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Long-Term Forest Landscape Transformation and Registered Forest Crimes in the Eastern Black Sea, Türkiye

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Abstract

Long-term forest landscape change in mountainous rural areas reflects interactions among land-use pressure, forest structure and human activities. This study had two primary objectives: (i) to quantify 53 years of change in forest extent, stand structure and landscape configuration in the Kümbet Planning Unit in the Eastern Black Sea Region of Türkiye and (ii) to evaluate associations of annual registered forest crime counts with election-year status and broader-scale population and real per capita income indicators while treating the crime records as contextual indicators of recorded pressure rather than as causal measures of landscape change. Forest stand-type maps from 1971, 2013 and 2024 were analyzed using LULC transition matrices and landscape metrics. Annual registered forest crime records for 1981–2025 were examined in relation to election-year status, the provincial population and real per capita income using correlation analysis and negative binomial regression, with linearly interpolated annual forest area included as an exposure offset. Total forest area declined from 6747.8 to 6298.1 ha, whereas agricultural land increased from 637.3 to 2177.7 ha. Degraded forest and open areas decreased, and 44.3% of the study area changed land-cover type. Landscape fragmentation increased between 1971 and 2013, followed by partial spatial consolidation between 2013 and 2024. Election-year status and real per capita income were not significantly associated with annual registered forest crime counts. Within the 1981–2025 study period, the provincial population showed a positive temporal association with registered forest crime counts. Each increase of 10,000 persons corresponded to an approximately 7.5% increase in the expected registered forest crime rate, but this relationship should not be interpreted as a direct local demographic effect. Registered forest crime density did not differ significantly among management-related periods. The temporal correspondence between higher crime density and stronger fragmentation was descriptive and did not establish causality. These findings demonstrate that forest conservation and landscape-restoration planning should integrate forest extent, stand structure, land-cover transitions, landscape configuration and appropriately scaled administrative indicators of recorded forest-related pressure.

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Keywords: land-use/land-cover change; stand-type maps; forest offences; landscape fragmentation; agricultural expansion; human pressure; crown closure; developmental stages

1. Introduction

Forests are among the natural resources most exposed to human-induced pressures because of their global extent, the dependence of rural communities on forest resources and their high sensitivity to land-use change [1,2]. They provide critical ecological and socioeconomic functions, including wood production, carbon storage, water-cycle regulation, climate stabilization and rural livelihood support [3]. However, overconsumption, unregulated resource use and land conversion have caused severe impacts on ecosystem services and climate systems [4–7]. Therefore, land-use/land-cover (LULC) change has become a key indicator for evaluating human pressure on forest ecosystems. Because many forest benefits are not directly traded in markets, changes in forest extent, stand structure and landscape configuration may also affect non-market ecosystem benefits, including biodiversity habitat, soil and water protection, carbon storage, recreation and cultural landscape values [8,9].

Population growth, technological development and industrialization have accelerated major transformations in land use and land cover, particularly through the conversion of natural covers into agricultural, grazing and artificial surfaces. Natural covers such as forests, agricultural lands and pastures have been degraded or converted, whereas artificial surfaces have expanded through urbanization and industrial development [10]. These transformations are particularly critical in forest-dominated rural landscapes, where land conversion, demographic change and livelihood strategies interact over time [11,12]. Economic, political, technological, cultural and demographic factors have been identified as key variables influencing forest cover change at different spatial scales [13]. In developing countries, land-use change has a particularly strong impact on forest ecosystems [13,14], and population growth, migration and rural livelihood strategies are among the main factors affecting forest areas [15–17]. Forest conversion into agricultural and grazing lands may initially increase local employment and income but may later result in a decline in forest resources [18]. Conversely, rural out-migration may reduce direct pressure on forest resources in some regions [11,19]. Thus, forest landscape change should be interpreted as a multidimensional process shaped by land-use demands, sociodemographic dynamics and institutional conditions.

