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GEOSPATIAL MODELLING AND SOCIOECONOMIC PROFILING OF FUELWOOD CONSUMPTION PATTERNS IN DOROK DISTRICT, PLATEAU STATE, NIGERIA

[1]Vincent Choji, [1]Kyalak Yakubu, [1]Barnabas David, [2]Magnus Chris and Ayodeji Ifegbesan

[1]Department of Geography, Plateau State University Bokkos, Plateau State, Nigeria.
[2]Foto tech Jos-South Plateau, Plateau State, Nigeria.
[3]Department of Arts and Social Sciences Education, Olabisi Onabanjo University, Ago-Iwoye, Ogun State, Nigeria.

*Corresponding authors' email: pololis2005@gmail.com

ABSTRACT

Household reliance on biomass energy is a major driver of land-cover change in rural Nigeria. This study used socio-economic surveys (n = 150), statistical analyses, and NDVI-based Land Use and Land Cover (LULC) assessment from multi-temporal Landsat imagery (1990–2025) to examine fuelwood consumption and vegetation dynamics in Dorok District, Plateau State. Results show high fuelwood use, with mean daily consumption of 14.27 kg per household (1.78 kg per capita). Female-headed households consumed more than male-headed households, and consumption increased with household size, while education had minimal effect. NDVI analysis revealed that vegetation loss was not significantly driven by fuelwood harvesting, with broader land-use changes as the dominant factor. The 2025 LULC classification showed high reliability: water bodies and built-up areas were mapped most accurately, while vegetation classes had moderate accuracy due to heterogeneous landscapes. Overall Accuracy (85%) and Kappa (0.77) confirm the dataset's robustness for spatial and ecological analysis. These findings highlight the need for gender-sensitive energy interventions, adoption of alternative household fuels, and community-based conservation. The study demonstrates the value of validated LULC datasets for monitoring landscape change, understanding vegetation dynamics, and informing sustainable land management in rural Nigeria.

Keywords: Biomass Energy Dependence, Socio-Demographic Determinants, Remote Sensing and NDVI, Rural Household Energy, Land-Cover Change Analysis

INTRODUCTION

Fuelwood remains a critical household energy source globally, particularly in low- and middle-income countries where access to clean cooking technologies is limited. Recent estimates indicate that more than 2.3 billion people continue to rely on biomass fuels, including fuelwood, charcoal, and agricultural residues, for cooking and heating (WHO, 2022; IEA, 2023). Persistent dependence on fuelwood reflects widespread energy poverty, low household incomes, and limited access to affordable modern fuels. Despite sustained clean-cooking initiatives, fuelwood demand remains high due to population growth, affordability, cultural preferences, and fuel-stacking behavior (Van der Kroon et al., 2013; Shankar et al., 2020).

Global assessments indicate that fuelwood removals constitute a significant share of total roundwood extraction, resulting in reductions in canopy cover, altered species composition, and increased carbon emissions where harvesting exceeds natural regeneration (FAO, 2020, 2024; WHO, 2024). Recent advances integrating household energy data with remote-sensing indicators such as the Normalized Difference Vegetation Index (NDVI) and land-cover time series have improved the identification of fuelwood extraction hotspots and associated vegetation change (IEA, 2023; FAO, 2024). The literature increasingly emphasizes the need for integrated socio-ecological frameworks that combine household-level energy assessment with spatial analysis to support sustainable land and energy management (Shankar et al., 2020; FAO, 2024).

In Africa, fuelwood accounts for approximately 60–70% of household energy consumption in many countries (FAO, 2020; IEA, 2023). Sub-Saharan Africa hosts over 900 million fuelwood users, with continued growth projected due to rapid population increase and persistent energy-infrastructure deficits (Zulu & Richardson, 2013; Jeuland et al., 2021). Sustained extraction places considerable pressure on forest and woodland resources, leading primarily to vegetation degradation rather than outright deforestation, particularly within savanna ecosystems characterized by slow regeneration rates (Arnold et al., 2006; Chidumayo & Gumbo, 2013).

In Nigeria, wood is the major source of energy (Salisu, Muhammad & Umar, 2019). Consequently, Nigeria is among the most fuelwood-dependent countries in Africa, with approximately 60–70% of households relying primarily on wood-based fuels, increasing to over 80% in rural areas (FAO, 2017; NBS, 2024). Although agricultural expansion and urbanization contribute to deforestation, unsustainable fuelwood harvesting remains a key driver of woodland degradation within the Guinea and Sudan savanna zones (FAO, 2020). Empirical studies in Plateau State and adjoining regions demonstrate strong associations between household socio-economic characteristics and fuelwood consumption, underscoring the need for integrated analyses linking energy use, livelihoods, and spatial vegetation change (Chaskda et al., 2021; FAO, 2024).

