



(RESEARCH ARTICLE)



IMPACT OF ANTHROPOGENIC ACTIVITIES (AGRICULTURE, MINING, URBANIZATION) ON VEGETATION AND SOILS IN MARITIME GUINEA (2002–2024)

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ABSTRACT

The sub-prefecture of Damakhanian, in Maritime Guinea, is undergoing rapid landscape transformation driven by the The landscapes of the Damakhanian sub-prefecture, in Maritime Guinea, are being rapidly reshaped by the combined effects of urban expansion, agriculture and climate variability. This study examines changes in vegetation and hydroclimatic conditions between 1986 and 2024, quantifies land-use/land-cover (LULC) change between 2002 and 2024, and explores possible trajectories up to 2100. Fifteen variables were analysed: seven Landsat-derived indices (NDVI, EVI, SAVI, MSAVI, NBR, NDWI and LST) and eight climatic and water-balance variables. Trends and change points were assessed with the Mann-Kendall, Sen's slope and Pettitt tests, and seasonal contrasts with Student's *t*-test and the Mann-Whitney test. LULC maps for 2002 (Landsat 5 TM) and 2024 (Landsat 8 OLI) were used to measure change and to build three prospective scenarios. EVI declined significantly ($\tau = -0.385$; $p < 0.001$), whereas land surface temperature rose by about 0.23 °C per year ($\tau = 0.397$; $p < 0.001$). The Pettitt test indicated significant inhomogeneity in the EVI, NBR and LST series, while precipitation, maximum air temperature and NDVI showed no significant trend. Over 22 years, wooded/shrub savanna and open forest lost 47.4% and 45.7% of their area, respectively, to the benefit of urban fabric (+203.4%), degraded areas and bare soil (+189.7%) and crops and fallow land (+33.5%). The scenarios suggest that, without conservation measures, natural vegetation could disappear before 2050. The observed degradation appears more closely related to human pressure than to an unfavourable rainfall trend, which calls for land-use planning that protects the remaining wooded areas.

Keywords: Land Use/Land Cover, Remote Sensing, Spatio-Temporal Dynamics, Anthropogenic Pressure, Maritime Guinea, Pressure Gradient

1 INTRODUCTION

Land-use and land-cover change is among the most direct drivers of present-day environmental change. It alters vegetation cover, the surface energy balance, the water cycle and habitat availability, with effects that often extend well beyond the local scale (Lambin *et al.*, 2001; Foley *et al.*, 2005). In the tropics, agricultural expansion, wood extraction and infrastructure development are the most frequent proximate causes of forest loss, and they are themselves governed by demographic, economic and institutional factors (Geist and Lambin, 2002; Lambin *et al.*, 2003). Across Africa, diachronic analyses based on satellite imagery have described a sustained conversion of natural vegetation into cropland and built-up land over several decades (Brink and Eva, 2009; CILSS, 2016).

Urbanisation adds a specific pressure to these dynamics. Global projections place sub-Saharan Africa among the regions where urban land is expected to expand fastest this century (Seto *et al.*, 2012). In Guinea, this trend has been documented in Conakry, where simulations to 2025 indicated that urban land already covered more than half of the city (Traore *et al.*, 2018), and in the Konkouré River basin, where nearly one third of the area was converted to built-up land between 2006 and 2021 (Bah *et al.*, 2024). Peri-urban areas and the road corridors linking the capital to inland towns are exposed to these changes, yet they remain poorly studied at fine scale.

Vegetation also responds to climate variability. In West Africa, rainfall has shown strong interannual and decadal fluctuations since the 1970s (Nicholson, 2013), and separating the climatic and human contributions to vegetation change is often difficult (Herrmann *et al.*, 2005). Spectral indices provide a convenient tool for this purpose. NDVI (Tucker, 1979) and EVI (Huete *et al.*, 2002) describe photosynthetic activity; soil-adjusted indices such as SAVI and MSAVI reduce the influence of bare soil (Huete, 1988; Qi *et al.*, 1994); and land surface temperature (LST) captures changes in the energy balance associated with vegetation loss and soil sealing (Weng *et al.*, 2004; Yuan and Bauer, 2007).

In Guinea, landscape dynamics must be interpreted with some caution. Fairhead and Leach (1996) showed that degradation narratives do not always withstand the scrutiny of local trajectories, and recent national mapping efforts have mostly addressed small-scale agro-ecological zoning (Jaffrain *et al.*, 2021). Few studies in Maritime Guinea combine, for the same territory, long time series of spectral indices and climatic variables, diachronic LULC mapping and the exploration of future trajectories. The Damakhania sub-prefecture, in Kindia prefecture, lends itself well to such an approach, as it brings together savanna and open forest, a large water body and areas undergoing urbanisation.

This study has four objectives: (i) to characterise trends and change points in fifteen biophysical and climatic variables between 1986 and 2024; (ii) to measure the contrast between the dry and rainy seasons for the main variables; (iii) to quantify LULC change between 2002 and 2024; and (iv) to explore possible changes in these classes to 2100 under three scenarios. Our working hypothesis is that the decline in vegetation cover is driven primarily by human pressure, with climate variability playing a modulating role.

2 MATERIALS AND METHODS

2.1 Study area

The Damakhania sub-prefecture belongs to the prefecture and administrative region of Kindia, in Maritime Guinea. The climate is humid tropical (Guinean type), with well-defined dry and rainy seasons. The landscape combines wooded and shrub savanna, open forest, crops and fallow land, expanding settlements and a large water body occupying the north-western part of the territory (about 9% of its area). The location of the study area is shown in Figure 1.