At broader human–environment scales, land-cover change has also been linked to sociodemographic structure, urbanization and increasing demand for ecosystem resources [20–23]. These pressures may be expressed differently across landscapes, including urban expansion, regional development, grazing-related land-use change and transformations in wetland or rural land-cover systems [24–30].

Previous studies have examined LULC change and forest dynamics from different perspectives, including land-cover transitions, forest degradation, landscape fragmentation, agricultural expansion, urbanization, grazing, demographic change and global market forces [11,12,14,31–33]. Collectively, these studies show that forest landscape transformation is rarely driven by a single factor; instead, it emerges from the combined effects of ecological, demographic, economic and institutional processes. In forest and mountainous landscapes, previous LULC studies have also emphasized changes in land-use composition, spatial configuration, forest dynamics and fragmentation, as well as the effects of population change and broader market forces on land-use trajectories [34–47]. However, many studies focus mainly on broad land-cover categories, whereas structural changes within forests, such as developmental stage transitions and crown closure dynamics, are less frequently integrated with socioeconomic and institutional indicators.

LULC change studies have benefited substantially from advances in remote sensing and Geographic Information Systems (GISs), which allow spatial and temporal changes in forests, agricultural areas and settlements to be analyzed more effectively [48]. However, in forest-dominated landscapes, stand-type maps provide an important methodo-

logical advantage over broad-scale land-cover products because they contain detailed information on tree species composition, developmental stage and crown closure. This is particularly relevant in the Eastern Black Sea Region of Türkiye, where complex mixed forests, steep terrain and small-scale fragmentation require fine-resolution structural characterization that broad-scale satellite classifications cannot fully capture. In Türkiye, stand-type mapping in even-aged forests is mainly based on tree species, developmental stage and crown closure, and these maps are commonly produced by interpreting high-resolution aerial photographs or satellite images supported by field observations and forest inventory data [49,50]. Therefore, stand-type maps enable the assessment of both LULC transitions and internal forest structural changes. Nevertheless, comparisons involving historical stand-type maps are subject to uncertainty because manual interpretation and polygon delineation practices used for analogue maps may differ from contemporary digital mapping procedures, potentially introducing interpreter subjectivity and positional discrepancies [51,52]. Such differences may produce apparent spatial transitions that do not necessarily represent actual land-cover change, commonly referred to as pseudo-change [53]. In the present study, this risk was reduced by georeferencing the 1971 map using 1:25,000-scale topographic maps, digitizing the polygons, projecting all maps to a common coordinate system, restricting the analyses to the common spatial extent, and correcting topological errors before overlay analysis. Small and spatially isolated transitions were therefore interpreted cautiously. The stand concept is commonly used to describe forest patches distinguished by structural and silvicultural characteristics such as species composition, crown closure, developmental stage, site quality and volume [54–57]. Remote sensing-based LULC studies have widely used multi-temporal satellite imagery and open-access land-cover products to quantify changes in forest, agricultural, urban and other land-cover classes [58–68]. These studies highlight the value of remote sensing and open-access land-cover products, while the present study uses stand-type maps to capture internal forest structural changes together with LULC transitions.

Forest crime and socioeconomic conditions have also been examined in relation to spatial and land-use patterns. Although the interaction between land use and crime has mostly been studied in urban, suburban and recreational contexts [69–79], the joint analysis of registered forest crime records and long-term LULC change remains relatively limited in forestry research. In long-term administrative datasets, consistently comparable information on individual offence types is not always available; therefore, aggregate annual crime counts may provide a temporally consistent, although indirect, indicator of recorded forest-related pressure. Such aggregate records can support the identification of broad temporal patterns, but they do not distinguish among offence types, ecological severity or the spatial location of individual incidents. Moreover, registered case numbers may reflect not only underlying illegal activities but also changes in detection effort, enforcement capacity, reporting practices and administrative priorities [80–82]. Accordingly, aggregate registered forest crime counts should be interpreted as contextual administrative indicators rather than as direct or complete measures of human pressure on forest ecosystems.

