



Temporal Non-Stationarity of Forest Loss and Land Reallocation Pathways in the Southern Senatorial District of Taraba State, Nigeria, 1990–2020

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ABSTRACT

Forest cover has declined sharply in the Southern Senatorial District of Taraba State, Nigeria, between 1990 and 2020. However, whether this decline was evenly distributed across decades, and which land-cover classes registered the offsetting gains, remains insufficiently examined. This study therefore assessed the temporal pattern of forest-cover loss and the associated net land-cover reallocation. It re-analysed a land use/land cover (LULC) time series for 1990, 2000, 2010, and 2020, originally derived by the author for an unpublished MSc thesis (Gbana, 2023) through supervised Maximum Likelihood Classification of 30 m Landsat imagery into five classes; that classification was not accompanied by a formal accuracy assessment, and the results are conditional on it. Three techniques not previously applied to the dataset were used: the compound annual rate of change of Puyravaud (2003); a Pearson chi-square goodness-of-fit test of the hypothesis that forest loss was equal across the three ten-year intervals ('stationarity' is used in this narrow, intensity-analysis sense, not in the time-series sense); and net-change accounting of the shares of lost forest and water-body area matched by built-up and cultivated/bare-land gains. The compound annual rate of forest-cover loss was $-0.64\%/year$ in 1990–2000, rose more than sixfold to $-4.22\%/year$ in 2000–2010, and moderated to $-3.36\%/year$ in 2010–2020. The chi-square test rejected equal decadal loss ($\chi^2 = 1,632.65$, $df = 2$, $p < .001$). Built-up gains equalled 83.6% and 66.4% of the net loss of forest and water-body area in 1990–2000 and 2000–2010, respectively, whereas cultivated/bare-land gains were larger (57.9%) in 2010–2020. These are net land-cover changes; their drivers were not measured. Forest loss was therefore temporally uneven and the dominant net-gain class changed over time, which supports periodic, decade-specific monitoring of the district using accuracy-assessed classifications and transition matrices.

Keywords: land change intensity, forest loss rate, land reallocation, non-stationarity, Taraba State

INTRODUCTION

Land use and land cover (LULC) change studies conventionally report the net extent of change between an initial and a final time point, together with the total area gained or lost by each class over the full study period (Lambin et al., 2003). This approach establishes that change has occurred and how much, but by construction it treats the intervening period as a single, undifferentiated span; it cannot show whether the underlying rate of change was constant across sub-periods, nor which land-cover class registered the offsetting gain at different points in time. Yet both questions matter for policy: a forest loss process that is accelerating calls for a different, more urgent institutional response than one proceeding at a constant pace, and knowing whether lost forest is matched mainly by gains in built-up surfaces or in cultivated/bare land indicates which sector of land management should be monitored most closely, although establishing why those changes occurred requires evidence beyond land-cover maps.

A classification of Landsat imagery for the Southern Senatorial District of Taraba State for 1990, 2000, 2010, and 2020, reported in the author's unpublished MSc thesis (Gbana, 2023), established that dense forest cover in the district fell from 36% to 8% of the total land area over the thirty-year period, with cultivated/bare land



and built-up area registering the principal gains. That analysis, like most LULC change studies conducted at the district or state scale in Nigeria (Danjuma et al., 2014; Gabriel & Audu, 2017; Nduka et al., 2022), reported total and simple linear inter-decadal change but did not test whether the pace of that change was itself stable over time, nor formally decompose which land-cover class registered the offsetting gain in each decade. This leaves two policy-relevant questions unanswered for Southern Taraba: first, whether forest loss has been accelerating, decelerating, or roughly constant; and second, whether the class that registered the largest gain has remained the same throughout the study period or has shifted.

This study addresses both questions by re-analysing the existing classified LULC time series for the district using three techniques not previously applied to it: the standardised compound annual rate of change formula proposed by Puyravaud (2003) specifically to make deforestation rates comparable across time intervals and study sites; a formal statistical test of whether the inter-decadal loss in forest cover is evenly distributed across the study period (i.e., stationary, in the sense defined in the Analytical Framework) or not; and a net-change reallocation accounting of the proportion of the net loss of forest and water-body area matched by the net gain of each of the two principal gaining classes, built-up area and cultivated/bare land, in every decade. Specifically, the study sought to: (i) compute and compare the compound annual rate of forest-cover change for each of the three inter-decadal intervals and the full 1990–2020 period; (ii) test statistically whether the magnitude of inter-decadal forest loss is stationary across the study period; and (iii) quantify, for each interval, the share of the net loss of forest and water-body area matched by gains in built-up area versus cultivated/bare land. The following hypothesis was tested: H_0 – the inter-decadal loss in forest cover of the Southern Senatorial District of Taraba State between 1990 and 2020 is stationary, that is, equal in magnitude across the three ten-year intervals, so that each interval accounts for one-third of the total 1990–2020 loss. The study describes observed land-cover change; it does not measure the drivers of that change.

ANALYTICAL FRAMEWORK

This study draws on the intensity analysis framework of Aldwaik and Pontius (2012), which was developed specifically to address the limitation that conventional LULC change reporting treats an entire study period as a single interval and cannot reveal whether the size and speed of change is stationary or varies across sub-periods, categories, or transitions. At the interval level - the level applied in this study - intensity analysis tests whether the annual rate of change in each time interval falls above, on, or below a uniform rate benchmark computed across the whole study period; a pattern is described as stationary when all intervals fall on the same side of that benchmark, and non-stationary when they do not (Aldwaik & Pontius, 2012). Applications of this framework to Nigerian land cover data, including in the classification-error context examined by Enaruvbe and Pontius (2015) for southern Nigeria, confirm that inter-decadal rates of land change in West African contexts frequently deviate from stationarity, underscoring the importance of testing rather than assuming a constant rate of change.

