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ASSESSMENT OF POPULATION DYNAMICS AND FOREST COVER CHANGE IN YUMBE DISTRICT, UGANDA

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ABSTRACT

Sub-Saharan Africa is well endowed with both renewable and non-renewable natural resources critical in supporting several forms of development on the continent. Key among these is natural forest resources. However, the population explosion in sub-Saharan Africa in general and Uganda, in particular, is threatening the survival of these forests due to the associated increasing demand for food, fodder, energy, and land for settlement. The study was conducted in Yumbe district where the forests considered included woodland and bushland since tropical high forests have been depleted or degraded by human activities. We used a predictive model to map future forest cover loss amidst the rapidly increasing population in Yumbe district in Uganda. Specifically, the study analyzed the relationship between population dynamics and forest cover change to predict future forest cover changes. To analyze changes in forest cover, the study utilized Landsat satellite imagery for 1990, 2000, 2010, and 2021; while the population data for the respective years was obtained from the Uganda Bureau of Statistics (UBOS). To explain the role of anthropogenic forces on forest cover change, the study considered different land use types as explanatory variables: planted forests, subsistence farmland, built-up areas, and other land use types. It then explored the interactions between these variables and forest cover change in the study area. Population-forest cover change model was developed to evaluate three decades of population and trends of forest cover to predict forest cover for 2032. The results indicate that in the three decades, the population increased by more than sixfold, and land area under subsistence agriculture, a proxy of population increased by 195.2%, but the forest cover declined by 80.3%. It is predicted that the forest cover will be lost completely by 2032 when the population reaches an estimated 838,078 from the current 657,430 people. This study, therefore, recommends that off-land employment opportunities such as tourism, apiary, transport, and manufacturing industries should be expanded in order to save forest resources from spatially extensive agricultural land uses.

Key words: Forest, Forest cover loss, Predictive modeling, Population dynamics, Land use

INTRODUCTION

Population explosion in sub-Saharan Africa (SSA) is threatening natural forests [1, 2]. Population statistics indicate that the population of the region has been increasing steadily. As a result, over the next 80 years, more than three-quarters of the world's population growth is expected to occur in SSA, where the population is projected to double by 2050 and almost quadruple by 2100 [3]. This will exert immense pressure on forest resources. It is practically impossible to give a universally accepted definition of a forest. A forest is a type of vegetation dominated by trees that are tall at maturity, should have a tree cover of at least 20% or more and the area should not be less than 0.5 ha in size [4]. Food and Agricultural Organization defines "forest land" as land spanning more than 0.5 hectares with trees higher than 5 meters, a canopy cover of more than ten percent, or trees able to reach these thresholds in situ [5, 2]. Several scholars contend that forest lands are important because they contain about two-thirds of the world's biodiversity [6, 7]. They provide a full suite of goods and services vital to humans and the ecosystem, often termed ecosystem services [9, 8].

A significant proportion of SSA's population including Yumbe district rely on these goods and services for food, fuel, herbal medicine, construction materials, and recreation [10, 11]. In addition, forests store carbon, preserve soil and nurture a diversity of floral and faunal species. In light of population changes, and the need to protect the forest for their sustained supply of both environmental and economic need, a combination of interventions from natural resource managers are vital. One such intervention is predictive modeling of the population dynamics and their implications on the spatial extent of natural forests. Several attempts have been put in place to aid predictive modeling to protect natural forests, and one of them is using remotely sensed data.

Remote sensing in particular is a valuable tool for forest-cover assessment, monitoring, and status prediction especially in developed nations [12, 13, 14]. Due to this progress, since the 1990s, there has been a dramatic decline in net forest cover loss and wildlife populations, particularly in nations that have embraced such advanced management techniques [8]. Nevertheless, despite these achievements, a growing human population has put too much pressure on forests in humid areas [16]. Demand for forest products and new agricultural land has significantly increased following rapid population growth. It has resulted in the encroachment of fragile forest ecosystems. Extensive resource extraction techniques like tropical logging, and mining, as well as large-scale commercial agriculture where the forest is replaced by pasture or crops, like the infamous Jari project in Brazil, fall under

this category [2]. As a result, more than 90 percent of deforestation in the last three decades (1990-2020) was in the tropical domain and the highest annual deforestation rate in 2015-2020 was in Africa (4.41 million ha.), followed by Latin America [2, 8]. The extent to which the above observation is true of Yumbe district is not yet known.