Fuelwood dependence in Plateau State is increasing due to population growth, widespread poverty, and limited access to clean cooking energy, yet its environmental impacts remain insufficiently examined (Chaskda et al., 2021; NBS, 2024). Recent studies indicate that biomass energy continues to dominate household energy use in the state, reflecting persistent energy poverty and constrained energy transitions (Chaskda et al., 2021). In the Jos Plateau, geospatial evidence reveals significant vegetation loss and land-cover change driven by human activities, underscoring the vulnerability of the savanna-woodland ecosystem to sustained biomass extraction (Alfred et al., 2023; Choji & Nanchang, 2025).

Given this context, this study aims to assess vegetation dynamics and household fuelwood consumption in Dorok

District, Shendam Local Government Area, Plateau State. Specifically, the study seeks to: examine the socio-demographic characteristics of households and their influence on fuelwood consumption; assess variations in daily per capita fuelwood use across gender, household size, and educational attainment; identify factors influencing the adoption of alternative energy sources among households; and analyze land-use and land-cover changes in Dorok District between 2000 and 2025. Moreover, to guide this investigation, the study tests four hypotheses: (1) there is no significant difference in per capita daily fuelwood use between male- and female-headed households; (2) household size does not significantly influence daily per capita fuelwood consumption; (3) educational attainment of household heads does not significantly affect fuelwood consumption patterns; and (4) land-use and land-cover changes in Dorok District between 2000 and 2025 are not significantly associated with household fuelwood extraction. By integrating household energy assessment with geospatial analysis, the study seeks to provide actionable insights for sustainable energy management and vegetation conservation in the region.

MATERIALS AND METHODS

The study was conducted in Dorok District, Shendam Local Government Area, Plateau State, Nigeria. A quantitative research design was adopted to examine household and socio-economic determinants of per-capita fuelwood consumption, enabling statistical assessment of relationships between socio-demographic factors and consumption outcomes. Geospatial analysis using NDVI and land-use classification was integrated to assess temporal and spatial vegetation dynamics and their link to household fuelwood harvesting.

The Study Area

Dorok District, in Shendam LGA, Plateau State, Nigeria (8°34'-8°46'N, 9°20'- 9°36'E), is a rural area heavily reliant on fuelwood. Located in the tropical savanna, its vegetation comprises tall grasses, scattered deciduous trees, and gallery forests along Fadama lowlands. With a population of ~ 170,833, the district experiences distinct wet and dry seasons, supporting mainly agrarian livelihoods, including cultivation of cereals, legumes, and tuber crops (Buba, 2014).