To operationalise the rate comparison at the core of this framework, the study adopts the compound annual rate of change formula proposed by Puyravaud (2003), $r = (100/n) \times \ln(A_2/A_1)$, where A_1 and A_2 are the areas of a class at the start and end of an interval of n years. Puyravaud (2003) proposed this formula specifically to standardise deforestation-rate reporting, noting that the simple linear percentage-change formulae commonly used in LULC studies are not directly comparable across intervals of different length or across studies, whereas the compound formula, derived from the mean annual rate of change, is. This is the same class of standardisation problem this study confronts in comparing three inter-decadal intervals of the Southern Taraba dataset, making the Puyravaud formula the appropriate tool. Because the base classification retained only class-level area totals for each date, and not the from-to (cross-tabulated) transition matrices that full intensity analysis requires, the framework is applied here in an adapted form: a rate-based, interval-level comparison for the combined forest class, rather than the gross-change intensities of all categories and transitions described by Aldwaik and Pontius (2012).

The term stationarity is used here in this land-change sense, and it should be distinguished from the statistical concept of stationarity in time-series analysis, in which a stochastic process is (weakly) stationary if its mean, variance, and autocovariance do not change over time (Box et al., 2015). That property cannot be examined

with four classified dates and three intervals, and no stochastic model of forest loss is fitted in this study. ‘Stationary’ has two narrow, descriptive meanings here. In the rate comparison, following Aldwaik and Pontius (2012), a pattern is stationary if the decadal rates fall on the same side of the uniform 30-year benchmark rate. In the hypothesis test, forest loss is stationary if the same absolute area of forest is lost in each of the three equal ten-year intervals, so that each interval accounts for one-third of the total 1990–2020 loss. ‘Non-stationary’ correspondingly means only that the rates or losses were unevenly distributed across the intervals; it implies nothing about the trend, persistence, or stochastic structure of the underlying process.

The land-use-change literature further motivates the reallocation-share component of the analysis. Lambin et al. (2003) and Geist and Lambin (2002) distinguish proximate causes of land cover change, the immediate human activities such as agricultural expansion or settlement construction that directly convert one land cover to another, from underlying driving forces such as population growth and policy failure. Because a single underlying driving force can express itself through different proximate causes at different times (Angelsen & Kaimowitz, 1999; Mertens et al., 2000), documenting which land-cover class registers the offsetting gain in each period, and whether that class shifts, is a useful descriptive step toward causal explanation but not a substitute for it. This study’s reallocation-share accounting therefore describes land-cover outcomes only: it tracks, decade by decade, the share of the net loss of forest and water-body area that was matched by net gains in built-up area and in cultivated/bare land. It does not measure proximate causes or underlying driving forces, and statements about urbanization, agricultural expansion, population growth, or policy failure are outside what these data can establish.

MATERIALS AND METHODS

Study Area

The study was conducted in the Southern Senatorial District of Taraba State, Nigeria, comprising five Local Government Areas (Wukari, Takum, Donga, Ussa, and Ibi) across a total land area of approximately 14,099 km². The climate is tropical hot and wet, with a distinct rainy season (May–October) and dry season (November–April). Tropical rainforest occurs around Ussa and Takum, whereas Wukari, Donga, and Ibi are largely savanna interspersed with riparian forest along watercourses, and drainage is governed by the Benue and Donga rivers (Gbana, 2023).

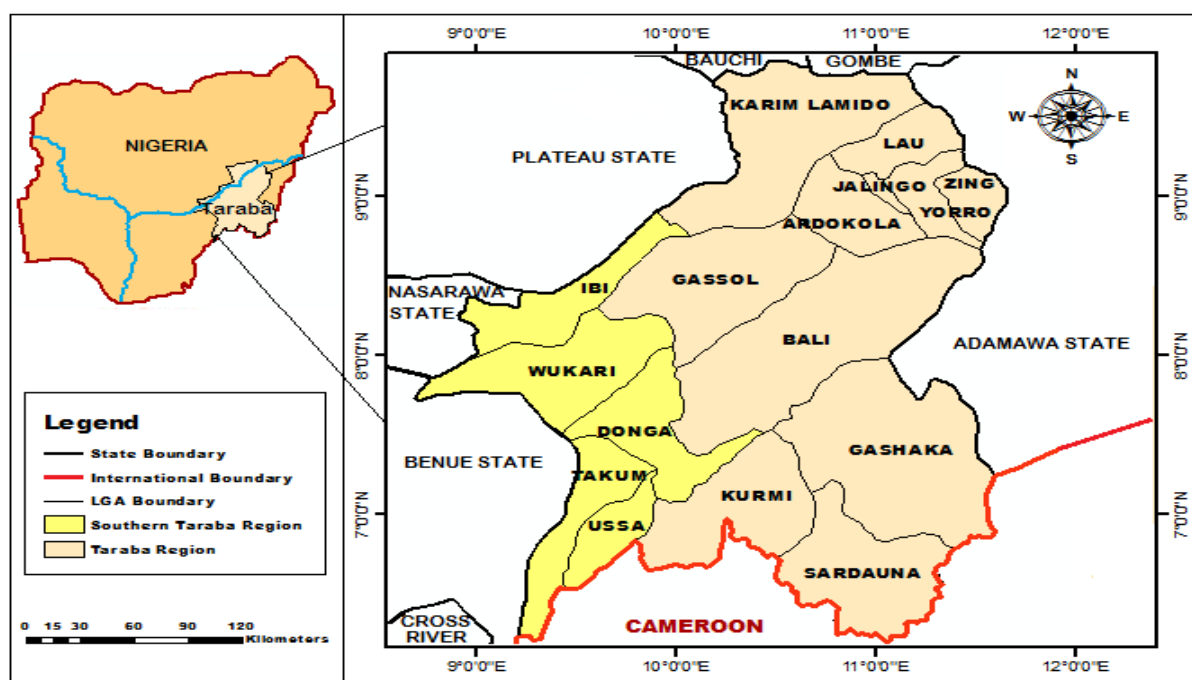


Figure 1: Taraba State showing the Southern Senatorial District.