Forest Ecosystems and Forest Cover Loss

Forests are complex ecological systems [9, 8] and include all alpine, tropical high and medium-altitude forests, wetland and riparian forests, plantations, and trees, on public or private land [17]. Forest ecosystems are both a stand-level and a landscape phenomenon characterised by periodic disturbances critical in the maintenance of their historical character and values. As long as the mechanisms of the forest ecosystem continue to function normally, short-term changes in the forest's structure do not amount to a loss of the forest [18]. Since the 1980s, natural resource dynamics have prompted many researchers and resource managers to concentrate on woodland and grassland mosaics, which have substantial tree cover and make up a significant portion of Sub-Saharan Africa, South America, Oceania, and other parts of the world, rather than "real" forests [11]. A forest has a canopy cover of more than 10 percent while woodland has a canopy cover of 5-10 percent, implying forests have more denser tree cover [8]. Consequently, in discussing the status of forest resources, woodlands are often included because many forests have extensive areas of woodland that provide similar goods and services as "real" forests [19]. Additionally, tree cover in grasslands and woodlands may increase because of dynamics in man-environment interaction, leading to the transformation of woodlands into "real" forests [18]. Thus, woodland and bushland have been categorized as forests in this study.

Predictive Modeling Operations

Predictive modeling is a statistical procedure used to predict future events or outcomes by analysing patterns in a given set of historical data [20]. At the global, regional, national, and local levels, it has been widely utilised to forecast changes in forest cover at both temporal and spatial scales. The model has shown success throughout the world, as evidenced by studies by Pahai & Murai [21], Heubes *et al.* [22] and Ishamael *et al.* [23]. However, the exclusive focus on formal models does not imply that these models are necessarily more useful or more accurate than informal studies based solely on descriptive studies [20]. This study borrows from the linear regression model to establish whether population growth was correlated to forest cover loss or not. This method has been chosen because of the lines of "best fit" whose equations have been used in the prediction. Understanding the

patterns of forest cover loss owing to population dynamics and putting appropriate management policies in place to prevent such a loss is essential given the significant role forests play in protecting and sustaining biodiversity, ecosystem services, and human livelihoods [13]. Much as it is assumed that human impact will substantially affect the forest ecosystems in sub-Saharan Africa, there are only a few studies that have been conducted to assess the future impact of human population growth on forest cover change (FCC) in Uganda [22]. Predictive modeling has become a crucial tool in this situation for examining unknowable future conditions of the Earth's forest ecosystem.

Several theories have evolved to explain the relationship between population growth and natural resources. For instance, according to Malthusian theory, population growth exerts pressure on forests resulting in population outstripping available forest resources [23, 24]. Inspired by the works of Malthus, Charles Darwin derived his theory about the struggle for scarce resources and survival of the fittest [24]. This causal relationship is important because the well-being of about 50 percent of the world's population remains directly dependent on local natural resources [25, 15]. This accounts for the high rate of global deforestation between 2015 and 2020 estimated at 10 million hectares per year [8]. On this, David Pimentel an entomologist at Cornell University highlighted that by 2100 if current trends continue, billions of people will fall into food insecurity trap as an estimated one billion are already chronically food insecure [18].

Studies have been conducted on changes in forest cover in several geographical areas, including Europe, the United States, South America, Asia, Africa, and others [2, 10, 13]. They claim that the expansion of agricultural land due to rapid population growth has been identified as the primary driver of Forest Cover Change (FCC). By the same logic, a rapid population rise seems to have been blamed for Yumbe's dwindling forest cover [1]. Understanding the dynamics and drivers of FCC is essential since it is anticipated that, evaluation and projection of their future status will be crucial to the sustainable management of forest resources-SMFR [7, 14]. The study used a correlative model to examine how human impact will change Forest Cover (FC) patterns in Yumbe district in the future. The following research questions were answered in the study: What are the primary drivers of FCC in the study area? How has the forest cover changed over the past three decades? What patterns of growth and change can be anticipated in the future?

MATERIALS AND METHODS

Study Area

Yumbe district is located in the West Nile sub-region of north-western Uganda (Figure 1). It is bounded by latitudes 3°11'18"N and 3°47'56"N and longitudes 31°02'58"E and 31°31'56"E. It lies in the climatic zone sub-type "Aw"- tropical savanna climate with mean annual rainfall ranging from 1,200-1,400 mm and mean temperature of 24.4°C or 75.9°F [26]. The soils are predominantly ferralitic in nature covering more than 75 percent of the land area [27]. The topography is generally flat with some notable residual hills in the north and several minor ones to the east. By the middle of 2020, there were 663,600 residents [28], approximately 92 percent of them live in rural areas and are primarily engaged in subsistence agriculture [29]. The majority of the streams have a cyclical nature, which reflects the seasonal rainfall regime. Yumbe is generally recognized as a district with huge potential for the conservation of forest resources in Uganda [1, 32].