Several studies have examined forest crimes in relation to socioeconomic conditions, migration, spatial patterns and broader land-use processes. Şen and Ünal [83] investigated how economic, social and cultural characteristics of rural communities affect forest crimes and concluded that forests are often perceived as a source of livelihood by people living in rural areas. Wing and Tynon [84] analyzed spatial patterns of crime incidents in national forests in the northwestern United States, while Pandit et al. [85] demonstrated that different forest crime types may show significant spatial clustering. Özden and Ayan [86] reported temporal decreases in several forest crime types in the Yeşilirmak River Basin, and Bayramoğlu and Kadioğulları [12] showed that increases in productive forest area

were partly associated with decreased forest crime, declining rural population and increased national income in northeastern Türkiye. Recent studies have further emphasized the role of governance, spatial context and human–environment interaction in forest-related offences [33,80,81,87–89]. These findings indicate that forest crimes may interact with land-use change in different ways depending on local socioeconomic, demographic and institutional contexts. Election periods and socioeconomic trends represent conceptually distinct dimensions of forest-crime dynamics. Election years may be associated with temporary changes in administrative priorities, enforcement intensity, inspection activities, expectations of regulatory leniency or local political influence, whereas population and income indicators reflect broader and more gradual demographic and economic conditions [90,91]. These mechanisms do not imply that elections directly cause forest offences; rather, election-year status can be examined as a contextual institutional variable that may coincide with short-term changes in the detection, reporting or occurrence of registered forest crimes. For this reason, election-year effects and socioeconomic associations were evaluated separately in the hypothesis framework.

Despite the growing literature on LULC change, forest fragmentation and forest crime, few studies have simultaneously examined long-term structural changes within forest ecosystems together with registered forest crime records and socioeconomic drivers over multi-decadal periods. In Türkiye, studies combining forest stand-type map analysis with forest crime data are scarce, and the joint evaluation of these dynamics together with election-period effects and broader-scale demographic and economic indicators remains limited [12,33,92,93]. This gap is important for forest conservation and landscape restoration because total forest area alone may hide changes in forest quality, canopy structure, fragmentation and human pressure that directly influence the ecological functions and non-market benefits of forest landscapes [94,95]. This is also relevant for forest protection practice because identifying local factors associated with forest landscape change can support deterrent measures, monitoring priorities and precautionary actions against illegal forest activities [96,97].

Against this background, this study examines long-term forest landscape transformation in the Kümbet Planning Unit, a mountainous Black Sea landscape in Türkiye, by combining forest stand-type maps, GIS-based change detection, landscape metrics, registered forest crime records and broader-scale contextual socioeconomic indicators. Specifically, the study aims to: (i) map LULC changes over a 53-year period; (ii) quantify changes in forest cover, degraded forest, open areas, agricultural land and settlements; (iii) assess changes in forest landscape structure using selected landscape metrics; (iv) examine whether election-year status is associated with annual registered forest crime counts; (v) examine whether broader-scale population and real per capita income indicators are associated with annual registered forest crime counts; and (vi) evaluate whether exposure-adjusted registered forest crime density differs among management-related periods and whether its temporal pattern descriptively corresponds with changes in forest landscape configuration. The population and income series were not measured at the village or planning-unit level and were therefore used only as contextual indicators of broader demographic and economic conditions, rather than as direct measures of local socioeconomic pressure.

Based on this framework, the following hypotheses were formulated: (H1a) annual registered forest crime counts differ between election and non-election years; (H1b) annual registered forest crime counts are associated with broader-scale population and real per capita income indicators; (H2) forest crime density varies among forest management periods when differences in forest area exposure are taken into account; and (H3) periods with higher registered forest crime density show descriptive temporal correspondence with greater changes in forest landscape configuration, particularly greater fragmenta-

tion. H1a addresses a short-term institutional context, whereas H1b addresses longer-term demographic and economic conditions. These hypotheses were formulated to examine statistical and temporal associations rather than direct causal effects.