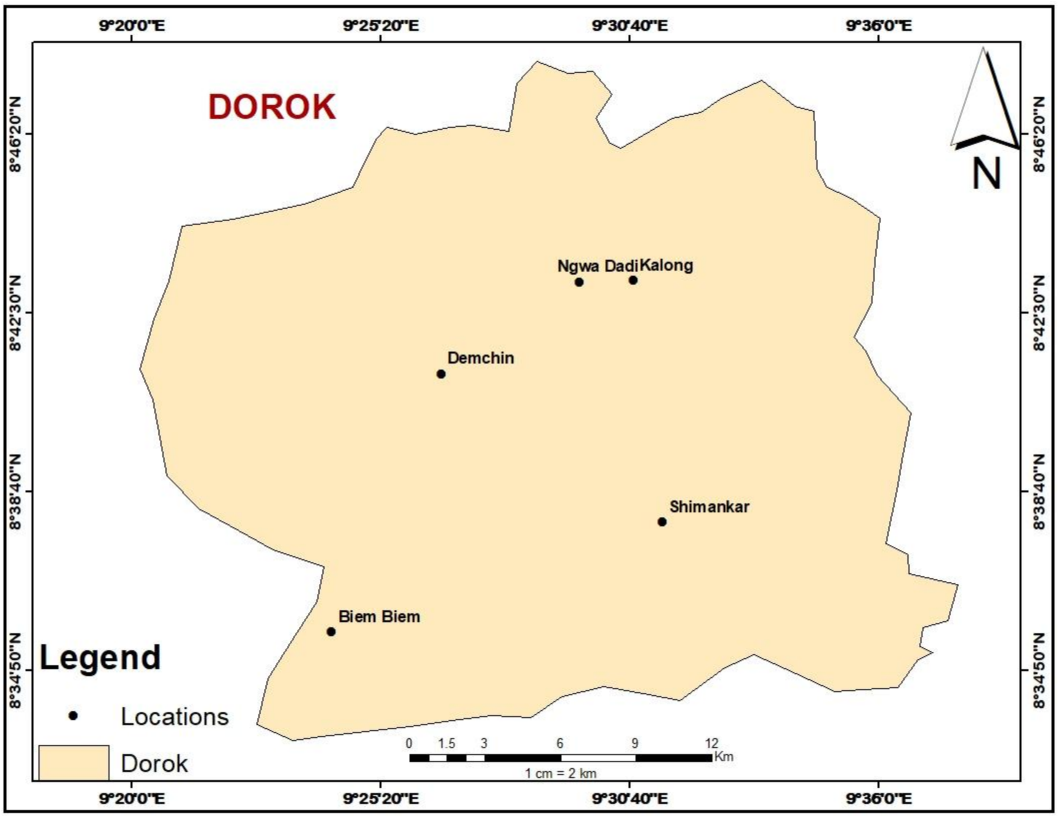

Figure 1: Map Showing the Study Area

Population and Sample Size

The study population consisted of households across five villages in Dorok, selected to provide a comprehensive representation of the area's socio-economic and demographic variability. Stratified random sampling was used to select respondents from the five districts. Stratification ensured proportional representation while reducing selection bias and facilitating meaningful socio-economic comparisons (Cohen, Manion & Morrison, 2018) A total of 150 structured questionnaires were administered, with 30 questionnaires distributed per district to ensure both adequate sample size and spatial representativeness. This distribution allows for meaningful comparisons across districts and reduces the likelihood of sampling bias. The sample size was sufficient to satisfy the requirements for Chi-square tests to examine associations between categorical variables, one-way ANOVA to assess differences in mean fuelwood consumption across groups, and non-parametric correlation tests for exploring monotonic relationships between variables. This comprehensive sampling approach provides a robust foundation for both inferential and descriptive statistical analyses.

Sampling Technique

Stratified random sampling was used to select respondents from the five districts. Stratification ensured proportional representation while reducing selection bias and facilitating meaningful socio-economic comparisons (Cohen, Manion & Morrison, 2018).

Data Collection Through Structural Questionnaires

Structured, closed-ended questionnaires were administered to household heads or adult representatives. Data captured included socio-demographic characteristics (age, sex, education, occupation, household size), fuelwood consumption metrics (quantity, frequency, collection distance), and adoption of alternative energy sources. Closed ended items facilitated standardization and robust quantitative analysis (Saunders Lewis & Thornhill, 2023).

Geospatial Data Collection and Analysis

Vegetation dynamics were assessed using multi-temporal Landsat imagery (1990-2025). Landsat 4 TM, 7 ETM+, and 8 OLI images (Path 187, Row 54) were acquired from USGS Earth Explorer based on minimal cloud cover and seasonal comparability. Preprocessing included radiometric and atmospheric correction to surface reflectance, geometric correction, reprojection to UTM (WGS84), subsetting, and gap-filling for SLC-off gaps.

NDVI was computed as NDVI = (NIR - Red) / (NIR + Red), where NIR and Red are reflectance values in the near-infrared and red bands. NDVI ranges from -1 to + 1, with higher values indicating denser, healthier vegetation. NDVI rasters were classified into water, built-up, barren, shrub/grassland, sparse, and dense vegetation using supervised classification guided by field data and high-resolution imagery. Zonal statistics and raster differencing were used to quantify the change in vegetation. Confusion matrices, overall accuracy, user and producer accuracy, and the Kappa coefficient were all used in the accuracy assessment.

Accuracy of Lulc Chage Classification

The 2025 land-use and land-cover (LULC) classification was evaluated using Overall Accuracy (OA), Kappa coefficient (κ), User's Accuracy (UA), and Producer's Accuracy (PA), derived from a confusion matrix based on ground truth reference samples. The matrix compares map classes (rows) to reference classes (columns), with diagonal elements representing correctly classified pixels and off-diagonal elements representing misclassifications. Overall Accuracy is the proportion of correctly classified pixels to total samples. The Kappa coefficient adjusts OA for agreement due to chance, calculated as:

$$\kappa = (Po - Pe) / (1 - Pe)$$

where Po is observed agreement (OA) and Pe is expected agreement by chance, calculated as:

$$Pe = \Sigma \text{ (Row total} \times \text{Column total)} / N^2$$

Here, Row total and Column total are the marginal totals for each class, and N is the total number of validation samples. Producer's Accuracy (PA) reflects omission error, calculated as the proportion of reference pixels correctly classified for a class. User's Accuracy (UA) reflects commission error, calculated as the proportion of map-classified pixels that are correct. Combined, these metrics provide a robust, class-specific evaluation of LULC change reliability, ensuring that NDVI-based vegetation analyses and landscape interpretations are based on validated data.