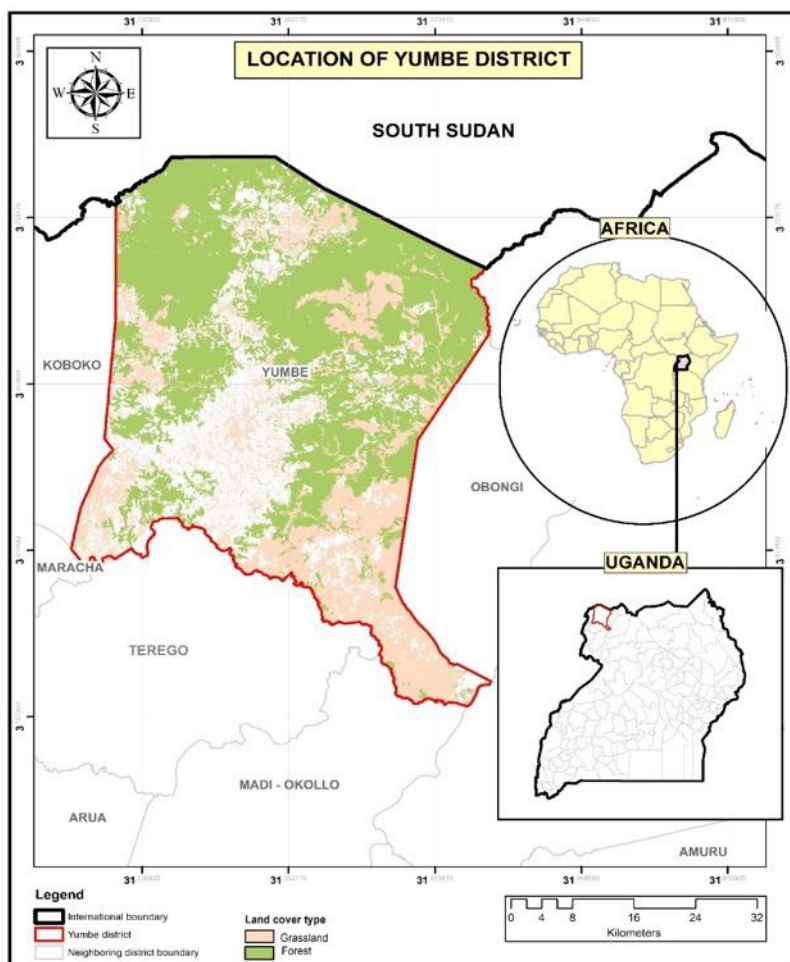


Figure 1: Location of Yumbe district

Due to past local land use practices and natural and man-made disruptions like agriculture, wood fuel, fire, and logging, the district no longer contains tropical forests [1, 20]. The northern part largely covered by Mt. Kei central forest reserve (CFR), is the most forested and has retained a greater portion of tree cover than other parts [32].

Land Use and Land Cover Classification

The National Biomass Study Classification (NBSC) data served as the basis for the classification of land cover employed in this study. The report for Uganda produced by the National Forestry Authority (NFA), details 12 land cover classes that combine land cover and land use [32]. Later, a 13th class was introduced to represent impediments that had previously been categorized under class 11 (Table 1). The classification score is determined by the overall dominating class.

Forest Cover Mapping

The Landsat satellite images for the corresponding years were used to create the land cover maps for 1990, 2000, 2010, and 2021 because the Landsat photos of the Earth's surface have multi-spectral content, are historical, and are of high quality. One mosaicked image of Yumbe district made up of data from multiple Landsat sensors—Landsat 1-3 for 1990, Landsat 4-5 for 2000 and 2010, and Landsat 8 for 2021—were downloaded from <https://sepal.io>. Using the composite algorithm, images with the lowest possible (<10%) cloud cover were chosen for picture composites. The images were classified in ArcGIS 10.5 software using the maximum likelihood algorithm of supervised classification for each colour composite, whereby 13 classes were identified by picking training samples from different parts of the district [33]. The predetermined classes were tropical high forests well stocked or degraded, woodland, bushland, grassland, wetland, subsistence farmland, built-up areas, water and impediment (Table 1). Plantation forests were masked out to meet the requirements of the study. The amount of land used for agriculture, a proxy to population was specifically tracked in order to ascertain the degree to which variations in forest cover were explained by agriculture. This was critical because the largest percentage of the population in the district practiced subsistence farming. Woodlands and bushlands on both public and private land were merged to form natural forests. To validate the classification, ground truthing was carried out using "Collect Earth" and Google historical imagery [12]. This was done on 60 random sites, which were then observed about the 1990, 2000, 2010, and 2021 classified land cover maps.