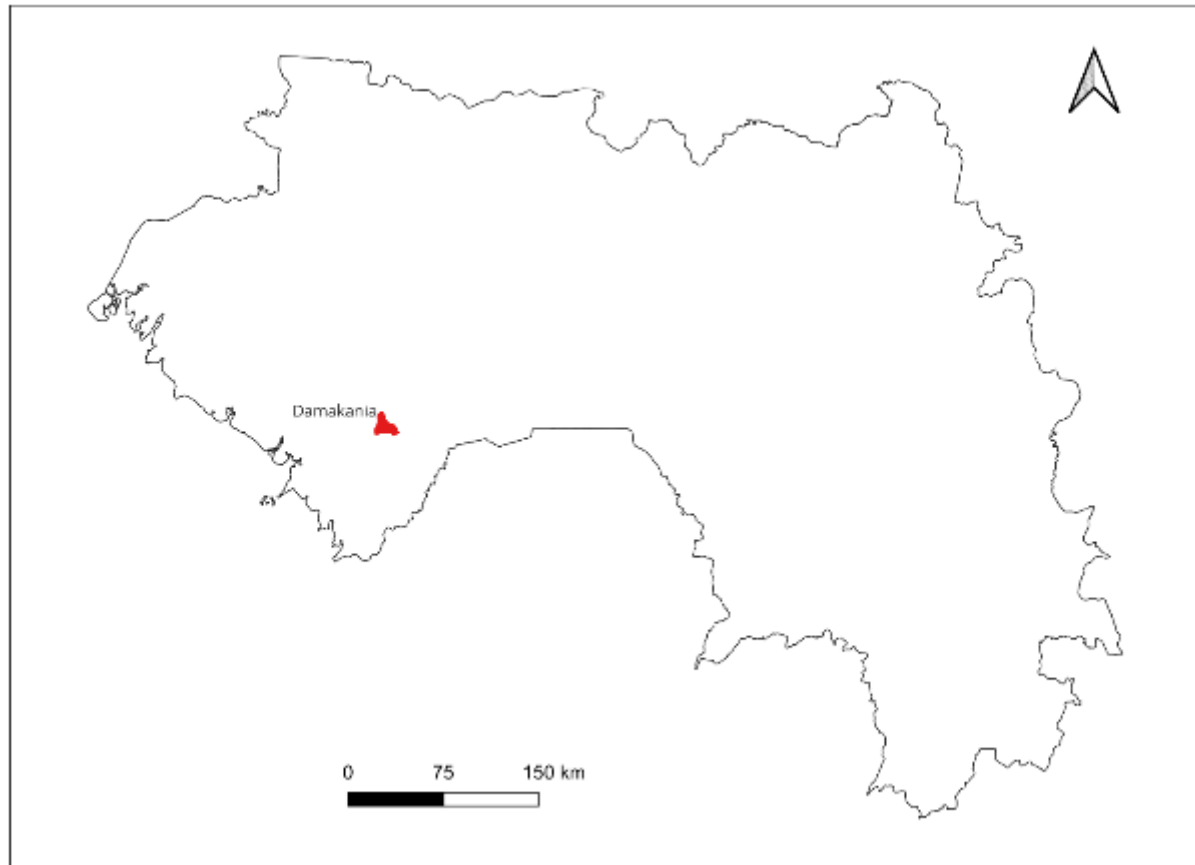


Figure 1: Study area

2.2 Satellite data

Fifteen variables were used (Table 1). Seven biophysical indices were computed from the Landsat 4–5 and 8: five vegetation indices (NDVI, EVI, SAVI, MSAVI and NBR), one moisture index (NDWI) and land surface temperature (LST). Eight climatic and water-balance variables, downloaded from the Climate Engine platform (Huntington *et al.*, 2017), complete the dataset: precipitation (PPT), maximum (Tmax) and minimum (Tmin) air temperature, actual (AET) and potential (PET) evapotranspiration, and three water-balance indicators denoted DHC, DPE and IGS.

The interannual series cover the period 1986–2024, with one value per year ($n = 39$). Their means coincide with those of the dry-season composites, indicating that the trend analysis refers to the dry season. For the seasonal comparison, five variables (NDVI, EVI, LST, AET and PET) were extracted separately for the dry and rainy seasons over 1987–2024 ($n = 38$ per season).

Table 1: Satellite data

Variable	Definition	Formula / unit	Reference
NDVI	Normalized Difference Vegetation Index	$(NIR - R) / (NIR + R)$	Tucker (1979)
EVI	Enhanced Vegetation Index	$2.5 (NIR - R) / (NIR + 6R - 7.5B + 1)$	Huete <i>et al.</i> (2002)
SAVI	Soil-Adjusted Vegetation Index	$(1 + L)(NIR - R) / (NIR + R + L)$, $L = 0.5$	Huete (1988)
MSAVI	Modified SAVI	$[2NIR + 1 - \sqrt{((2NIR + 1)^2 - 8(NIR - R))}] / 2$	Qi <i>et al.</i> (1994)

NBR	Normalized Burn Ratio	$(\text{NIR} - \text{SWIR2}) / (\text{NIR} + \text{SWIR2})$	Key and Benson (2006)
NDWI	Normalized Difference Water Index	$(\text{G} - \text{NIR}) / (\text{G} + \text{NIR})$	McFeeters (1996)
LST	Land surface temperature	Thermal infrared band; °C	
PPT	Precipitation	mm	
Tmax / Tmin	Maximum and minimum air temperature	°C	
AET / PET	Actual and potential evapotranspiration	mm	
DHC, DPE, IGS	Water-balance and drought indicators		

NIR: near infrared; R: red; B: blue; G: green; SWIR2: shortwave infrared 2. AET and PET are labelled ETR and ETP in Figures 2–4.

2.3 Statistical analysis of time series

Each variable was first described by its mean, standard deviation, standard error, 95% confidence interval of the mean, extreme values and coefficient of variation (CV). Annual departures from the period mean were plotted as anomalies, together with a LOESS smoother to show the overall pattern.

Monotonic trends were tested with the non-parametric Mann-Kendall test (Mann, 1945; Kendall, 1975), whose τ statistic indicates the direction and strength of the trend. Trend magnitude was estimated with Sen's slope (Sen, 1968), expressed in units of the variable per year. The Pettitt (1979) test was used to detect a possible shift in the mean of each series. A 5% significance level was used for all tests.

Seasonal comparisons followed a conditional procedure. Normality was checked with the Shapiro-Wilk test (Shapiro and Wilk, 1965) and homogeneity of variances with Fisher's F-test. Student's t-test was applied when both distributions were normal (NDVI and EVI); otherwise, the Mann-Whitney test (Mann and Whitney, 1947) was used (LST, AET and PET). All analyses were performed in R.

2.4 Land-use/land-cover mapping and analysis

LULC was mapped for 2002 from a Landsat 5 TM image and for 2024 from a Landsat 8 OLI image. Six classes were defined: water bodies, wooded savanna/shrub savanna, open forest/wooded savanna, urban fabric, degraded areas/bare soil, and crops/fallow land. For each class, change was expressed in percentage points of the total area and as relative change, computed as $(S_{2024} - S_{2002}) / S_{2002} \times 100$.