Statistical Analyses

Statistical analyses were employed to examine socio-demographic determinants of fuelwood consumption and the adoption of alternative energy sources. Chi-square tests were used to assess associations between categorical variables, while one-way ANOV A tested differences in mean per-capita fuelwood consumption across educational groups. Spearman's rank correlation was applied to evaluate monotonic relationships between household size and per-capita fuelwood use. Repeated measures ANOV A was applied to NDVI time-series data to evaluate temporal changes in vegetation cover while accounting for within-unit correlations. All analyses were conducted at a 5% significance level.

Ethical Considerations

Ethical standards were strictly observed. Respondents were informed of the purpose of the study, assured of confidentiality, and participation was voluntary. No personal identifiers were included in the dataset. The study adhered to recognised ethical guidelines for social science research and environmental studies (WHO).

RESULTS AND DISCUSSION

This study examined household fuelwood consumption, socio-demographic characteristics, and land-use dynamics in Dorok District, integrating survey data and remote sensing analyses to understand patterns of biomass energy use, environmental perceptions, and vegetation changes over a 25-year period.

Results of Socioeconomic Characteristics

This section presents the socioeconomic characteristics of the 150 surveyed households in Dorok District, including demographic, educational, and occupational profiles (Table 1) The survey assessed socio-demographics, fuelwood consumption, environmental perceptions, and adaptation strategies among 150 households across five districts of Dorok (Table 1).

Males constituted 60% of respondents, with 60% married and 40% aged 31-45 years. Education levels were varied, with secondary school graduates and BSc/HND holders each at 27%. Farmers formed the largest occupational group (47%), and most households had 4-6 members (40%).

Fuelwood remained the dominant household energy source (67%), collected mainly weekly (40%) from farmlands and nearby forests (30% each). Daily consumption was typically 5-10 kg (40%), driven by affordability (50%) and availability (30%). Half of respondents perceived a decline in fuelwood availability, traveling mainly 1-3 km (40%) for collection.

Regarding environmental perception, 80% noticed vegetation changes, primarily decreases (60%), attributed to fuelwood harvesting (40%), farming (30%), and population growth (20%). Awareness of local harvesting regulations was moderate (60%).

For adaptation, only 27% had adopted alternative energy sources. Barriers included cost (40%), limited availability of alternatives (30%), and cultural preference (20%). Proposed solutions highlighted afforestation (50%), alternative energy promotion (40%), government policies (30%), and community education (35%). A majority (70%) expressed willingness to participate in tree-planting initiatives, indicating potential for community-based conservation interventions.

Table 1: Socio-Demographics, Fuelwood Use, Environmental Perception, and Adaptation (n = 150)

Section/ Variable	Category	Frequency (n)	Percentage (%)	
A. Demographics	Sex	Male	90	60
		Female	60	40
	Marital Status	Single	45	30
		Married	90	60
		Divorced	15	10
	Age Group	18–30	40	27
		31–45	60	40
		46–60	35	23
		>60	15	10
	Education	No formal	10	7
		FSLC	20	13
		GCE/WAEC/NABTEB	40	27
		Diploma/NCE	30	20
		BSc/HND	40	27
		Masters/PhD	10	7
	Occupation	Farmer	70	47
		Business	50	33
		Civil Servant	20	13
	Household Size	1–3	20	13
		4–6	60	40
		7–9	40	27
		≥10	30	20
B. Fuelwood Use	Main Energy Source	Fuelwood	100	67
		Charcoal	25	17
		Gas	15	10
	Frequency of Collection	Daily	45	30
		Weekly	60	40
		Monthly	30	20
		Occasionally	15	10
	Source of Firewood	Farmland	45	30
		Nearby forest	45	30
		Market	22	15
		Own land	15	10
	Daily Quantity Used	<5kg	30	20
		5–10kg	60	40
		11–20kg	45	30
C. Environmental Perception	Vegetation Change Noticed	Yes	120	80
		No	30	20
	Type of Change	Decrease	72	60
		Increase	18	15
		No significant change	30	25
	Causes of Change	Fuelwood harvesting	60	40
		Farming	45	30
		Urban expansion	22	15
		Grazing	15	10
		Population growth	30	20
		Climate change	22	15
D. Adaptation & Alternatives	Adopted Alternatives	Yes	40	27
		No	110	73
	Challenges	Cost	60	40
		Availability of alternatives	45	30
		Cultural preference	30	20
		Lack of awareness	15	10
	Proposed Solutions	Afforestation	75	50
		Alternative energy	60	40
		Government policies	45	30