Validation of the accuracy of both the predicted map and classified outcomes was determined using the Kappa statistic. Kappa being such a measure of "true"

agreement. It indicates the proportion of agreement beyond that expected by chance, that is, the achieved beyond-chance agreement as a proportion of the possible beyond-chance agreement [34]. The Kappa statistic (K) was determined by examining randomly selected points and checking if their classification met the NBSC standards. Equation 1 was then used to compute the significance of the accordance between each of the classifications and predicted outcomes [12]

$$K = \frac{\text{Observed} - \text{Expected}}{1 - \text{Expected}} \dots\dots\dots \text{Equation 1}$$

Where:

Observed = Overall value for percent correct and

Expected = Estimate of the contribution of a chance agreement to the observed percent correct.

The reliability of the computed Kappa statistic for each year of study was determined by the use of a Z score based on Kappa variance using the equation given by Congalton and Green [35].

$$Z = \frac{K}{\sqrt{\text{var}(K)}} \dots\dots\dots \text{Equation 2}$$

Where:

K = kappa statistic

The Kappa coefficient values obtained were 0.61-1990; 0.665-2000; 0.677-2010 and 0.703-2021.

Population Data

The population data used in the study was obtained from the past and projected population figures by the Uganda Bureau of Statistics-UBOS [29, 28]. The actual population figures were for 1990, 2000, and 2010, while the figure for 2021 was population estimate by UBOS, a body officially mandated to produce such data. Whereas, a current population growth rate of more than five percent was used to project the district's population, this rate appeared to be unsustainable and therefore may have affected the results of the model. As a result, ground truthing was done to verify and validate the figures for 2021. In the ground truthing, Mt. Kei CFR was visited to ascertain the extent of population encroachment into forested areas. The results showed several new settlements in areas legally gazetted as forest reserves.



Predictive modeling operations

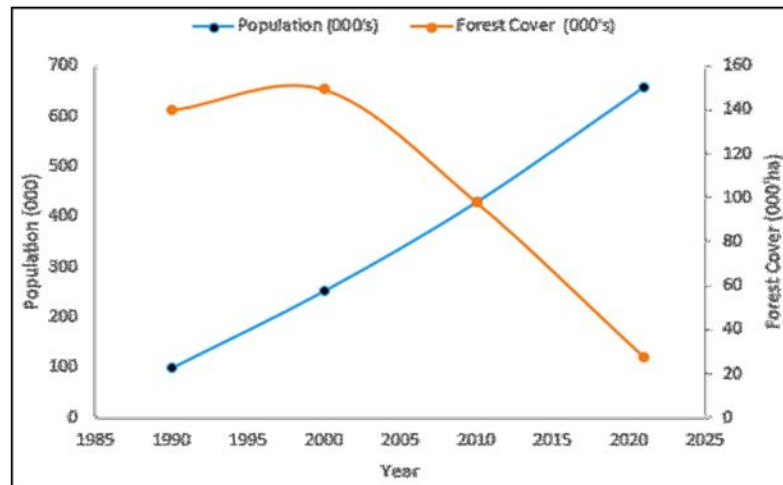
To operationalize the model, three graphs were produced using population and forest cover change data for the years 1990, 2000, 2010, and 2021. The graphs (a) Yumbe district population growth and forest cover change trends for four observations: 1990, 2000, 2010, and 2021; (b) a population graph for Yumbe district from 1990 to 2021; (c) and a graph showing an analysis of Yumbe district population growth and forest cover trends from 1990 to 2021. Lines of best fit were produced by plotting the population and forest cover change values against time for graphs b) and c). Two linear equations were generated using the lines of best fit for graphs b) as $y = 18.01x - 35755$ (equation 3) and for graph c) as $y = -0.2164x + 181.36$ (equation 4). Since the model's linear equations had the potential to yield more precise and accurate results than the graphs, they were preferred to predict the future loss in forest cover. Whereas, equation 3 was used to predict the anticipated year when Yumbe district may no longer have forests, equation 4 was used to predict the estimated population at the time. Statistical significance was tested using regression analysis and two assumptions were made; that is, a linear relationship exists between population growth and forest cover change, and all the variables had normal distributions.