2.5 Prospective scenarios

Three scenarios were built from the 2024 situation for the 2050, 2075 and 2100 horizons: a Business-As-Usual (BAU) scenario extending the observed dynamics; a mitigation scenario assuming the implementation of conservation policies; and a degradation scenario corresponding to intensified pressures. Class shares were rescaled to 100% of the total area for each horizon.

3 RESULTS AND DISCUSSION

3.1 General characteristics of the variables

The vegetation indices show moderate values and comparable interannual variability, with coefficients of variation between 18% and 21%, NBR being the exception (34.2%) (Table 2). Mean NDVI reaches 0.422 and mean EVI 0.258, values typical of partly open dry-season vegetation in which soil and dry grass contribute strongly to reflectance. Mean land surface temperature is 35.8 °C, with a considerable range between years (16.6 to 51.5 °C).

Air temperatures are remarkably stable: the standard deviation of Tmax does not exceed 0.78 °C, and that of Tmin is 0.74 °C. Water-balance terms, by contrast, vary widely. The CV of precipitation exceeds 113%, and AET, with a mean of 61.9 mm, has a standard deviation of 42.5 mm. This contrast suggests that, from one year to the next, water availability weighs more heavily on vegetation functioning than the thermal regime, which remains broadly constant.

Table 2: Descriptive statistics of the variables (interannual series 1986–2024, n = 39)

Variable	Mean	SD	Minimum	Maximum	CV (%)
NDVI	0.422	0.085	0.210	0.690	20.1
EVI	0.258	0.055	0.157	0.431	21.3
SAVI	0.254	0.047	0.150	0.410	18.4
MSAVI	0.227	0.046	0.135	0.388	20.1
NBR	0.281	0.096	0.108	0.571	34.2
NDWI	−0.469	0.068	−0.668	−0.257	—
LST (°C)	35.81	6.08	16.58	51.49	17.0
PPT (mm)	50.8	57.6	0.0	263.0	113.3
Tmax (°C)	36.23	0.78	34.90	38.20	2.2
Tmin (°C)	23.61	0.74	22.10	25.50	3.1
AET (mm)	61.9	42.5	13.7	182.8	68.7
PET (mm)	125.8	5.0	117.1	141.8	3.9
DHC	117.0	42.7	0.0	168.8	36.5
DPE	−128.0	58.4	−182.5	97.8	—
IGS	−1.17	2.33	−4.31	4.05	—

SD: standard deviation; CV: coefficient of variation. CV is not computed for variables with a negative or near-zero mean (DPE, IGS, NDWI).

3.2 Trends and change points in the interannual series

Of the five variables tested with Mann-Kendall, two show a significant trend (Table 3). EVI decreases ($\tau = -0.385$; $p = 0.0006$) with a Sen's slope of -0.0021 per year, i.e. a cumulative decline of about 0.08 over the period, close to 30% of its mean value. LST increases markedly ($\tau = 0.397$; $p = 0.0004$), at a rate of 0.23 °C per year. NDVI has a negative but non-significant slope ($\tau = -0.153$; $p = 0.178$). The same holds for Tmax, whose slight increase ($+0.017$ °C per year) does not reach significance ($p = 0.112$), and for precipitation ($\tau = -0.067$; $p = 0.560$).

Table 3. Mann-Kendall test results and Sen's slope (1986–2024)

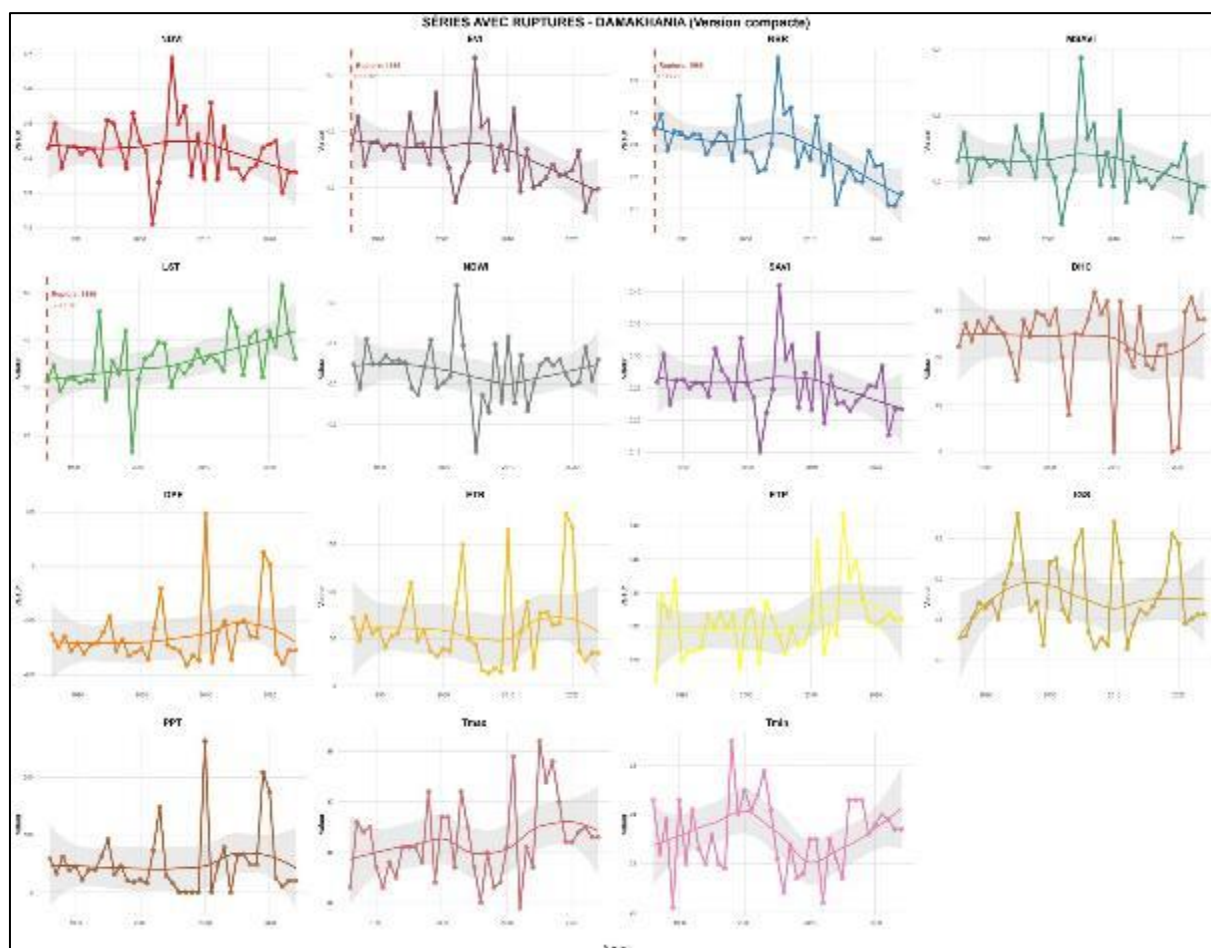
Variable	Kendall's τ	p-value	Sen's slope (yr^{-1})	Trend
NDVI	−0.153	0.178	−0.0017	Not significant
EVI	−0.385	0.0006 ***	−0.0021	Significant decrease
LST	0.397	0.0004 ***	+0.232 °C	Significant increase
Tmax	0.182	0.112	+0.017 °C	Not significant
PPT	−0.067	0.560	−0.344 mm	Not significant