Source: Google Earth (2021)



Base Land Use/Land Cover Classification

This study builds on a classified land use/land cover (LULC) time series for the Southern Senatorial District previously derived by the author for an unpublished MSc thesis (Gbana, 2023). No new image classification was undertaken here. Because every rate, test statistic, and share reported below depends directly on the reliability of that classification, its essential characteristics, as documented in the thesis, are summarised in this section, together with the aspects that the thesis did not record.

Source Imagery

One Landsat scene-date was used for each epoch: Landsat 5 Thematic Mapper (TM) imagery of 2 August 1990 and 17 May 2000, and Landsat 7 imagery of 25 January 2010 and 1 March 2020 (Table 1). The imagery was obtained from the Global Land Cover Facility (GLCF), the United States Geological Survey (USGS), and SASPlanet, at a spatial resolution of 30 m, using four spectral bands, with cloud interference of approximately 5%. Under the climate description given in the Study Area section, the 1990 and 2000 scenes fall in the rainy season and the 2010 and 2020 scenes in the dry season.

Table 1: Landsat imagery used for the base LULC classification

Epoch	Acquisition date	Satellite	Source	Season
1990	2-Aug-90	Landsat 5 TM	GLCF	Rainy
2000	17-May-00	Landsat 5 TM	USGS	Rainy
2010	25-Jan-10	Landsat 7	USGS	Dry
2020	1-Mar-20	Landsat 7	SASPlanet (sasgis.org)	Dry

Note: Compiled from Gbana (2023). The season classification follows the rainy (May–October) and dry (November–April) seasons described for the district.

Pre-Processing

The imagery was geometrically corrected and projected to Universal Transverse Mercator (UTM) zone 32 (Minna datum), and six distributed ground control points were used for georeferencing (Gbana, 2023). Each date was classified separately and the resulting maps were compared after classification.

Classification Scheme, Training Samples, And Procedure

Each date was classified in ArcGIS 10.1 using supervised Maximum Likelihood Classification into five classes: water body, cultivated/bare land, light forest, built-up area, and dense forest. Training samples were drawn as polygons on the imagery with the Training Sample Manager, guided by an unsupervised classification of the same scenes, and were merged into class signatures that were saved as a signature file and applied to the input raster bands to produce the classified raster for each date (Gbana, 2023). Class areas were then computed from the classified rasters and reconcile to the district total of 14,099 km² on every date (Table 2).

Analytical Techniques

Three analytical techniques were applied to the base classification that had not previously been applied to this dataset. First, the compound annual rate of change for each LULC class in each interval was computed using the formula of Puyravaud (2003): $r = (100/n) \times \ln(A_2/A_1)$, where A_1 and A_2 are the class area at the start and end of the interval and n is the interval length in years (for combined forest, A is the summed area of light and dense forest). This formula was applied to each of the three inter-decadal intervals (1990–2000, 2000–2010, 2010–2020) and to the full 1990–2020 period, the latter serving as the uniform (stationary) rate benchmark



against which the three decadal rates were compared, following the interval-level logic of intensity analysis (Aldwaik & Pontius, 2012).

Second, a Pearson chi-square goodness-of-fit test was applied to the net loss of combined forest area in each interval. The observed values (O) were the interval losses computed from the class areas in Table 2: 554 km² in 1990–2000 (8,918 to 8,364 km²), 2,880 km² in 2000–2010 (8,364 to 5,484 km²), and 1,565 km² in 2010–2020 (5,484 to 3,919 km²), a total of 4,999 km². The expected value (E) for each interval was 1,666.33 km², one-third of the total. The statistic is $\chi^2 = \sum(O - E)^2/E$, evaluated against a chi-square distribution with $k - 1 = 2$ degrees of freedom at $\alpha = .05$ (critical value 5.99).

An equal expectation was adopted as the null because the three intervals are of equal length and the hypothesis concerns whether the absolute area of forest lost differed among them: if forest had been lost at a uniform absolute pace, each decade would account for one-third of the total loss. This is the simplest reference for ‘no temporal variation’ and corresponds directly to the equal-loss hypothesis stated in the Introduction. It is not the only possible baseline: a constant proportional (compound) rate of loss of –2.74%/year would instead imply declining absolute losses as the forest stock shrinks (expected losses of 2,138, 1,625, and 1,236 km²). The test was therefore repeated against that expectation as a sensitivity check.

Two caveats apply to interpretation. First, the statistic is computed on areas rather than on independent counts, so its magnitude depends on the unit of measurement and the p-value is not a sampling probability in the usual sense; the test is best read as a formal measure of departure from equality. Second, the areas are census totals from classified maps, not random samples, and they include unquantified classification error and spatial autocorrelation among pixels. The test can therefore show that the decadal losses differ far more than the uniform expectation allows, but not that they are free of measurement error.

Third, reallocation-share accounting was applied to the net changes in class area between successive dates. For each interval, the net loss of forest (light plus dense) and water body, L, was compared with the net gains of built-up area, G₁, and of cultivated/bare land, G₂, and the share of each gaining class was computed as $G_i/(G_1 + G_2) \times 100$. Water body was included among the losing classes because its area also declined in every interval. Because the five classes sum to the same total area (14,099 km²) on every date and only these two groups changed in a consistent direction, the total gain equals the total loss exactly ($L = G_1 + G_2$); Table 5 shows this balance for every interval.