Objectives i–iii are descriptive and address long-term LULC transitions, forest structural change and landscape configuration. Objective iv corresponds to H1a, while objective v corresponds to H1b. Objective vi addresses both H2, through inferential comparison of exposure-adjusted registered forest crime density among management-related periods, and H3, through descriptive evaluation of temporal correspondence with changes in landscape configuration. H1a, H1b and H2 were evaluated inferentially, whereas H3 was assessed descriptively and does not imply causality.

2. Materials and Methods

2.1. Study Area

The study was conducted in the Kümbet Planning Unit (PU), which corresponds to the Kümbet Forest Sub-District under the Dereli Forest Enterprise Directorate of the Giresun Regional Directorate of Forestry, Türkiye. The study area is located in the Eastern Black Sea Region, within the administrative boundaries of Giresun Province. Kümbet represents a mountainous Black Sea forest landscape where long-term forest management records, forest cover dynamics, socioeconomic indicators and registered forest crime data can be evaluated together.

The Kümbet PU is located between 40°32′21″–40°41′17″ N latitude and 38°23′30″–38°31′25″ E longitude. The forest management maps were prepared using 1:25,000 topographic map sheets and projected in the WGS 84 UTM Zone 37N coordinate system. The planning unit covers the Giresun G40c2, G40c3, G41d1 and G41d4 map sheets. Elevation ranges from approximately 600 m along the Semail Stream to 2463 m at Gök Tepe, with a mean elevation of 1532 m, indicating a highly mountainous and topographically heterogeneous landscape (Figure 1).

According to the current forest management plan, the Kümbet PU covers 9745.7 ha, including 6558.5 ha of forest area and 3187.2 ha of non-forest area [98]. The planning unit is managed within a multifunctional forest management framework that includes timber production, nature conservation, old-growth forest conservation, seed stands, socially pressured areas, soil protection, drinking water protection and recreation/ecotourism.

The sociodemographic structure of the study area is closely linked to forest resources and rural land-use practices. Local livelihoods are mainly based on agriculture, livestock husbandry, forestry activities and highland tourism. Hazelnut production is one of the main agricultural income sources. In addition, local right holders meet part of their subsistence fuelwood and construction wood needs through the Kümbet Forest Sub-District, while forestry operations provide seasonal employment opportunities during production periods. Livestock grazing, particularly cattle and small ruminant grazing, is practiced in forested areas and highland zones outside the winter season.

The forest management plan also indicates that the surrounding rural population is spatially dispersed and that limited socioeconomic conditions may increase pressure on forest resources. Irregular grazing, illegal logging and forest clearing are among the main human-induced pressures in the area. Therefore, the Kümbet PU provides a suitable case for examining forest landscape transformation not only as a biophysical land-cover process but also as a social–ecological process shaped by rural livelihoods, demographic dynamics and forest–related offences.