RESULTS AND DISCUSSION

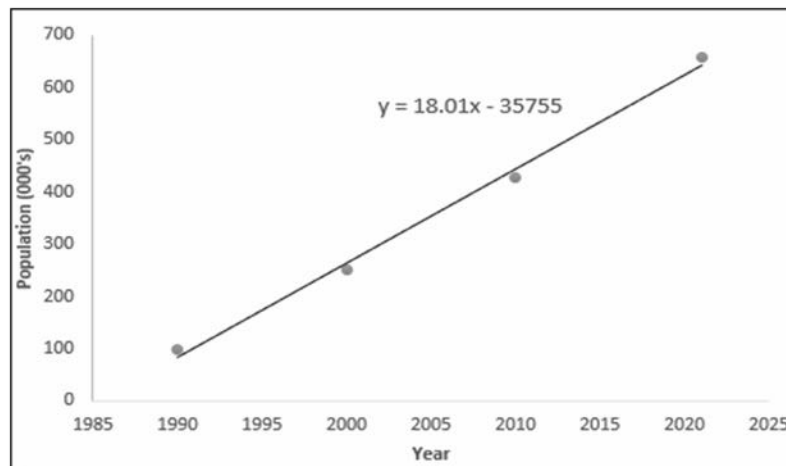
The Forest Cover Change Analysis

The district's forest cover has undergone a great deal of change in time and space. Deforestation rates were typically low in the 1990s, despite the human population more than doubling between 1980 and 1990. This can be explained by the fact that many people had fled to Sudan in the 1980s to escape a civil war and were beginning to return from exile. The aftermath of this period witnessed a drastic decline in natural forest cover by 80.33% (Table 2 and Figures 2a, and 2c). From the land use and land cover matrix in Tables 3 and 4, natural forests (tropical high forest well-stocked, woodland, and bushland) made up 58.1% of the total land area in 1990; but reduced to 11.4% in 2021. With a tree cover of 62.3%, the period 1990-2000 appears to have been the forest cover climax in the three decades.

a)



b)



c)

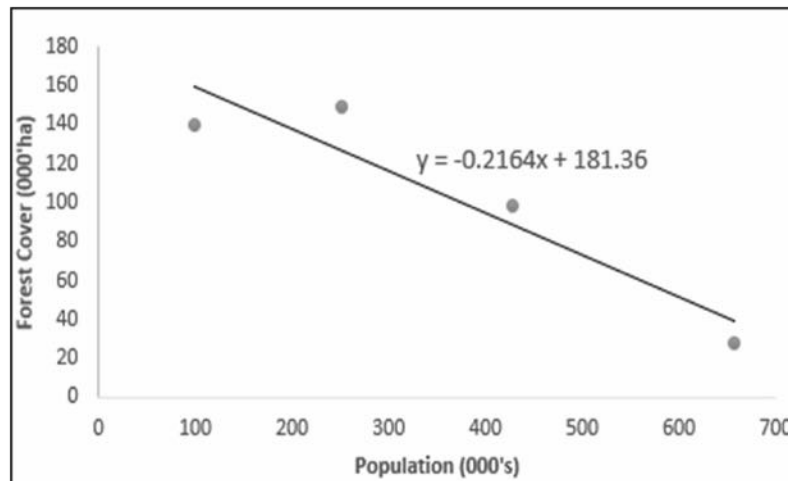


Figure 2a: Historical trends of population growth and forest cover in Yumbe district for four observations, 1990,2000,2010 and 2021; b) Population growth curve for 1990-2021; c) Analysis of historical trends of population growth and forest cover loss in Yumbe 1990-2021

By 2010, tropical high forests well stocked and degraded had been completely wiped out. The largest shift in tree cover was noted in the woodland; it declined by 81.3%. In 1990, it covered 57.8% of the land area but reduced to 10.8% in 2021. The biggest percentage decline occurred between 2000 and 2010, at 75.36%.

The examination of forest cover trends revealed that this region is under serious threat from deforestation as an estimated 3,600 ha of forest land was lost annually in the last three decades. The relationship illustrated was statistically significant. Though weak, R-square equals 0.878; implying that population growth accounts for 87.8% of the changes in forest cover loss. The remaining percentage is explained by other variables. The model confirms that human population dynamics correlates with the geographic distribution and variations in tree cover at the scale seen in the study. Subsistence farmland continues to expand northward into public and private or communal forests. Mt. Kei Central Forest Reserve (CFR) in the north has been significantly impacted by this shift. The replacement of natural forests by subsistence agriculture is consistent with findings by [5, 36, 8], who correlated forest cover decline to population growth. According to the model, this pattern can be produced by human population influence alone since the use of different predictor variables frequently makes it difficult to compare modeling results from various studies [13]. The findings also revealed that there is no significant change in grassland, implying that people were probably seeking fresh farmland from the forest with reasonably high initial yields.