These shares are net-change accounts, not gross transitions. They show which classes’ net gains matched the net loss of forest and water body, but not which pixels changed from which class. A pixel-level from-to (cross-tabulation) matrix, from which forest-to-built-up and forest-to-cultivated/bare-land transitions could be read directly, could not be produced because the thesis retained class-level areas only. Because gross change can exceed net change (for example, when forest is converted to cultivated land while other cultivated land becomes built-up), the shares must not be interpreted as the fraction of lost forest that was converted to each class.

RESULTS

Baseline Land Use/Land Cover Pattern, 1990–2020

Dense forest was the dominant land cover class in 1990 (5,119 km², 36%), while cultivated/bare land (4,982 km², 35%) and built-up area (4,696 km², 34%) had become co-dominant by 2020, with dense forest reduced to 1,131 km² (8%) (Table 2, Figure 2). This baseline pattern is the input to the rate, stationarity, and reallocation analyses that follow.

Table 2: Baseline land use/land cover of the Southern Senatorial District of Taraba State, 1990–2020

S/N	LULC Class	1990 (km ²)	%	2000 (km ²)	%	2010 (km ²)	%	2020 (km ²)	%
1	Water Body	866	6	751	5	651	4	502	3

2	Cultivation / Bare Land	2,879	20	2,989	21	3,989	29	4,982	35
3	Light Forest	3,799	27	4,985	35	3,544	25	2,788	20
4	Built-up Area	1,436	10	1,995	14	3,975	28	4,696	34
5	Dense Forest	5,119	36	3,379	24	1,940	14	1,131	8

Source: Gbana (2023), derived from supervised classification of Landsat imagery.

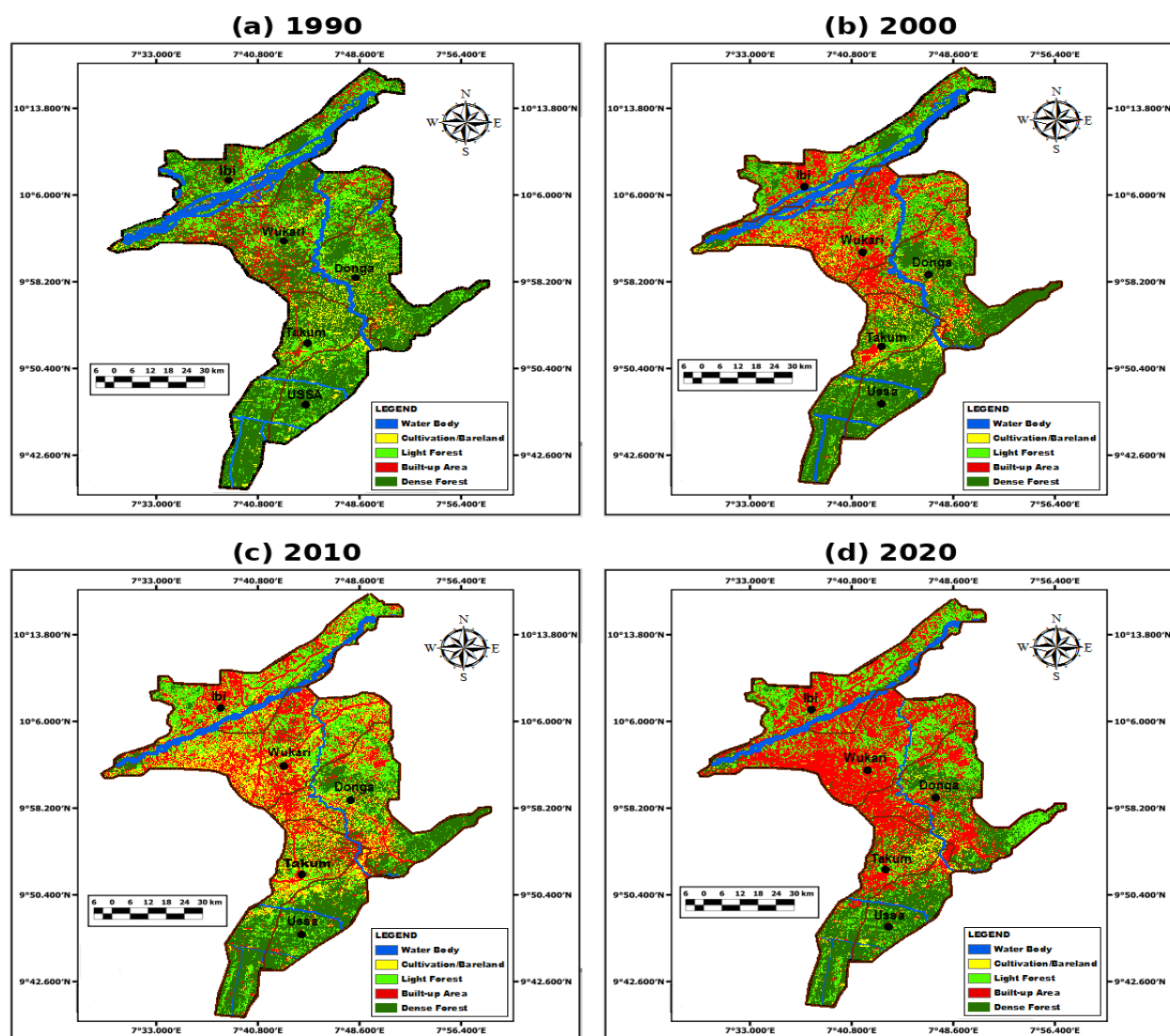


Figure 2: Classified land use/land cover of the Southern Senatorial District of Taraba State: (a) 1990, (b) 2000, (c) 2010, (d) 2020.