Section/ Variable	Category	Frequency (n)	Percentage (%)	
		Community education	52	35
	Willingness for Tree Planting	Yes	105	70
		No	45	30

Household Size and Fuelwood Consumption

Table 2 presents the distribution of household sizes in Dorok District. Households were grouped into size classes, and the midpoint of each class was calculated as the average of the lower and upper limits:Midpoint = (Lower limit + Upper limit) ÷ 2

The midpoint represents the typical household size for each class. Each midpoint was then multiplied by its class frequency (f × x) to obtain the total contribution of that class. Summing these products (Σ f × x = 1,192) and dividing by the total number of households (Σ f = 150) gives the average household size:Mean Household Size = Σ (f × x) ÷ Σ f

Mean Household Size = 1,192 ÷ 150 ≈ 7.95 ≈ 8 persons/household

This indicates that the typical household in Dorok District comprises about 8 members.

Table 2: Household Size Classes, Midpoints, Frequencies, and F × X for Dorok District

Household Size Class (persons)	Midpoint (x)	Frequency (f)	f × x
1–3	2	3	6
4–6	5	45	225
7–9	8	64	512
10–12	11	30	330
13–15	14	7	98
16–19	17.5	0	0
20–22	21	1	21
Total	-	150	1,192

Calculation of Average Daily Fuelwood Consumption

Average daily household fuelwood consumption was estimated using the grouped mean method. Households were classified into <5 kg, 5-10 kg, and 11-20 kg per day (Table 3). As no household consumed less than 5 kg, this category was excluded. Midpoints of 7.5 kg (5-10 kg) and 15.5 kg (11-20 kg) were multiplied by their frequencies, yielding a total weighted consumption of 2,141.0 kg across 150 households. The mean daily consumption was therefore:

$\bar{x} = \sum fx / \sum f = 2141.0 / 150 = 14.27$ kg day^{-1}

Households thus consume an average of ~14.3 kg/day, reflecting a strong dependence on biomass energy.

Table 3: Distribution and Average Daily Fuelwood Consumption

Fuelwood (kg/day)	Midpoint (kg)	Frequency	%	f × x
< 5	-	0	0	0.0
5–10	7.5	23	15.33	172.5
11–20	15.5	127	84.67	1968.5
Total		**150**	**100**	**2141.0**

Most households (84.7%) consume 11-20 kg/day, indicating heavy reliance on fuelwood due to traditional cooking practices and limited alternative energy access.

Land Use and Land Cover (LULC) Changes in the Study Area (2000-2025)

Land Use and Land Cover (LULC) analysis from 2000 to 2025 are presented in (Table 4) and Figure 2. The results revealed that dense vegetation declined from 5.59 km2 (2.84%) to 0.49 km2 (0.33%), sparse vegetation from 82.70 km2 (41.91 %) to 10.36 km2 (6.96%), shrubs and grassland fluctuated, peaking at 21.80 km2 (14.67%) in 2020 and slightly decreasing to 20.96 km2 (14.08%) in 2025, barren land increased from 13.83 km2 (7.01 %) to 18.51 km2 (12.43%), built-up areas expanded from 15.27 km2 (7.74%) to 87.25 km2 (58.62%), and water bodies decreased from 64.57 km2 (32.73%) to 11.30 km2 (7.59%), reflecting urbanization and landscape transformation

Table 4: Land Use and Land Cover (LULC) Changes in the Study Area (2000-2025)

Year	Dense Vegetation (km²/%)	Sparse Vegetation (km²/%)	Shrubs &Grassland (km²/%)	Barren Land (km²/%)	Built-up (km²/%)	Water Body (km²/%)	Total Area (km²)
2000	5.59/2.8%	82.70/41.91%	15.34/7.77%	13.83/7.01%	15.27/7.74%	64.57/32.73%	197.29
2005	60.79/31.69%	17.09/8.91%	16.76/8.74%	11.19/5.83%	62.72/32.69%	23.29/12.14%	191.83
2010	61.02/33.34%	13.15/7.19%	18.21/9.95%	14.67/8.01%	66.25/36.20%	9.71/5.31%	183.00
2015	56.70/37.19%	12.10/7.94%	14.22/9.33%	13.55/8.89%	9.55/6.27%	46.30/30.37%	152.42
2020	0.64/0.43%	10.42/7.01%	21.80/14.67%	17.63/11.86%	80.35/54.08%	17.80/11.98%	148.63
2025	0.49/0.33%	10.36/6.96%	20.96/14.08%	18.51/12.43%	87.25/58.62%	11.30/7.59%	148.85

