, human activities can
675 alter this protective dynamic.
676 Fire impacts on vegetation recovery and degradation are complex. While regenerative fire is
677 essential in fire-prone ecosystems like the northern savannah, frequent anthropogenic fires
678 prevent full vegetation recovery and create conditions for long-term degradation. Hoffmann
679 et al. (2012) noted that fire frequency changes species composition by favouring fire-tolerant
680 species at the expense of fire-sensitive ones. Over the last two decades, the frequent fire
681 disturbances in rangeland have increasingly led to forest loss in the study area, following the
682 global trends of reduced ecosystem resilience to frequent fire disturbances (Pettorelli et al.,
683 2005).
684
685 **Fire and Vegetation Dynamics: Species Composition, Ecological Gradients, and**
686 **Environmental Factors**
687 The phytogeographic analysis and the species composition in the northern savannah
688 indicate that fire-tolerant species, such as *Vitellaria paradoxa* (shea), *Parkiabiglobosa*
689 (dawadawa), and *Diospyros mespiliformis* proliferate under fire-prone conditions due to their
690 adaptive attributes of thick bark, deep roots, and resultant sprouting. These species thrive in
691 the savannah fire regime, exacerbated by natural causes and human land clearing and
692 agriculture activities. In support, Bond & Keeley (2005) noted that fire-adapted species
693 possess specific characteristics that allow them to survive frequent disturbances caused
694 by fire in savannahs. This is due to their ecological adaptations, which give them an
695 advantage over fire-sensitive species. Hoffmann et al. (2012) mentioned that eliminating the
696 fire-sensitive species from fire-prone landscapes results in the floristic composition shift in
697 this savannah.
698 The Detrended Correspondence Analysis (DCA) identified three main vegetation groups
699 along the fire and deforestation gradients: the Open Forest Group, the Mosaic of
700 Shrubby/Tree Savannah and Dry Forest, and the Wooded/Tree Savannahs. The Open
701 Forest Group includes fire-sensitive pioneer species that happen to survive in low
702 frequencies of fires but have been declining with the rise and increasing frequency of fires.
703 As explained by Pettorelli et al. (2005), fire-sensitive species are usually confined to fire-
704 protected areas. The Mosaic of Shrubby/Tree Savannah and Dry Forest is a transitional

705 ecosystem with coexisting fire-tolerant and fire-sensitive species. However, the domination
706 of fire-tolerant species increases with increasing disturbance due to fires. Wooded/Tree
707 Savannahs were dominated by fire-tolerant species that can withstand frequent and intense
708 fires, and their domination increased with increasing fire intensity. According to Bond and
709 Keeley (2005), fire regulates the relative dominance between woody and herbaceous
710 vegetation in savannahs.
711 Canonical Correspondence Analysis (CCA) revealed that environmental variables like
712 elevation, distance to water, and soil type are significant in explaining fire regimes within the
713 northern savannahs, which agrees with global observations. For example, Pettorelli et al.
714 (2005) assess that fire frequencies tend to be lower at high elevations because of reduced
715 human activities and sometimes microclimatic conditions. Human activities and expansion of
716 agriculture in lower elevations and riparian zones thus foster fire risk in fire-prone regions
717 such as California and Australia. Another essential factor influencing fire frequency concerns
718 soil type: the sandier the soils, the quicker they dry out, and hence, the more frequent the
719 fires occur in Australia and parts of Southern Africa (Bradstock et al., 2012). This interaction
720 between fire intensity, human disturbances, and these other environmental factors improves
721 the performance of fire-tolerant species at the expense of fire-sensitive species. This more
722 general pattern has implications for biodiversity and ecosystem services. In summary, these
723 patterns underscore how fire management strategies must be tailored analogously to
724 account for human and environmental drivers of fire risk. These patterns underscore the
725 need for tailored fire management strategies that account for both human and environmental
726 drivers of fires.
727
728
729 **Fire-Induced Vulnerability of Ecosystems in Ghana's Northern Savannah zone**
730 From the spatial relation between wildfires and water bodies in the savannah ecosystems of
731 Northern Ghana, an inverse correlation may be seen in that areas closer to water bodies
732 have fewer incidences of fire. Water bodies can be considered a natural firebreak, which
733 limits the number of wildfire occurrences within their surroundings with reduced intensity of
734 the wildfires. This also calls for the conservation of water bodies, as they serve a vital
735 function in mitigating fire risks and protecting the surrounding ecosystem. Other studies have
736 identified that not only rivers and lakes provide a natural barrier against wildfire but have
737 again raised calls for these bodies of water to be treated in a conservation effort with
738 intensified fire mitigation. (Caroni et al., 2024; Kraaij et al., 2013).
739 The vulnerabilitymap identifies the classes of the area by wildfireexposure. It shows that the
740 areas of very high vulnerability, such as forest preserves and major rivers, have extreme
741 threats to key ecosystems, including water supply and agricultural productivity. Wildfires can
742 seriously degrade ecosystems by reducing water quality and affecting vegetation dynamics
743 and biodiversity. Because of the proximity to fire-prone zones, high-vulnerability areas
744 usually associated with human activities like agriculture are highly vulnerable. Land-use
745 change increases wildfire vulnerability and enhances ecosystem degradation, similar to what
746 is recorded in other analyses of fire-prone ecosystems.
747 Moderate-vulnerability areas represent potential for resilience since these zones are less
748 exposed to the most severe wildfire risks and thus may have greater capacity to recover and
749 adapt. In this regard, implementing adaptive management practices, such as community-
750 based fire management and sustainable land-use strategies, may reduce vulnerability in
751 these regions. Local knowledge in rural savannahs globally has been critical in implementing
752 effective fire mitigation, thereby improving resilience with community fire management. Other
753 ways include implementing more fire-resistant agroforestry systems to reduce the incidence
754 of wildfire spread and maintaining ecosystem functionality for productive agriculture.
755 These maps further indicate that areas with high human activities, like agricultural expansion
756 and settlement growth, tend to be highly prone to wildfires. These human-induced pressures,
757 added to natural fire-prone conditions, exacerbate fire risks and degradation of ecosystem

services. Indeed, a study by Jolly et al. (2015) and Bowman et al. (2009) have 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.

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 *Parkiabiglobosa* (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.

AUTHORS' CONTRIBUTIONS

'AMN' designed the study, performed the statistical analysis, wrote the protocol, andwrote the first draft of the manuscript. 'FF' 'DM' WK and BK managed the analyses ofthe study and the literature searches. All authors read and approved the final manuscript."

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