*** significant at the 0.1% level.

Applied to all fifteen variables, the Pettitt test reveals significant inhomogeneity in three of them: NBR ($p = 0.0006$), EVI ($p = 0.003$) and LST ($p = 0.014$) (Table 4). Tmax approaches the threshold without reaching it ($p = 0.091$). The remaining variables, notably the water-balance terms and precipitation, are homogeneous. The change-point year returned by the analysis is the first year of the series (1986), which is most likely a computational artefact; the timing of the shift is therefore not interpreted here. The smoothed curves (Figure 2) and anomalies (Figure 3) nevertheless show that the decline in EVI, NBR, SAVI and MSAVI intensifies from the late 2000s, with negative anomalies becoming dominant during the 2010s, while positive LST anomalies become more frequent over the same period.

Table 4: Results of the Pettitt homogeneity test (1986–2024)

Variable	p-value	Change point	Variable	p-value	Change point
NBR	0.0006	Yes ***	PET	0.181	No
EVI	0.003	Yes **	NDWI	0.868	No
LST	0.014	Yes *	AET	0.868	No
Tmax	0.091	No	DPE	0.884	No
MSAVI	0.124	No	IGS	0.916	No
SAVI	0.160	No	DHC	0.932	No
NDVI	0.259	No	PPT	0.948	No
Tmin	0.593	No			

* $p < 0.05$; $p < 0.01$; * $p < 0.001$.**Figure 2: Interannual variation of the fifteen variables in Damakhania (1986–2024), with LOESS smoother and confidence band**

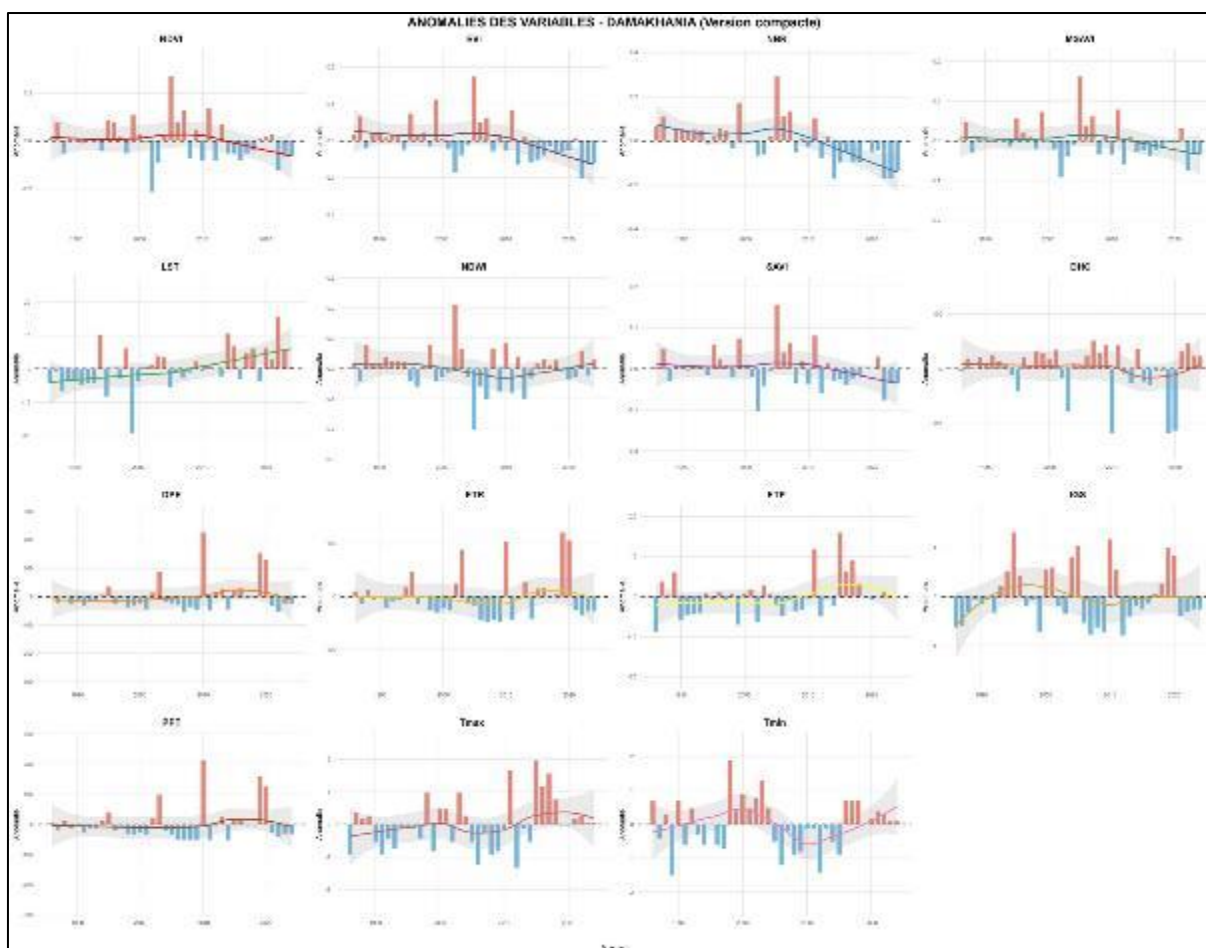


Figure 3: Interannual anomalies of the fifteen variables relative to the 1986–2024 mean (red bars: positive anomalies; blue bars: negative anomalies)

The fact that EVI detects a significant decline where NDVI does not is partly explained by the design of the two indices. NDVI tends to saturate over dense canopies and remains sensitive to soil and atmospheric effects, whereas EVI, which includes the blue band and a correction term, retains greater sensitivity to changes in canopy structure (Huete *et al.*, 2002). The sharp decrease in NBR points in the same direction. This index, which combines near and shortwave infrared, responds to the loss of woody biomass, reduced vegetation moisture and burned surfaces (Key and Benson, 2006). Taken together, these signals reflect a depletion of the woody layer rather than a mere fluctuation in chlorophyll activity.