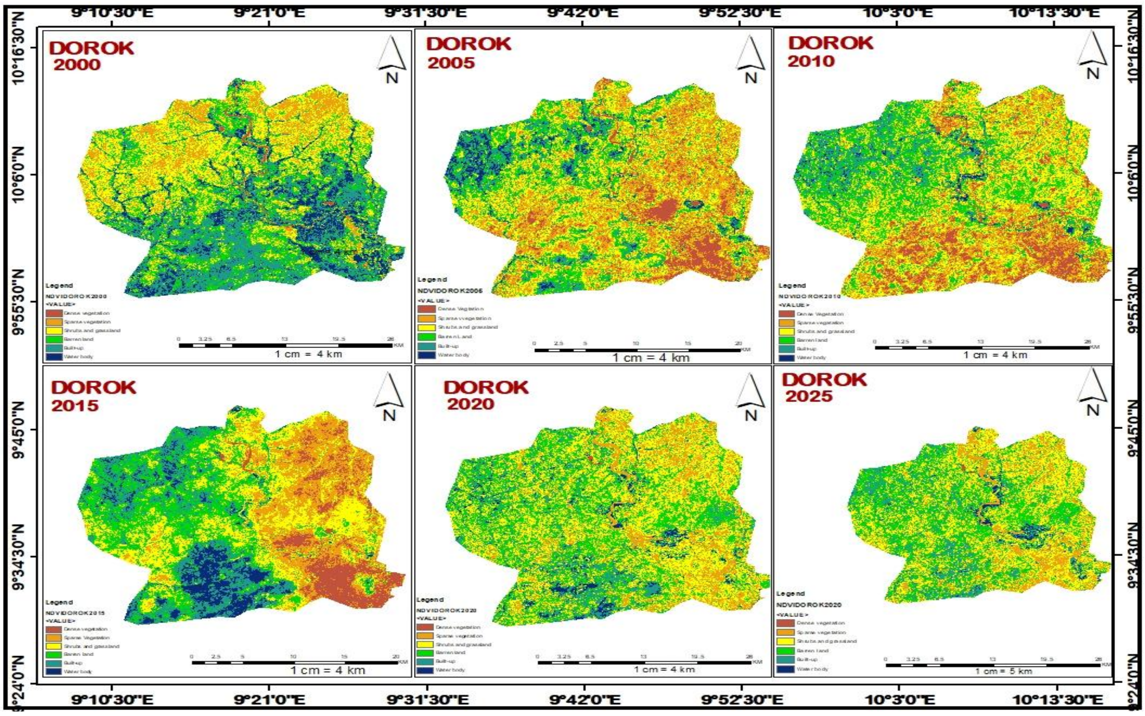

Figure 2: Satellite Images Showing Land use and Land Cover Change of Dorok District Between 2000-2025

Association Between Sex and Per Capita Fuelwood Consumption

Chi-square analysis (n = 150) examined the relationship between respondents' sex and daily per capita fuelwood consumption (Table 2). Females predominated in the higher consumption category (11-20 kg/day).

Table 5: Test of Daily per Capital Fuelwood Consumption by Sex (kg/day, n = 150)

Sex	<10 kg/day (O/E)	11–20 kg/day (O/E)	χ^2 Contribution
Male	5 / 2.30	10 / 12.70	3.74
Female	18 / 20.70	117 / 114.30	0.41
Total χ^2	—	—	**4.15**

Result: χ^2 calculated (4.15) > χ^2 critical (3.84, df = 1, $\alpha = 0.05$). Females consume significantly more fuelwood than males.

Per Capita Fuelwood Consumption by Educational Qualification

One-way ANOVA assessed differences in mean daily per capita fuelwood consumption across educational levels (Table 3). Although mean consumption varied slightly among groups, the differences were not statistically significant $F(5, 144) = 0.92$, $p = 0.47$), indicating that education does not influence household fuelwood use.

Table 6: Mean Daily Per Capita Fuelwood Consumption by Educational Qualification (kg/day, n = 150)

Educational Qualification	N	Mean Daily Consumption (Kg)	Std. Dev.
First School Leaving Certificate	52	15.8	2.1
GCE/WAEC/NABTEB	52	16.2	2.3
Diploma	31	15.1	1.9
NCE	9	14.9	1.8
HND	3	15.4	2.0
B.Sc./B.A./Master’s	2	14.7	1.5

Note: Values represent mean daily per capita fuelwood consumption. The total mean and standard deviation are overall sample statistics and not arithmetic sums of subgroup means. Standard deviation is not computed for categories with a single observation *(n = 1)*. Result: No significant difference was observed ($p > 0.05$).

Household Size and Fuelwood Consumption

In Table 4, Spearman's rank correlation showed a strong positive association between household size and per capita fuelwood consumption ($p = 1$, $P < 0.05$). Larger households consumed more, with an average household size of 8, daily household consumption of 14.27 kg, and per capita consumption of 1.78 kg/day.