Source: Gbana (2023), classified from Landsat imagery (GLCF, USGS, and SASPlanet).

Compound Annual Rate of Change and Test of Stationarity

Table 3 reports the compound annual rate of change for every LULC class in each of the three inter-decadal intervals and over the full 1990–2020 period. Over the full period, dense forest recorded the steepest compound decline ($-5.03\%/year$), followed by water body ($-1.82\%/year$) and light forest ($-1.03\%/year$), while built-up area recorded the steepest compound increase ($3.95\%/year$), followed by cultivated/bare land ($1.83\%/year$). At the decadal level, every class's rate varied across intervals rather than remaining constant: built-up area's rate of increase, for example, rose from $3.29\%/year$ in 1990–2000 to a peak of $6.89\%/year$ in 2000–2010 before falling to $1.67\%/year$ in 2010–2020, while light forest gained area in the first decade ($2.72\%/year$) before declining thereafter ($-3.41\%/year$, then $-2.40\%/year$). The first-decade light-forest gain

coincides with a larger loss of dense forest and may reflect transfer of area from dense to light forest, regrowth, or differences in image season and class separability (see Base Land Use/Land Cover Classification); these cannot be distinguished without transition-level or reference data.

Table 3: Compound annual rate of land use/land cover change, Southern Senatorial District of Taraba State, 1990–2020

LULC Class	1990–2000 (%/yr)	2000–2010 (%/yr)	2010–2020 (%/yr)	1990–2020 (%/yr)
Water Body	−1.42	−1.43	−2.60	−1.82
Cultivation / Bare Land	0.37	2.89	2.22	1.83
Light Forest	2.72	−3.41	−2.40	−1.03
Built-up Area	3.29	6.89	1.67	3.95
Dense Forest	−4.15	−5.55	−5.40	−5.03
Combined Forest (Light + Dense)	−0.64	−4.22	−3.36	−2.74

Note: Rate computed as $r = (100/n) \times \ln(A_2/A_1)$, following Puyravaud (2003). The stationarity test below concerns combined forest cover (light plus dense), the class of primary policy interest.

For combined forest cover specifically, the compound annual rate of loss was −0.64%/year in 1990–2000, accelerated to −4.22%/year in 2000–2010, more than six times the first-decade rate, before moderating to −3.36%/year in 2010–2020 (Figure 3). None of the three decadal rates equals the uniform 30-year benchmark rate of −2.74%/year, and the three rates fall on both sides of that benchmark (the 1990–2000 rate below it in magnitude, the other two above it), indicating non-uniform, or non-stationary, forest loss in the interval-level sense of Aldwaik and Pontius (2012), as adapted in this study.

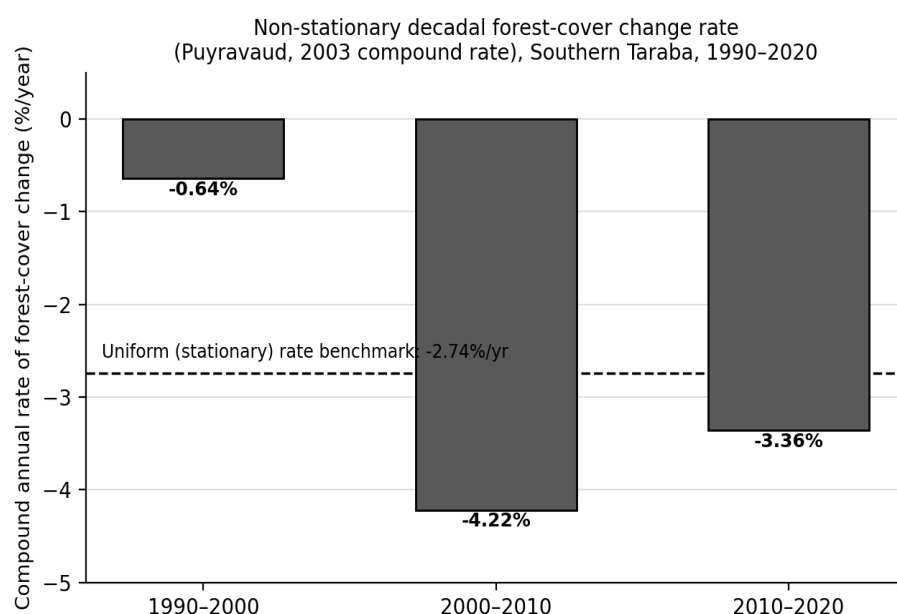


Figure 3: Compound annual rate of forest-cover change by decade against the uniform 30-year benchmark rate.

This visual non-stationarity was assessed formally with the Pearson chi-square test described in the Methods (Table 4). The observed net forest losses were 554, 2,880, and 1,565 km² for 1990–2000, 2000–2010, and 2010–2020, respectively, against an expected 1,666.33 km² in each interval. The test rejected the null hypothesis of stationary (equal) decadal loss, $\chi^2(2) = 1,632.65$, $p < .001$ (critical value at $\alpha = .05$: 5.99). The 2000–2010 interval accounted for 57.6% of the total 30-year loss on its own, against 11.1% in 1990–2000 and 31.3% in 2010–2020. The departure from equality was driven mainly by the low 1990–2000 loss and the high



2000–2010 loss (contributions of 742.52 and 883.97), whereas the 2010–2020 loss was close to the expected value (contribution of 6.16). Repeating the test against the constant-compound-rate expectation gave $\chi^2(2) = 2,229.62$, $p < .001$, so the rejection does not depend on the choice of the equal-loss expectation. Given the caveats on interpreting the p-value (see Analytical Techniques), the result is best read as showing that decadal forest loss departed markedly from uniformity, conditional on the classification.