The rise in LST calls for careful interpretation. It is not accompanied by a significant trend in T_{max}, which suggests that it mainly reflects a change in surface properties rather than regional air warming. Converting vegetation to bare soil and built-up surfaces reduces evapotranspiration and increases heat storage, a mechanism well established in urban heat island studies (Oke, 1982; Weng *et al.*, 2004; Yuan and Bauer, 2007). The magnitude of the trend, which would amount to nearly 9 °C over the period, should nonetheless be viewed with caution: Landsat-derived LST depends on acquisition date, atmospheric conditions and sensor, and the succession of the TM, ETM+ and OLI sensors may introduce discontinuities. The minimum of 3.5 °C recorded in the rainy season (Table 5) very probably results from cloud contamination.

The absence of a significant precipitation trend is an important result for interpretation. If rainfall has not decreased detectably, the decline in vegetation indices can hardly be attributed primarily to a rainfall deficit; it appears instead to be associated with non-climatic factors, in line with the reasoning that separates the climatic and residual components of vegetation change (Herrmann *et al.*, 2005). This conclusion remains tentative, however. The series are short, dry-season rainfall is inherently low and irregular, and possible serial correlation, which was not corrected, may affect the Mann-Kendall results (Hamed and Rao, 1998; Yue *et al.*, 2002).

3.3 Contrasts between the dry and rainy seasons

All five variables differ highly significantly between seasons ($p < 0.001$ in every case; Table 5, Figure 4). NDVI rises from 0.424 in the dry season to 0.617 in the rainy season (+45.5%) and EVI from 0.259 to 0.425 (+64.1%). AET increases by

63.3%, from 62.6 to 102.2 mm. Conversely, LST falls from 35.8 to 27.9 °C (–22.0%) and PET from 125.8 to 74.4 mm (–40.9%).

Table 5: Comparison of variables between the dry and rainy seasons (1987–2024, n = 38 per season)

Variable	Test	Mean DS (± SD)	Mean RS (± SD)	CV DS / RS (%)	RS vs DS	p-value
NDVI	Student	0.424 ± 0.085	0.617 ± 0.085	20.1 / 13.7	+45.5%	3.2×10^{-15}
EVI	Student	0.259 ± 0.055	0.425 ± 0.052	21.1 / 12.3	+64.1%	1.2×10^{-21}
LST (°C)	Mann-Whitney	35.8 ± 6.2	27.9 ± 6.9	17.2 / 24.8	–22.0%	7.8×10^{-7}
AET (mm)	Mann-Whitney	62.6 ± 42.8	102.2 ± 6.1	68.4 / 6.0	+63.3%	2.6×10^{-8}
PET (mm)	Mann-Whitney	125.8 ± 5.0	74.4 ± 1.6	4.0 / 2.1	–40.9%	6.5×10^{-14}

DS: dry season; RS: rainy season; SD: standard deviation.

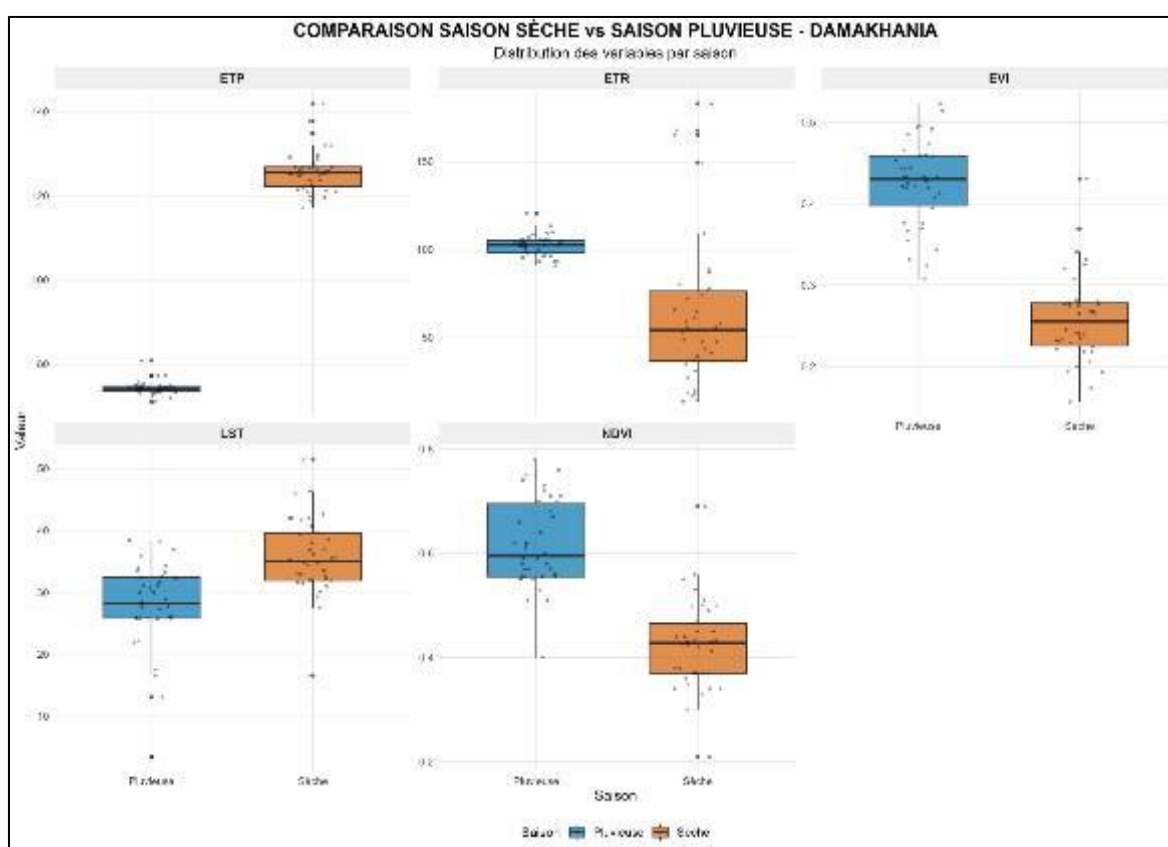


Figure 4: Distribution of the variables by season in Damakhania, 1987–2024 (Pluvieuse: rainy season; Sèche: dry season; ETR: AET; ETP: PET)