However, given that Uganda's current deforestation rate is strongly linked to population growth [4, 32], it is predicted that the forest cover will continue to shrink or fragment as a result of changing patterns of human activity. It is also vital to keep in mind that the region's predicted population appears to be significantly affecting the forest resources, particularly in the west, south, and east leaving the CFR in the north vulnerable which supports the findings of the model of loss of forest cover.

Major Drivers of Forest Cover Change in the Study Area

According to land use and land cover change data for Yumbe district, the loss in natural forest cover in the past three decades has been driven by one key population-related factor, agriculture. This is in line with the findings in Ethiopia [36]; Brazil [7], and the Central African Republic [10]. The most prevalent human activity and land use during this time was subsistence agriculture, which saw an overall increase of 195.2%. For instance, only 23.7% of the land area was used for subsistence farming in 1990; by 2021, it increased to 69.9%. The period between

2010 and 2021 saw the largest increase, of 63.5%, suggesting that as the population grew, so did the demand for new farmland. Along with subsistence farming, urbanization a proxy for population saw an enormous surge in urban land usage from 1990 to the present, representing an increase of almost 188 times or 18,137.4%. For instance, the proportion of land covered by built-up areas increased from 0.002 percent in 1990 to 0.4 percent in 2021. Most of this was realised between 2000 and 2010.