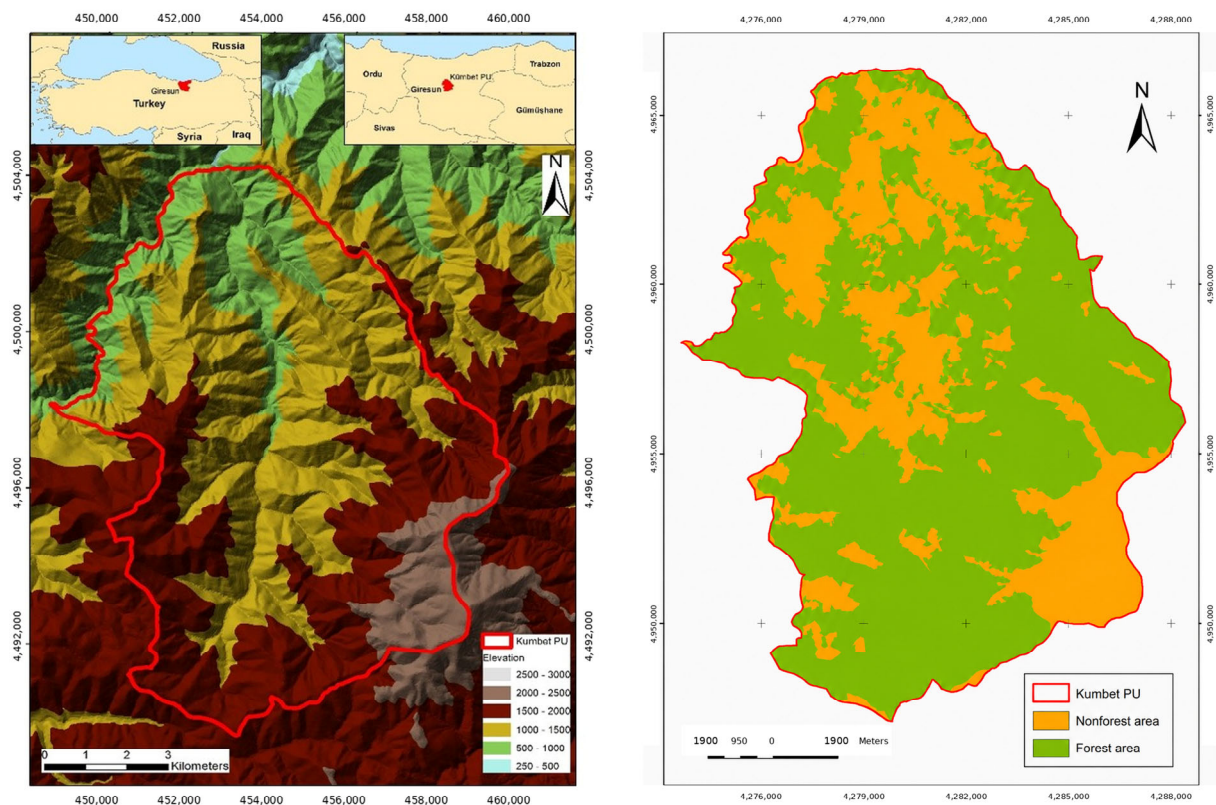


Figure 1. Spatial location and forest–non-forest area of the Kümbet PU.

The current administrative area of the Kümbet PU and the harmonized spatial analysis area are not identical. The current forest management plan reports a total planning-unit area of 9745.7 ha. However, the boundaries and area categories of the planning unit changed among forest management periods. Therefore, to ensure consistent temporal comparison, the 1971, 2013 and 2024 forest management maps were harmonized to their common spatial extent. The common spatial intersection derived from the 1971, 2013 and 2024 forest management maps covered 9658.1 ha and was used for all LULC transition matrices, forest-cover comparisons and landscape-metric calculations [98–100]. The current planning-unit area of 9745.7 ha was used only to describe the present administrative unit, whereas the 9658.1 ha harmonized area was used for all multi-temporal spatial analyses. This distinction prevents area-related bias caused by changing planning-unit boundaries. The 9658.1 ha harmonized extent was used exclusively for the multi-temporal spatial analyses. In contrast, the forest crime dataset consisted of annual aggregate administrative records reported for the Kümbet Forest Sub-District. Because the historical records did not contain georeferenced locations for individual incidents, the registered cases could not be retrospectively clipped to the 9658.1 ha common spatial extent.

2.2. Forest Crime and Socioeconomic Dataset

The forest crime and socioeconomic dataset covered 45 complete calendar years from 1981 to 2025 and was organized on an annual basis. The dataset included six variables: year, estimated annual forest-area exposure, annual registered forest crime count, election-year status, population and real per capita income. Annual registered forest crime count was used as the response variable, whereas election-year status, population and real per capita income were used as explanatory variables representing institutional, demographic and economic conditions.