Table 4: Chi-square goodness-of-fit test of equal inter-decadal forest loss (combined light and dense forest)

Interval	Forest area at start (km ²)	Forest area at end (km ²)	Observed loss, O (km ²)	Expected loss, E (km ²)	O – E (km ²)	(O – E) ² /E
1990–2000	8,918	8,364	554	1,666.33	–1,112.33	742.52
2000–2010	8,364	5,484	2,880	1,666.33	1,213.67	883.97
2010–2020	5,484	3,919	1,565	1,666.33	–101.33	6.16
Total	–	–	4,999	4,999.00	0	1,632.65

Note: $E = 4,999/3 = 1,666.33 \text{ km}^2$. $\chi^2 = \Sigma(O - E)^2/E$, $df = 2$. Sensitivity check: expected losses under a constant compound rate of $-2.74\%/year$ are 2,138, 1,625, and 1,236 km² ($\chi^2 = 2,229.62$, $df = 2$).

Net-Change Reallocation of Forest and Water-Body Loss

Table 5 sets out the net change in area of each class between successive dates. In every interval the two forest classes combined and the water body lost area, while built-up area and cultivated/bare land gained it. Because the district area is fixed at 14,099 km², the total net gain equalled the total net loss exactly (balance = 0), so the shares reported below can be verified directly from the table.

Table 5: Net change in area by LULC class and net-change balance, by interval (km²)

LULC class	1990–2000	2000–2010	2010–2020	1990–2020
Water Body	–115	–100	–149	–364
Cultivation / Bare Land	110	1,000	993	2,103
Light Forest	1,186	–1,441	–756	–1,011
Built-up Area	559	1,980	721	3,260
Dense Forest	–1,740	–1,439	–809	–3,988
Combined forest (light + dense)	–554	–2,880	–1,565	–4,999
Net loss of forest and water body (L)	669	2,980	1,714	5,363
Net gain of built-up and cultivated/bare land (G₁ + G₂)	669	2,980	1,714	5,363
Balance (G – L)	0	0	0	0

Note: Computed as the difference between class areas at the end and start of each interval (Table 2). Positive values are gains and negative values are losses. Overall (1990–2020) balance computed on the net change between 1990 and 2020.

Table 6 and Figure 4 report the resulting shares. In 1990–2000, the net gain of built-up area (559 km²) equalled 83.6% of the combined net loss of forest and water body (669 km²: forest 554 km², water body 115 km²), with the net gain of cultivated/bare land (110 km²) accounting for the remaining 16.4%. This pattern persisted, though less strongly, in 2000–2010 (built-up area 1,980 of 2,980 km², 66.4%; cultivated/bare land 1,000 km², 33.6%). By 2010–2020 the order had reversed: the net gain of cultivated/bare land (993 of 1,714 km², 57.9%) exceeded that of built-up area (721 km², 42.1%) for the first time in the study period. Read as net changes, built-up gains were the largest counterpart of forest and water-body loss in the first two decades and

cultivated/bare-land gains were the largest in the third. These figures are consistent with, but do not demonstrate, direct conversion of forest to either class; that would require a from-to transition matrix (see Discussion).

Table 6: Net-change reallocation shares of the loss of forest and water-body area, by interval

Interval	Net loss of forest and water body (km ²)	Built-up area gain, km ² (share)	Cultivated/bare land gain, km ² (share)	Larger share
1990–2000	669	559 (83.6%)	110 (16.4%)	Built-up area
2000–2010	2,980	1,980 (66.4%)	1,000 (33.6%)	Built-up area
2010–2020	1,714	721 (42.1%)	993 (57.9%)	Cultivated/bare land
1990–2020 (overall)	5,363	3,260 (60.8%)	2,103 (39.2%)	Built-up area

Note: Share = net gain of each class ÷ total net gain of built-up area and cultivated/bare land (equal to the net loss of forest and water body; Table 5) × 100. These are net-change shares, not gross from-to transitions.

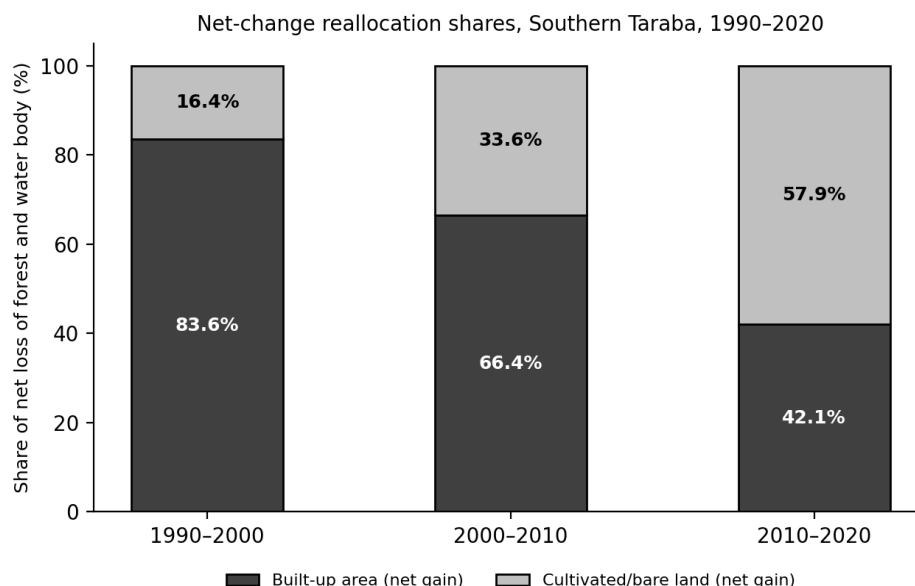


Figure 4: Net-change reallocation shares of the loss of forest and water-body area, by interval.