These contrasts reflect the expected functioning of a tropical environment with sharply defined seasons. In the rainy season, water availability sustains photosynthesis and evapotranspiration, which cools the surface; in the dry season, high radiation and drier air increase evaporative demand while available water becomes scarce. The gap between PET and AET in the dry season, more than 60 mm on average, gives a measure of the water deficit to which vegetation is exposed during this period.

Interannual variability provides additional insight. The CVs of NDVI and EVI are markedly higher in the dry season (20.1% and 21.1%) than in the rainy season (13.7% and 12.3%), and that of AET rises from 6.0% to 68.4%. In the rainy season, abundant water homogenises the canopy response, whereas in the dry season vegetation behaviour depends more on soil water reserves and on the condition of woody formations. Dry-season composites therefore appear more sensitive to degradation, which supports their use for analysing long-term trends.

3.4 Land-use/land-cover dynamics between 2002 and 2024

Land cover changed profoundly over 22 years (Table 6, Figures 5 to 7). In 2002, natural vegetation dominated the landscape: wooded/shrub savanna covered 36.32% of the sub-prefecture and open forest 31.25%, i.e. 67.6% in total. By 2024, these two classes accounted for only 19.10% and 16.97%, i.e. 36.1%. Their relative losses are almost identical: 47.4% for savanna and 45.7% for open forest.

Table 6: Change in land-use/land-cover classes between 2002 and 2024

Class	2002 (%)	2024 (%)	Change (points)	Relative change (%)	Trend
Water bodies	9.20	9.10	−0.10	−1.1	Stable
Wooded savanna/Shrub savanna	36.32	19.10	−17.22	−47.4	Strong decline
Open forest/Wooded savanna	31.25	16.97	−14.28	−45.7	Strong decline
Urban fabric	8.74	26.52	+17.78	+203.4	Strong increase
Degraded areas/Bare soil	5.74	16.63	+10.89	+189.7	Strong increase
Crops/Fallow land	8.75	11.68	+2.93	+33.5	Moderate increase
Total	100	100			

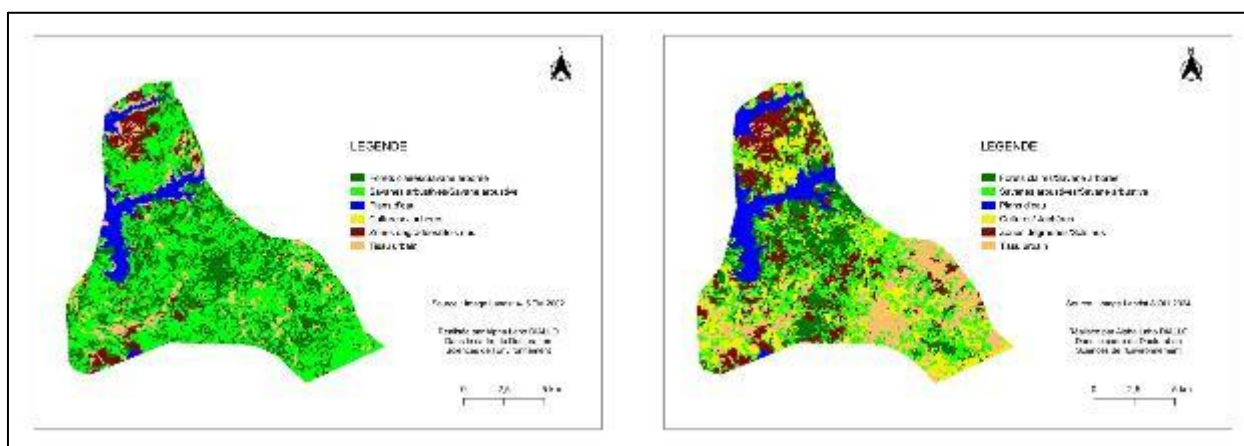


Figure 5: Land use/land cover of the Damakhania sub-prefecture in 2002 (a, Landsat 5 TM) and 2024 (b, Landsat 8 OLI)

Urban fabric shows the strongest increase. Its share rose from 8.74% to 26.52%, a threefold increase, making it the largest land-cover class in 2024. Degraded areas and bare soil followed a similar path, from 5.74% to 16.63% (+189.7%). Crops and fallow land increased more moderately (+2.93 points), while the water body remained stable. Human-modified classes as a whole (urban fabric, degraded areas and crops) thus expanded from 23.2% to 54.8% of the area. The maps (Figure 5) show that urban growth occurred mainly in the southern and south-eastern parts of the sub-prefecture, whereas degraded areas are concentrated around the water body and in the north.