Registered forest crime data were obtained from the official administrative records of the Kümbet Forest Sub-District, maintained by the Dereli Forest Enterprise Directorate [101]. The dataset consisted of annual aggregate cases recorded for the administrative reporting area of the Kümbet Forest Sub-District and did not include incident-level geographic coordinates. Consequently, individual crime records could not be retrospectively restricted to the 9658.1 ha harmonized map intersection. The crime and landscape datasets were therefore evaluated through contextual and temporal comparisons and were not treated as perfectly spatially matched datasets.

Consistently comparable information on individual offence categories was not available for the entire study period. Therefore, annual total registered forest crime counts were used rather than separate offense-type counts. Although partial forest crime records were available for 2026, the 2026 observation was excluded from all descriptive and inferential analyses because it did not represent a complete 12-month observation period. Accordingly, the analytical dataset consisted of 45 complete annual observations from 1981 to 2025.

Election-year status was represented by a binary variable. Years in which at least one national or local election was held were coded as 1, whereas years without an election were coded as 0. When more than one election occurred during the same calendar year, the year was still coded as 1 because the variable represented the presence or absence of an election year rather than the number or type of elections [102,103].

Population and real per capita income were used as broader-scale contextual indicators rather than as direct measures of socioeconomic conditions within the Kümbet Planning Unit. Both series represented Giresun Province and were obtained from the Turkish Statistical Institute (TURKSTAT) [104,105]. Because the Kümbet Planning Unit is located entirely within Giresun Province and a complete and temporally consistent annual population series at the village or planning-unit level was not available for the full 1981–2025 period, the provincial population was used as the most consistent official indicator of broader demographic change in the administrative and socioeconomic setting surrounding Kümbet. It was not treated as a direct estimate of the population residing within the planning unit. The real per capita income series was used directly in the form reported in the TURKSTAT database. No additional inflation adjustment, CPI-based deflation, or re-basing was performed by the authors, and 2026 was not used as a base year.

Because directly observed forest-area values were available only for the reference map years 1971, 2013 and 2024, annual forest-area exposure was estimated by linear interpolation between consecutive map years. The observed forest areas were 6747.8 ha in 1971, 6597.0 ha in 2013 and 6298.1 ha in 2024. For a year t located between two reference years a and b annual forest area was estimated as

$$F_t = F_a + \frac{t - a}{b - a} (F_b - F_a)$$

where F_t is the estimated forest area in year t ; t is the year for which forest area is estimated; a and b are the preceding and subsequent reference map years, respectively; and F_a and F_b are the observed forest areas in those reference years. The 1971 and 2013 map years were used as a and b , respectively, to estimate annual forest area for 1981–2012. Similarly, the 2013 and 2024 map years were used to estimate annual forest area for 2013–2024. Because no subsequent reference map was available after 2024, linear interpolation could not be applied to 2025; therefore, the observed 2024 forest area of 6298.1 ha was carried forward to 2025. These annual estimates were used only as forest-area exposure values and were not interpreted as directly observed annual forest-cover measurements.

The forest crime dataset represents officially registered administrative cases rather than all illegal forest activities that may have occurred in the field. The annual counts may therefore be influenced by detection effort, enforcement capacity, reporting intensity and

administrative recording practices. Accordingly, registered forest crime counts were treated as contextual indicators of recorded forest-related pressure rather than as a complete measure of illegal activity. Because the crime records lacked incident-level geographic coordinates and the LULC maps and landscape metrics were available only for 1971, 2013 and 2024, the crime series was not used to explain annual or spatial forest-cover change directly. Instead, it was compared contextually and temporally with period-based changes in forest area, agricultural land, degraded forest and landscape fragmentation.

2.3. LULC and Forest Stand-Type Dataset

An appropriate classification scheme is essential for reliable LULC mapping, especially in forest-dominated landscapes where changes occur not only among broad land-cover categories but also within forest structure. In this study, LULC classes were derived from forest stand-type maps and classified according to tree species composition, developmental stage and crown closure. The classification followed the criteria defined by the GDF [106].