Table 7: Household Size Versus Daily Per Capita Fuelwood Consumption (kg/day, n = 150)

Household Size	Mean (kg/day)	Rank (Size)	Rank (Consumption)	d^2
1–3	10.2	1	1	0
4–6	13.8	2	2	0
7–9	16.5	3	3	0
10–12	18.1	4	4	0
13–15	19.0	5	5	0
20–22	20.0	6	6	0

Household Fuelwood Use and Vegetation Dynamics

Repeated-measures ANOVA of NDVI-derived vegetation cover (2000-2025) Table 5, considering household size and fuelwood consumption, showed no significant change ($F(5, 10) = 0.469$, $p = 0.792$), indicating household fuelwood harvesting was not a dominant driver of vegetation change at the landscape scale.

Table 8: Ndvi-derived Vegetation Cover (%) from 2000 to 2025

Year	Dense	Sparse	Shrubs/Grass	Total
2000	2.84	41.91	7.77	52.52
2005	31.69	8.91	8.74	49.34
2010	33.34	7.19	9.95	50.48
2015	37.19	7.94	9.33	54.46
2020	0.43	7.01	14.67	22.11
2025	0.33	6.96	14.08	21.37

Summary: Household fuelwood consumption is influenced by sex and household size but not education. NDVI trends suggest that land-use changes, rather than household fuelwood harvesting, are the main drivers of vegetation dynamics, consistent with regional and international studies.

Accuracy Assessment of LULC Classification (2025) Percent- Ages

Table 6 presents the land-use and land-cover (LULC) changes in the study area from 2000 to 2025, alongside a detailed classification accuracy assessment for 2025. The 2025 classification was validated using a confusion (error) matrix constructed from reference ground truth data. The matrix allows calculation of class-specific accuracy metrics, including User's Accuracy (UA), which indicates the reliability of the map in representing each land-cover class, and Producer's Accuracy (PA), which reflects the extent to which reference pixels are correctly mapped. The overall reliability of the classification is summarized using Overall Accuracy (OA) and the Kappa Coefficient (κ), which accounts for agreement occurring by chance. The table shows the number of correctly classified pixels, total map pixels (row totals), and total reference pixels (column totals), providing a clear framework for assessing omission and commission errors for each LULC class. This combined presentation of LULC change and accuracy metrics ensures that subsequent spatial and ecological analyses are based on validated, reliable data.

Table 9: LULC Changes (2000–2025) and 2025 Classification Accuracy

LULC Class	Correctly Classified Pixels	Total Map Pixels (Row Total)	Total Reference Pixels (Column Total)	User's Accuracy (%)	Producer's Accuracy (%)
Dense Vegetation	33	43	42	76.7	78.6
Sparse Vegetation	40	54	54	74.1	74.1
Shrubs/Grassland	47	64	66	73.4	71.2
Barren Land	38	50	49	76.0	77.6
Built-up	61	67	67	91.0	91.0
Water Body	46	46	46	100.0	100.0
Overall Accuracy (OA)	**275**	**324**	–	**85.0**	–
Kappa Coefficient (κ)	–	–	–	**0.77**	–

Notes:

i. User's Accuracy (UA) = Correctly Classified Pixels ÷ Total Map Pixels × 100
ii. Producer's Accuracy (PA) = Correctly Classified Pixels ÷ Total Reference Pixels × 100
iii. Overall Accuracy (OA) = Sum of Correctly Classified Pixels ÷ Total Samples × 100
iv. Kappa (κ) = OA adjusted for chance agreement using the confusion matrix

Discussion

Household fuel wood consumption in Dorok District reflects long-established patterns in rural Nigeria, where traditional biomass remains the dominant household energy source due to affordability, accessibility, and limited availability of modern alternatives (Arnold et al., 2006; Karekezi & Kithyoma, 2003; Abubakar et al., 2024). The predominance of male, married household heads and farming households is consistent with earlier studies demonstrating that household structure and livelihood type significantly influence domestic energy demand in rural settings (Bhattacharya et al., 2002; Igbe Akeh et al., 2023).

Fuelwood consumption was significantly higher among female-headed households than male-headed households ($\chi^2 = 4.15, p < 0.05$), reflecting the gendered division of labour in cooking and fuelwood collection. This finding aligns with long-standing evidence from sub-Saharan Africa that identifies women as the primary managers of household biomass energy (Bhattacharya et al., 2002; Arnold et al., 2006). Household size exhibited a strong positive correlation with fuelwood consumption (p = 1, P < 0.05), confirming that larger households require greater quantities of biomass fuel to meet daily cooking needs, as observed in comparable rural African contexts (Arnold et al., 2006; Alem et al., 2023).