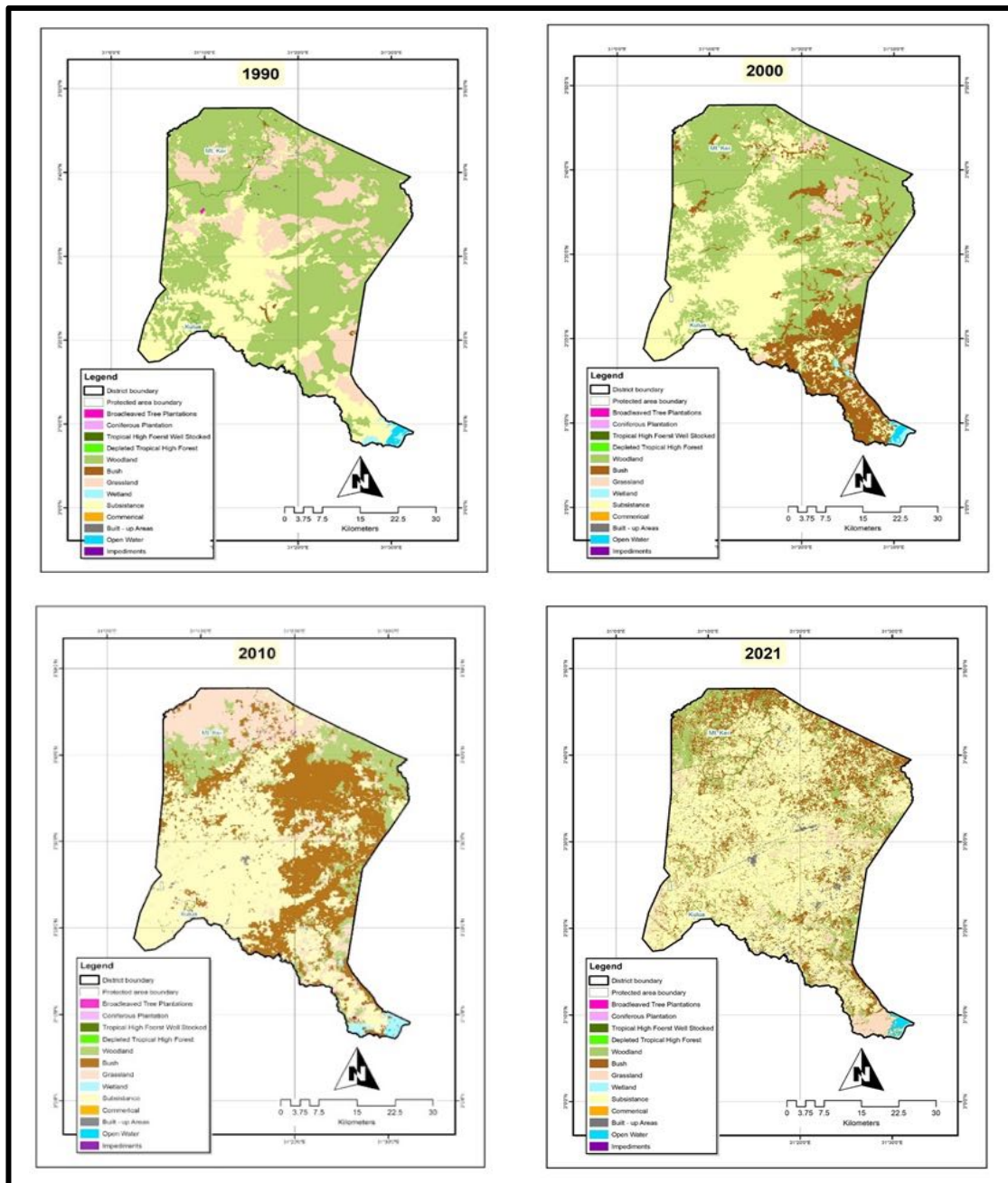


Figure 3: Yumbe district forest cover and forest cover change 1990, 2000, 2010 and 2021

In describing future changes in forest cover, emphasis was put on the significance of taking into account at least ten percent tree canopy for a forest as recommended by FAO [15] rather than just presence. The “real forest cover” was modeled as opposed to potential forest cover using satellite images that depicted the historical status of the forest cover. According to earlier case studies in Kenya [37] and West Africa [22], human activity has a detrimental impact on forest cover similar to the findings on the maps generated (Figure 3). However, using human population variables as a standard for human environment impact assessment, encompasses a wide range of human endeavors, making it almost impossible to pinpoint the primary factors behind changes in forest cover. In Yumbe district, the expansion of subsistence farmland is a major cause of forest degradation and loss, with the aid of other human endeavours like the harvest of woodfuel.

Because so many people were still living in exile in Sudan after president Idd Amin was overthrown in 1979, the comparatively low population from 1990–2000 may have contributed to the increase in forest cover. Similarly, the local rebellion thereafter occurred at a time when people were in exile or had just returned. Many were unable to venture into remote areas for security reasons. As a result, the forest resources remained mostly undisturbed. However, this contrasts other findings that political upheaval in the Kivu area of the Democratic Republic of Congo was to blame for the country's extensive deforestation in the late 1990s and 2000s [13].

In the north and east, there was a trend of the emergence of bushland. This seems to indicate either internal changes or a reduction in the intensity of human efforts, such as shifting cultivation or rotational bush fallowing. For example, there has been migration from the district's densely inhabited areas and beyond to the less populated regions to the north and northeast. As a result, both gazetted and ungazetted forest resources in these regions have been severely degraded to farmland. This is consistent with the findings that deforestation in areas close to the Budongo forest reserve was brought by the immigration of people into the sub-region as a result of a lack of arable and grazing land in densely populated areas across the country [17, 32].

The demand for wood fuel has increased as a result of the rapid increase in population within and without the district. The predominance of biomass as energy appears to have created a significant challenge to the management of forest resources [1, 38]. In recent years, the situation has been compounded further by high levels of poverty that have led to a significant increase in charcoal production,

to meet the energy demands of the urban population [39]. Fuelwood accounts for more than 96% and nearly 100% of domestic energy needs in most households in the district [29, 28]. This has significantly contributed to the loss of forest cover and the extinction of some valuable tree species. In addition, logging may have contributed to the decline in forest cover but may not be a good predictor of forest cover change in the study area because the tropical high forests have been long-degraded to woodland, and bushland.

The results also demonstrate that the forest cover gain is still hypothetical. It seems that the decreasing tendency in the reduction of forest cover is a concerning trend. Even in the implausible scenario of a steady population, this should be a cause for concern. To minimise the loss, immediate action is required. This certainly gives an underestimating of future forest cover loss, which might start the desertification process, given the district's present population growth rate of more than five percent [29].

Future Changes in Forest Cover in Yumbe District

It was discovered that with the current rate of population growth, the district's forest cover is expected to be completely wiped out by around 2032 when the total population is expected to reach about 838,078. Increasing population simply means increasing demand for food, shelter, energy, herbal medicine, and other needs. The provision of more of the above goods and services requires more space, hence encroachment into forest resources. However, this crisis may be avoided, if the population pressure is reduced through birth control or human activities that have a spatial extensification which are regulated by providing alternative activities that are not entirely land-based.