Temporal LULC changes were analyzed using forest management maps from 1971, 2013 and 2024. These maps were produced from aerial photographs, satellite images, forest inventory data, field surveys and ground sample plot controls, and were obtained from the corresponding forest management plans of the study area [98–100]. The 1971 map was available in analogue format and was later georeferenced and digitized, whereas the 2013 and 2024 maps were obtained as digital stand-type maps.

The original stand-type codes were reclassified into the harmonized LULC classes presented in Table 1. The table summarizes the class codes and the criteria used to distinguish the forest and non-forest land-cover categories.

Table 1. LULC classes [106].

LULC Class	Explanation
Kn	Pure productive (crown closure > 10%) <i>Fagus orientalis</i> high forest stands
L	Pure productive (crown closure > 10%) <i>Picea orientalis</i> high forest stands
Kz	Pure productive (crown closure > 10%) <i>Alnus glutinosa</i> high forest stands
Mixed Forest	Mixed productive (crown closure > 10%) high forest stands
Degraded Forest	Degraded (crown closure < 10%) mixed and pure high forest stands
Open Areas	Bare lands, wood yard, mine, lake, water, etc.
Agriculture	Agriculture
Residential Areas	Settlements, houses and commercial areas

The developmental stage classes were determined based on mean diameter at breast height, while crown closure classes represented the canopy cover of forest stands (Tables 2 and 3).

Table 2. Developmental stage categories [106].

Development Stage	Description	dbh (cm)
a	Juvenile stage	dbh < 7.9
b	Sapling-pole stage	8 ≤ dbh < 20
c	Small tree–large pole stage	20 ≤ dbh < 36
d	Medium tree stage	36 ≤ dbh < 52
e	Large tree stage	dbh ≥ 52
k	Multi-story	
Degraded	Degraded forest where the canopy covers less than 10%.	

Table 3. Crown closure categories [106].

Crown Closure Category	Description	Canopy (%)
0	Degraded forest	<10%
1	Dispersed forest	11–40%
2	Middle-covered forest	41–70%
3	Dense-covered forest	71–100%

This classification structure enabled the study to evaluate LULC change at two complementary levels. First, broad land-cover transitions were assessed among productive forest, degraded forest, open areas, agricultural lands and residential areas. Second, internal forest structural changes were examined through tree species composition, developmental stage and crown closure classes. This approach allowed the analysis to capture not only forest area change but also forest degradation, structural improvement, agricultural expansion and landscape reorganization over the 53-year period.

2.4. GIS-Based LULC Change Analysis

Geographic Information System (GIS) techniques were used to construct, harmonize and analyze the spatial database for the 1971–2024 period. All spatial analyses were conducted using ArcGIS 10.8 [107]. The 1971 forest stand-type map was available in analogue format and was georeferenced using 1:25,000-scale topographic maps before being digitized, whereas the 2013 and 2024 stand-type maps were obtained in digital format from the GDF. Because the 1971 map was produced using historical interpretation and manual delineation procedures, its geometric and thematic precision may differ from that of the 2013 and 2024 digital stand-type maps, potentially introducing positional discrepancies and apparent or “pseudo-changes” [108,109]. The source imagery, polygon-delineation procedures and forest-inventory practices were not identical across the three management periods. Nevertheless, all maps followed the General Directorate of Forestry stand-type classification framework and were reclassified into common LULC, developmental-stage and crown-closure categories before temporal comparison.

To improve spatial and temporal comparability, all datasets were projected to the WGS 84 UTM Zone 37N coordinate system and restricted to their common spatial extent using the intersection procedure. Polygon boundaries were checked, and topological errors, including overlaps, gaps and sliver polygons, were identified and corrected before overlay analysis. Nevertheless, residual positional and classification differences may remain, particularly for small or narrow polygons; therefore, fine-scale and spatially isolated transitions were interpreted cautiously.