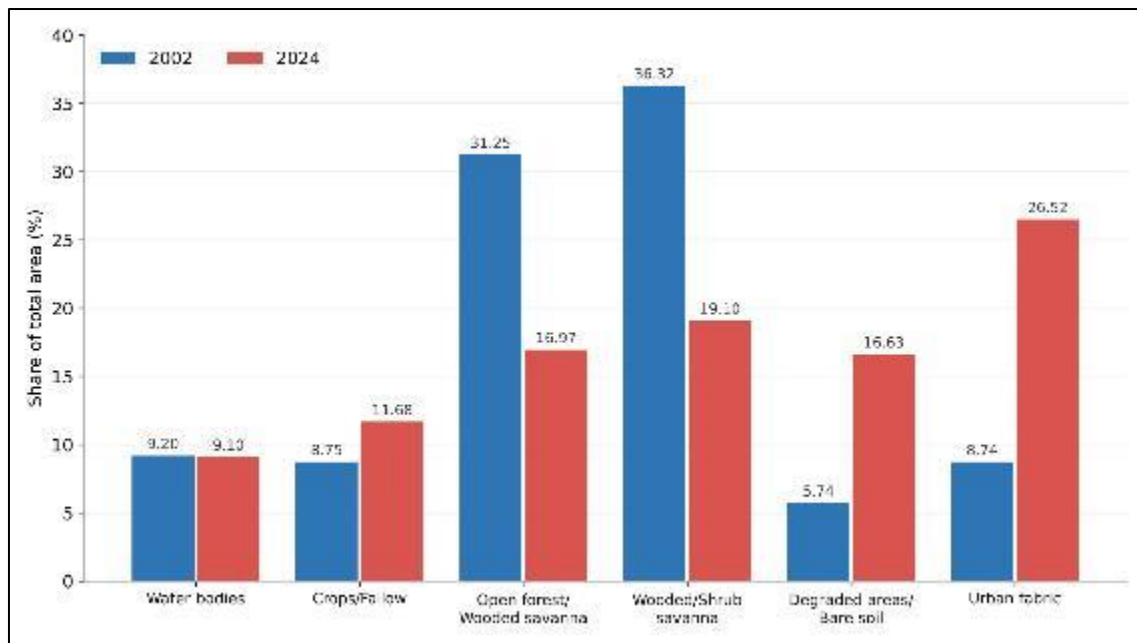


Figure 6: Shares of land-use/land-cover classes in 2002 and 2024

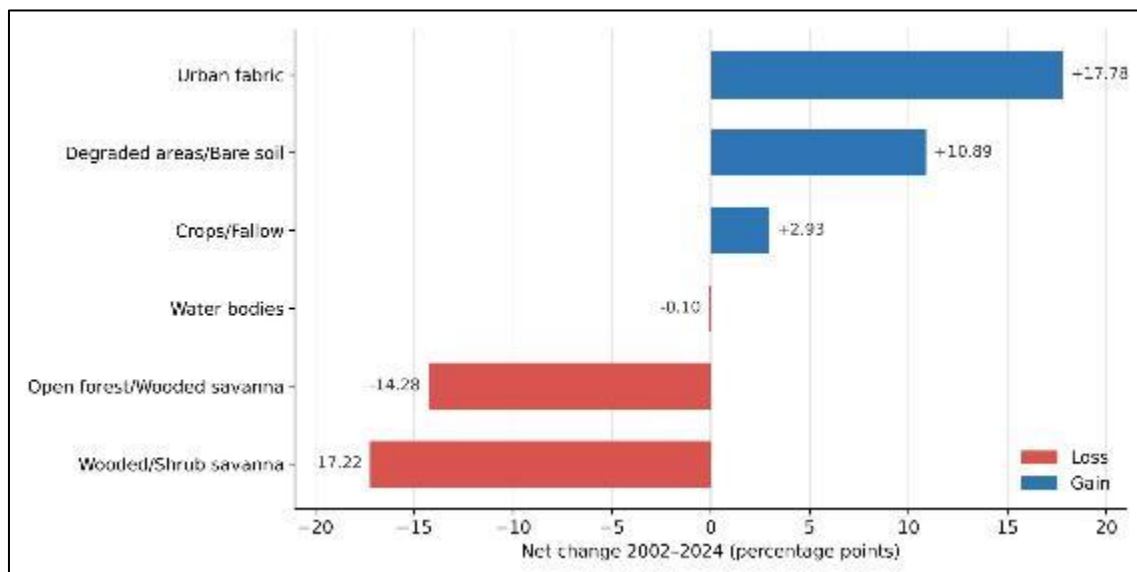


Figure 7: Net change in land-use/land-cover classes between 2002 and 2024 (percentage points)

The scale of these changes is consistent with observations elsewhere in Maritime Guinea. In the Konkouré River basin, Bah *et al.* (2024) reported that about 32% of the area was converted to built-up land between 2006 and 2021, and Traore *et al.* (2018) described a continuous expansion of urban land at the expense of vegetation in Conakry. The dynamics observed in Damakhania follow the classic pattern of a peri-urban frontier, where settlements spread over former savanna while farming and wood collection shift to the remaining natural vegetation (Geist and Lambin, 2002; Lambin *et al.*, 2003). Population growth, urban demand for fuelwood and building land, and improved accessibility are plausible drivers, but their respective roles were not measured in this study and will need to be established through field surveys.

These results are consistent with those of Section 3.2. The conversion of nearly one third of the territory from woody vegetation to urban or bare surfaces offers a coherent explanation for both the decline in EVI and NBR and the rise in LST, in the absence of any notable change in rainfall. Two caveats apply. The first concerns possible confusion between shrub savanna, fallow land and bare soil in the dry season, which only an accuracy assessment of the classifications can quantify (Olofsson *et al.*, 2014). The second is that net change per class says nothing about actual transitions: a transition matrix would be needed to determine whether urban land expanded directly onto open forest or onto already degraded savanna (Pontius *et al.*, 2004). As Fairhead and Leach (1996) pointed out, the interpretation of vegetation trajectories also benefits from being checked against the knowledge and practices of local communities.

3.5 Prospective scenarios to 2100

The three scenarios share a common trajectory of declining natural vegetation, but at different rates (Figure 8, Table 7). Under BAU, wooded/shrub savanna and open forest disappear by 2050, and urban fabric would cover nearly half of the territory (47.0% in 2050 and 50.9% in 2100), degraded areas about 30% and crops 13–15%. The degradation scenario leads to the same disappearance of natural vegetation, with a higher urban share (50.7% in 2050 and 55.4% in 2100). Only the mitigation scenario retains remnants of open forest (8.0%) and savanna (6.5%) in 2050; open forest persists only as a residual patch in 2075 and disappears by 2100.