CONCLUSION

The study focused on the role of population dynamics and how it influences other land uses and types of land cover to impact the district's deforestation rate. Although the model may have exaggerated the severity of the problem, considering population dynamics alone reveals an interesting insight into prospective forest cover changes. The models' analysis of the human influence revealed that subsistence agriculture as a proxy of population growth significantly impacted the loss in forest cover in the last three decades. With the current trend, it appears population may continue to be a key factor in predicting future gains and losses in Yumbe district's forest cover. Indeed, serious measures ought to be taken to save the forest cover from being completely lost by 2032. The study, therefore,

recommends expansion into off-land employment opportunities to save the situation.

Table 1: The National Biomass Study Classification

Class	Land cover and Land use
1	Plantations and woodlots – deciduous trees/broadleaves (“hardwood”)
2	Plantations and woodlots – coniferous trees
3	Tropical High Forest (THF) – normally Stocked
4	Tropical High Forest (THF) – depleted/encroached
5	Woodland – trees, and shrubs (average height > 4m)
6	Bushland - bush, thickets, scrub (average height < 4m)
7	Grassland – rangelands, pastureland, open Savannah; May include scattered trees shrubs, scrubs, and thickets.
8	Wetlands – wetland vegetation; swamp areas, papyrus, and other sedges
9	Subsistence farmland – mixed farmland, small holdings in use or recently used, with or without trees
10	Uniform commercial farmland – mono-cropped, non-seasonal farmland usually without any trees for example tea and sugar estates
11	Built-up area – Urban or rural built-up areas
12	Open water – Lakes, rivers and, ponds.
13	Impediments (bare rocks and soils)

Source: National Biomass Study: Technical Report of 1996-2002

Table 2: Population-Forest Cover Statistics for Yumbe 1990-2021

Year	Population (000's)	Forest Cover (000 ha.)
1990	99,000	139.8
2000	251,700	149.3
2010	428,500	98.0
2021	657,430	27.8

Source: Uganda Bureau of Statistics and National Forestry Authority

Table 3: Transition Matrix for Land Use Land Cover Types in Yumbe 1990-2021

S/ N	Land Cover Type	1990	2000	2010	2021
1	Plantation broad-leaved	85.23	10.17	84.6	49.9
2	Plantation coniferous	49.32	49.32	81.12	7.89
	Subtotal for plantation forests	134.55	59.49	165.72	57.79
3	Tropical high forest well stocked	3.06			
4	Tropical high forest degraded		5.13		
5	Woodland	138,937.50	116,115.60	28,606.18	25,974.70
6	Bushland	638.37	33,507.27	70,029.43	1,485.11
	Subtotal for natural forests	139,578.93	149,628.00	98,635.61	27,459.81
7	Grassland	41,171.76	9,437.40	35,630.51	41,217.00
8	Wetland	1,356.57	1,411.68	2,439.70	2,172.51
9	Subsistence farmland	56,853.81	78,902.38	102,642.60	167,835.00
10	Built-up areas	5.13	7.25	492.81	935.58
11	Water	1,000.08	726.48	121.01	454.61
12	Impediment	71.82		44.71	40.35
	Total	240,172.56	240,172.68	240,172.72	240,172.65

Natural Forests

Source: Landsat satellite images for Yumbe district-1990, 2000, 2010 and 2021

Table 4: Percentage Change in Land Use Land Cover Change for Yumbe 1990 - 2021

	Land Cover Type	1990	2000	2010	2021	Total % Change
1	Plantation broad-leaved	0.04	0.004	0.035	0.02	-41.45
2	Plantation coniferous	0.02	0.02	0.03	0.003	-84
	Subtotal for Plantation Forests					-57.05
3	Tropical high forest well stocked	0.001				
4	Tropical high forest degraded		0.002			
5	Woodland	57.8	48.3	11.9	10.8	-81.3
6	Bushland	0.3	14	29.2	0.6	132.64
	Subtotal for Natural Forests					-80.33
7	Grassland	17.1	3.9	14.8	17.2	0.12
8	Wetland	0.6	0.6	1.065	0.9	60.15
9	Subsistence farmland	23.7	32.9	42.7	69.9	195.2
10	Built-up areas	0.002	0.003	0.2	0.367	18,137.43
11	Water	0.407	0.271	0.05	0.19	-54.54
12	Impediment	0.03		0.02	0.02	-43.82
	Total	100	100	100	100	

Source: Landsat satellite images for Yumbe district 1990, 2000, 2010 and 2021

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