DISCUSSION

The finding that forest loss in the Southern Senatorial District accelerated sharply between 2000 and 2010 before moderating somewhat in 2010–2020, rather than proceeding at the constant rate an average-based reading of the 1990–2020 total would imply, is consistent with the broader expectation from intensity analysis that land change rarely proceeds uniformly across an entire study period (Aldwaik & Pontius, 2012). The scale of the acceleration is nonetheless striking: a compound rate of loss of $-4.22\%/year$ in the middle decade is more than six times the $-0.64\%/year$ rate of the first decade. Comparable district-level Nigerian studies that report simple linear or total change; including for Donga Local Government Area within this same district (Gabriel & Audu, 2017), Kurmi Local Government Area in the Central Taraba State Bordering the Study Area (Nduka et al., 2022), and Jalingo metropolis to the North (Danjuma et al., 2014); are not positioned to detect this kind of within-period acceleration, since none tested or reported interval-specific rates against a stationarity benchmark; the present finding is accordingly a genuine addition to, rather than a restatement of, that literature.

The net-change accounting shows that gains in built-up area were the largest counterpart of the net loss of forest and water-body area in the first two decades, whereas gains in cultivated/bare land were larger in 2010–2020. This shift is a description of land-cover outcomes and is compatible with more than one process. It could reflect settlement expansion that had already covered much of the land near existing infrastructure by 2010, followed by conversion of more remote land to farming; it could equally reflect differences in the spectral separability of built-up and bare or cultivated surfaces between the rainy-season (1990, 2000) and dry-season (2010, 2020) images, or the classification errors discussed above. None of these explanations was tested, because population, settlement, agricultural, infrastructure, and policy variables were not measured for the intervals. The thesis from which the classification is drawn recorded respondents' perceptions of the causes of deforestation in the district, including expansion of farmland, construction activities, and weak enforcement of forest laws (Gbana, 2023), but those perceptions were collected at a single point in time and are not linked spatially or temporally to the decadal changes reported here, so they cannot attribute the observed shift to any specific driver. In the proximate-cause framework of Lambin et al. (2003) and Geist and Lambin (2002), attributing land-cover change to urbanization, agricultural expansion, population growth, or policy failure requires direct evidence on those factors (Angelsen & Kaimowitz, 1999; Mertens et al., 2000). The present results are therefore a pattern to be explained rather than an explanation.

These results also carry a methodological implication for LULC research on Southern Taraba and comparable Nigerian districts. Enaruvbe and Pontius (2015), applying intensity analysis to land change data from southern Nigeria, demonstrated that apparent land change patterns can depart substantially from a uniform-intensity expectation, and that the size of this departure is itself informative about the underlying change process. The present study's chi-square rejection of equal decadal loss ($\chi^2 = 1,632.65$, $p < .001$) for Southern Taraba's forest loss is consistent with the case made by that literature: single-period average rates, of the kind conventionally reported in district-level Nigerian LULC studies, can obscure policy-relevant variation in the pace and the destination of land change that only an interval-disaggregated analysis can reveal. Enaruvbe and Pontius (2015) also examined how classification errors influence intensity analysis, which underlines why the lack of an accuracy assessment for the present base classification limits how far the interval-level patterns can be interpreted.

SCOPE OF INFERENCE AND DIRECTIONS FOR FURTHER WORK

The findings should be read within the following scope. First, the analysis is a secondary analysis of an existing four-date classification that applied the same supervised procedure to every date; formal accuracy metrics were not generated when the maps were produced. The central result, uneven decadal loss of combined forest, is comparatively robust to this constraint because it does not depend on separating light from dense forest, whereas class-level estimates, particularly for the spectrally difficult built-up class in savanna landscapes, are more sensitive to it. Validating the four maps against an independent probability-based reference sample (Olofsson et al., 2014) is therefore the most valuable extension. Second, the scenes are single dates from different seasons, so some apparent change may be unrelated to conversion; seasonally matched or multi-date composites would address this. Third, the reallocation results are net-change accounts. Re-classification that retains from-to matrices for each decade would allow forest-to-built-up and forest-to-cultivated/bare-land conversions to be quantified directly and would permit the full category- and transition-level intensity analysis of Aldwaik and Pontius (2012). Fourth, the chi-square test compares three intervals against an equal-loss null and is used as a formal descriptor of temporal unevenness, not as an inference about time-series stationarity. Finally, the study documents land-cover outcomes without testing their drivers; linking the pattern to population, agricultural, infrastructural, and institutional data is a natural next step.

Any policy reading of these results should be conditional. If the pattern were confirmed by an accuracy-assessed classification and supported by evidence on its causes, it would suggest that a single, uniform conservation intervention is unlikely to have been equally effective throughout the study period, and that periodic reassessment of land-use policy would be more appropriate than a one-off design. The present data do not, however, show which activities produced the shift in the dominant net-gain class, and so cannot by themselves justify a specific intervention such as urban containment or agricultural intensification.



CONCLUSION

This study has shown that forest loss in the Southern Senatorial District of Taraba State between 1990 and 2020 was not evenly distributed across decades. The compound annual rate of forest-cover loss varied more than sixfold across the three inter-decadal intervals examined, and a formal chi-square test showed that the decadal losses departed markedly from an equal distribution, a result that is conditional on a classification whose accuracy was not formally assessed. The class with the largest net gain against the loss of forest and water-body area also changed over the study period, from built-up area in 1990–2010 to cultivated/bare land in 2010–2020. Neither of these findings would have been visible from a conventional single-period average change analysis of the kind previously reported for this district or for comparable Nigerian localities (Danjuma et al., 2014; Gabriel & Audu, 2017; Nduka et al., 2022).