Educational attainment did not significantly influence per-capita fuelwood consumption (Fs, 1 4 4 = 0.92, P = 0.47), suggesting that education alone does not automatically lead to energy transition without supportive infrastructure, affordability, and policy interventions. This finding supports earlier arguments that structural constraints, rather than awareness alone, shape rural household energy choices (Karekezi & Kithyoma, 2003; Abubakar et al., 2024). Only 27% of households reported using alternative energy sources, with high costs, limited access, and cultural preferences acting as major patterns widely documented in rural African energy studies (Karekezi & Kithyoma, 2003).

NDVI-based land-use and land-cover (LULC) analysis revealed substantial landscape transformation between 2000 and 2025, including significant declines in dense and sparse vegetation, expansion of built-up areas, and reduction in water bodies. These trends are consistent with foundational land-change research identifying urban expansion and agricultural intensification as dominant drivers of vegetation loss in developing regions (Lambin et al., 2003; Song et al., 2018). Repeated-measures ANOV A further showed that household fuelwood consumption did not significantly influence landscape-scale NDVI change (FO,O 0 = 0.469, P = 0.792), reinforcing evidence that broader land-use conversion processes, rather than localized biomass harvesting, primarily control vegetation dynamics (Lambin et al., 2003; Song et al., 2018).

Community perceptions supported the quantitative fmdings, with most respondents reporting noticeable vegetation decline and expressing willingness to participate in tree-planting initiatives. This aligns with established literature emphasizing community participation as a critical factor for successful environmental restoration and sustainable land management (Pretty & Smith, 2004; Reed, 2008).

The 2025 LULC classification shows that water bodies and built-up areas were mapped with the highest reliability, with User's and Producer's Accuracies of 100% and 91%, respectively. Dense and sparse vegetation and shrubs/grassland exhibited moderately high accuracies (UA 73–77%, PA 71–79%), reflecting challenges in heterogeneous landscapes where spectral overlap and mixed pixels can cause misclassification (Adepoju & Salami, 2024; Lawal & Gulma, 2024). This suggests caution is needed when interpreting vegetation-dominated classes.

Overall Accuracy (85%) and Kappa Coefficient (0.77) indicate strong agreement beyond chance, confirming the classification's reliability for spatial and ecological analyses. Comparable accuracies have been reported in Nigeria and sub-Saharan Africa for Landsat- and Sentinel-based LULC classifications (Akinyemi & Sangodoyin, 2022; Ologunde, Kelani, Biru, Olayemi, & Nunes, 2025), and internationally in India and Southeast Asia (Lambin, Geist, & Lepers, 2003; Song, Hansen, Stehman, et al., 2018). These results underscore the importance of confusion matrices in validating LULC data and ensuring confidence in subsequent analyses.

High UA and PA for water bodies reflect the ease of mapping spectrally distinct classes, while lower accuracies for vegetation classes reveal limitations of remote sensing in complex land covers. Nevertheless, the dataset is suitable for monitoring landscape change, analyzing vegetation dynamics, and guiding land management. Overall, the study highlights the need for careful validation of vegetation classes and demonstrates the value of rigorous accuracy assessment in remote sensing-based LULC research.

CONCLUSION

Household fuelwood consumption in Dorok District remains heavily dependent on traditional biomass due to affordability, accessibility, and limited availability of modern energy alternatives. Consumption patterns are influenced by household structure, livelihood, and gender roles, with women primarily responsible for cooking and fuel collection. Education alone is insufficient to drive adoption of alternative energy without supportive infrastructure and policy interventions.

Land-use and land-cover (LULC) analysis from 2000 to 2025 revealed significant vegetation loss and expansion of built-up areas, indicating that broader land-use conversion, rather than local fuelwood harvesting, is the dominant driver of landscape transformation. The 2025 LULC classification demonstrated high reliability for water bodies and built-up areas (UA 100%, PA 91%) and moderate accuracies for vegetation classes (UA 73–77%, PA 71–79%), with an Overall Accuracy of 85% and Kappa Coefficient of 0.77. This confirms that the dataset is robust for spatial and ecological analyses while highlighting the need for careful validation of vegetation-dominated classes.

Given these findings, it is recommended that interventions combine the promotion of accessible and affordable alternative energy sources with supportive policies and infrastructure. Local communities should be actively engaged in conservation and restoration efforts to ensure sustainable land management. Furthermore, continued monitoring and careful validation of vegetation classes using high-resolution remote sensing data are essential to inform evidence-based strategies for ecosystem management and landscape sustainability.

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