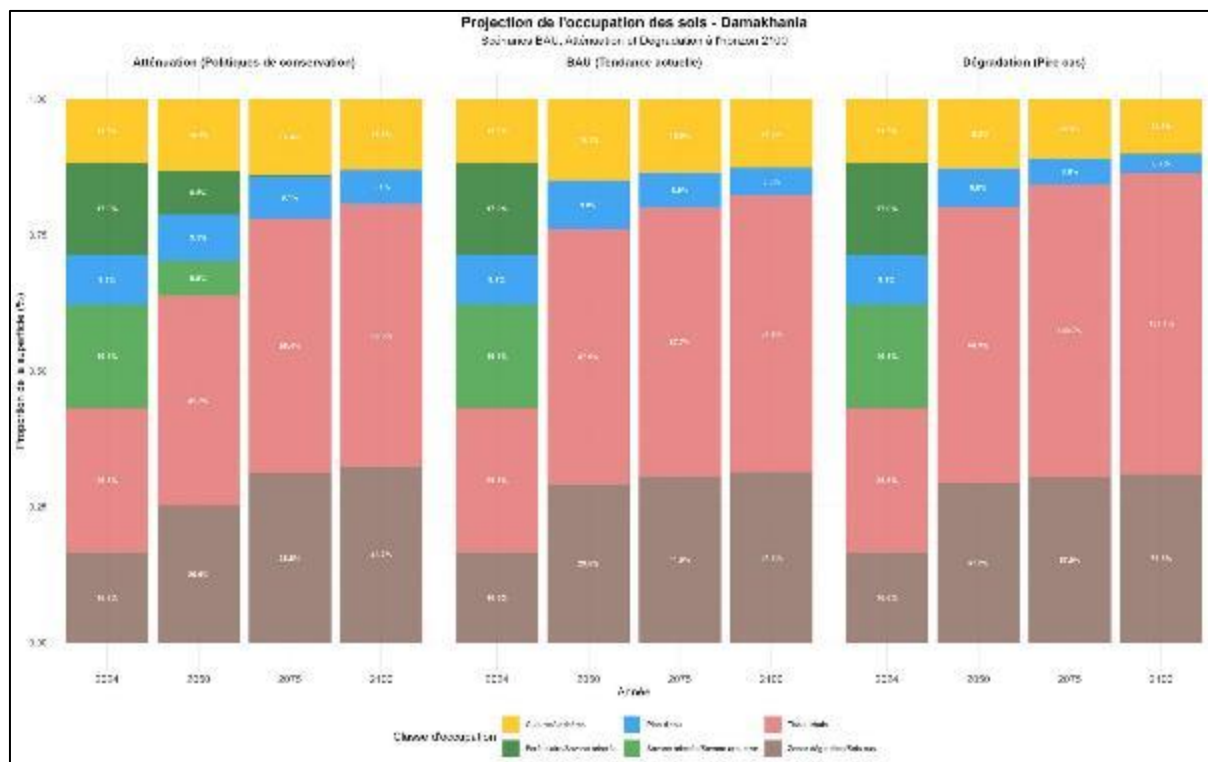


Figure 8: Projected land use/land cover in Damakhania under the mitigation, Business-As-Usual (BAU) and degradation scenarios for 2050, 2075 and 2100

Table 7: Projected shares of land-use/land-cover classes (% , rescaled to 100%)

Scenario	Horizon	Urban fabric	Degraded areas	Crops	Water bodies	Open forest	Savanna
Baseline	2024	26.5	16.6	11.7	9.1	17.0	19.1
Mitigation	2050	38.6	25.2	13.2	8.5	8.0	6.5
	2075	47.1	31.3	13.9	7.7	< 0.5	0
	2100	48.2	32.4	13.0	6.3	0	0
BAU	2050	47.0	29.2	14.9	8.9	0	0
	2075	49.4	30.6	13.5	6.5	0	0
	2100	50.9	31.4	12.6	5.1	0	0
Degradation	2050	50.7	29.4	12.8	7.1	0	0
	2075	53.9	30.5	11.0	4.7	0	0
	2100	55.4	31.0	10.0	3.5	0	0

Values obtained by rescaling to 100% the raw values shown in Figure 8. The apparent decrease of the water body results from this rescaling and should not be interpreted as an actual loss.

These projections should be read as exploratory trajectories rather than forecasts. The raw values produced by the model exceed 100% of the area as early as 2050 for some classes, indicating that the method extrapolates observed rates without a total-area constraint; rescaling corrects the scale but not the logic of the projection, and it artificially

reduces the share of the water body. Approaches that explicitly incorporate transition probabilities and spatial structure, such as the combined cellular automata–Markov chain models already applied in Conakry (Traore *et al.*, 2018), would yield more robust projections. The main message is nonetheless consistent across scenarios. Even under mitigation, natural vegetation does not survive beyond 2075, which suggests that the conservation assumptions adopted are insufficient given the intensity of the pressures observed between 2002 and 2024.

4 CONCLUSION

For the Damakhan sub-prefecture, this study relates the behaviour of fifteen biophysical and climatic variables over nearly four decades to the land-cover changes that occurred between 2002 and 2024. It reveals a significant decline in EVI and marked inhomogeneity in the EVI, NBR and LST series, whereas precipitation and air temperature show no significant change. Over the same period, natural vegetation lost nearly half of its area, urban fabric tripled and degraded areas almost tripled.

The convergence of these results supports the hypothesis that vegetation degradation is mainly driven by human pressure, with climate variability acting chiefly through the seasonal contrast and the dry-season water deficit. Despite their methodological limitations, the prospective scenarios indicate that a continuation of current trends could lead to the disappearance of natural vegetation before mid-century. Validating the classifications, building a transition matrix, correcting the change-point dates and adopting spatially explicit modelling are the next steps of this work.

Recommendations

In light of these results, several courses of action can be proposed to land managers and researchers.

- Regulate urban expansion through a local land-use plan that delimits building zones, protects the remaining patches of open forest and wooded savanna, and directs urban growth towards already developed areas.
- Protect the banks of the water body, where degraded areas are concentrated, with a vegetated buffer strip and land-use rules agreed with riparian communities.
- Restore degraded areas and bare soil through reforestation, assisted natural regeneration and agroforestry suited to local conditions.
- Support a shift towards farming systems that limit land clearing, through longer fallow periods, the integration of trees into fields and fire management.
- Reduce pressure on fuelwood resources by promoting improved cookstoves and establishing village woodlots for local supply.
- Set up regular environmental monitoring based on satellite imagery (EVI, NBR, LST) and field surveys to detect degradation fronts early.
- Extend the research through accuracy assessment of the LULC maps, analysis of class transitions, correction for serial correlation, socio-economic surveys of the drivers of change and spatially explicit prospective modelling.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript.

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