The practical implication is that forest monitoring for the district should be interval-based and repeated periodically rather than designed once and left unrevised. The dominant land-cover destination of lost forest changed once within the 30-year study period; whether that reflects a change in the underlying drivers remains to be established through accuracy-assessed classifications, from-to transition matrices, and direct evidence on population, agricultural, infrastructural, and institutional factors.

RECOMMENDATIONS

- The Taraba State Ministry of Environment should adopt a decadal (rather than one-off) land-use policy review cycle for the Southern Senatorial District, given the uneven pace of forest loss and the observed shift in the largest net land-cover gain from built-up area (1990–2010) to cultivated/bare land (2010–2020).
- Where field verification confirms that cultivated/bare land is expanding into remaining forest, agricultural intensification programmes (improved seed varieties, extension services, and irrigation where feasible) should be prioritised over further land clearing, to reduce the incentive for continued areal agricultural expansion.
- Settlement planning in the district should continue to be guided by updated land cover monitoring, since built-up gains, although no longer the largest net gain, still equalled 42.1% of the net loss of forest and water-body area in the most recent decade examined.
- Future LULC monitoring of the district should use accuracy-assessed classifications (reporting the error matrix and overall, user's, and producer's accuracy), retain from-to transition matrices for every interval, and routinely report interval-level compound rates of change and reallocation shares, rather than only total or simple linear change, so that any future shift in the dominant land-cover pathway can be detected promptly and verified against gross transitions.
- Studies that seek to explain the pattern should collect direct data on candidate drivers (population and settlement growth, farm expansion, infrastructure, and enforcement of forest laws) for the same intervals, so that observed land-cover changes can be attributed with evidence rather than inference.
- Given the observed net decline in water-body extent alongside forest cover, buffer zones around remaining rivers and water bodies should be formally protected as part of any land-use plan responding to these findings.

DECLARATIONS

Conflict of Interest

The author declares that there is no conflict of interest.



Author Contributions

Sike-Uwbu Daude Gbana is the sole author of this article and was responsible for the analytical design, computation, and manuscript development.

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Data Availability Statement

The base classified land use/land cover data re-analysed in this study are as reported in the author's unpublished MSc thesis (Gbana, 2023); the derived rate, stationarity, and reallocation computations are available from the corresponding author upon reasonable request.

REFERENCES

1. Aldwaik, S. Z., & Pontius, R. G., Jr. (2012). Intensity analysis to unify measurements of size and stationarity of land changes by interval, category, and transition. *Landscape and Urban Planning*, 106(1), 103–114. <https://doi.org/10.1016/j.landurbplan.2012.02.010>
2. Angelsen, A., & Kaimowitz, D. (1999). Rethinking the causes of deforestation: Lessons from economic models. *The World Bank Research Observer*, 14(1), 73–98. <https://doi.org/10.1093/wbro/14.1.73>
3. Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: Forecasting and control* (5th ed.). Wiley.
4. Danjuma, A. K., Ali, A. Y., Lagan, A. N., Jeb, D. N., & Karma, I. M. (2014). Determination of change matrix among the land use/land cover types in Jalingo metropolis, Nigeria. *International Journal of Innovation and Applied Studies*, 8(1), 213–224.
5. Enaruvbe, G. O., & Pontius, R. G., Jr. (2015). Influence of classification errors on intensity analysis of land changes in southern Nigeria. *International Journal of Remote Sensing*, 36(1), 244–261. <https://doi.org/10.1080/01431161.2014.994721>
6. Gabriel, A. T., & Audu, Z. A. (2017). Land use and its implication on natural environment of Donga LGA, Nigeria. *Physical Science International Journal*, 16(4), 1–10.
7. Gbana, S. D. (2023). *Deforestation and conservation practices in the Southern Senatorial District of Taraba State, Nigeria* [Unpublished MSc thesis]. Department of Geography, University of Nigeria, Nsukka.
8. Geist, H. J., & Lambin, E. F. (2002). Proximate causes and underlying driving forces of tropical deforestation. *BioScience*, 52(2), 143–150. [https://doi.org/10.1641/0006-3568\(2002\)052\[0143:PCAUDF\]2.0.CO;2](https://doi.org/10.1641/0006-3568(2002)052[0143:PCAUDF]2.0.CO;2)
9. Lambin, E. F., Geist, H. J., & Lepers, E. (2003). Dynamics of land-use and land-cover change in tropical regions. *Annual Review of Environment and Resources*, 28, 205–241. <https://doi.org/10.1146/annurev.energy.28.050302.105459>
10. Mertens, B., Sunderlin, W. D., Ndoye, O., & Lambin, E. F. (2000). Impact of macroeconomic change on deforestation in South Cameroon: Integration of household survey and remotely-sensed data. *World Development*, 28(6), 983–999. [https://doi.org/10.1016/S0305-750X\(00\)00007-3](https://doi.org/10.1016/S0305-750X(00)00007-3)
11. Nduka, O. V., Yusha'u, A. M., & Dinshiya, U. (2022). Assessment of changes in land cover by deforestation in Kurmi LGA, Taraba State, Nigeria, using remote sensing/geographic information system. *Aswan University Journal of Environmental Studies*, 3(1), 67–87. <https://doi.org/10.21608/aujes.2022.114556.1055>



12. Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., & Wulder, M. A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, 148, 42–57. <https://doi.org/10.1016/j.rse.2014.02.015>
13. Puyravaud, J. P. (2003). Standardizing the calculation of the annual rate of deforestation. *Forest Ecology and Management*, 177(1–3), 593–596.