A consistently documented minimum mapping unit and formal positional-accuracy statistics were not available for all three historical datasets. In addition, the archived documentation for the digitized 1971 map did not provide a reproducible georeferencing RMSE value. Therefore, unsupported quantitative accuracy values were not reported. These unavailable quality parameters were treated as limitations, and emphasis was placed on broad and persistent transition patterns rather than on very small or spatially isolated changes.

The original stand-type codes were then reclassified into the standardized LULC classes described above. This harmonization allowed comparisons among maps prepared in different forest management periods. Temporal LULC changes were analyzed for three comparison periods: 1971–2013, 2013–2024 and 1971–2024.

Change matrices were produced by overlaying the harmonized map layers for each comparison period and cross-tabulating the area transferred from each initial class to each final class. These matrices quantified conversions among productive forest classes, degraded forest, open areas, agricultural lands and residential areas. In addition to broad

LULC transitions, changes in tree species composition, developmental stages and crown closure categories were analyzed to evaluate internal forest structural change.

Because this study used official forest management stand-type maps rather than newly classified satellite images, a conventional pixel-based classification accuracy assessment was not applicable. Instead, temporal comparability was strengthened by using official forest management maps prepared from aerial photographs, satellite images, field surveys and forest inventory data and by reclassifying all maps into a harmonized classification scheme before change analysis.

2.5. Landscape Metrics

Landscape configuration and fragmentation were assessed using metrics calculated from the harmonized LULC maps for 1971, 2013 and 2024. The metrics were generated using the Patch Analyst extension in ArcGIS 10.8 [110–112]. Number of patches, mean patch size and area-weighted mean shape index were selected based on their established use in evaluating landscape subdivision, patch-area distribution and shape complexity [113,114]. The number of patches was used to evaluate spatial subdivision within the landscape. An increase in patch number was interpreted as an indication of increasing fragmentation, particularly when accompanied by a decrease in mean patch size. Mean patch size was used to represent the average area of landscape patches and to assess whether the landscape became more fragmented or more consolidated over time. The area-weighted mean shape index was used to evaluate changes in patch shape complexity, giving greater weight to larger patches.

Landscape metrics were calculated for the three reference years and compared across the 1971–2013, 2013–2024 and 1971–2024 periods. The metrics were interpreted together with LULC transition matrices to distinguish between changes in total land-cover area and changes in spatial configuration. This distinction was important because a land-cover class may show limited net area change while still undergoing substantial spatial fragmentation or consolidation.

The selected metrics characterize landscape subdivision, average patch area and patch-shape complexity, but they do not directly quantify edge effects, core habitat area, patch isolation, contagion or functional connectivity. Accordingly, the terms fragmentation and consolidation are used here in a structural sense, as represented by changes in patch number, mean patch size and area-weighted mean shape index, rather than as complete measures of ecological connectivity.

2.6. Forest Crime Density and Statistical Analysis

Annual forest crime records were evaluated together with the LULC and landscape-metric outputs. Because LULC maps and landscape metrics were available only for the three reference years 1971, 2013 and 2024, annual forest crime records were not directly linked to annual forest-cover change. Instead, they were treated as contextual indicators of recorded forest-related pressure and compared with period-based changes in forest area, agricultural land, degraded forest and landscape configuration.

For descriptive comparisons, annual forest crime records for 1981–2025 were grouped into three management-related periods: 1981–2012, 2013–2023 and 2024–2025. Because forest crime records began in 1981, the first period represents the available crime-record portion of the broader 1971–2013 LULC-change interval. The final period contains the two complete calendar years 2024 and 2025.

Annual forest crime density was calculated using the linearly interpolated annual forest-area exposure values described in Section 2.2. For each year (t), forest crime density was calculated as

$$D_t = \frac{Y_t}{F_t} \times 1000$$

where D_t is the annual registered forest crime density per 1000 ha, Y_t is the annual number of registered forest crimes, and F_t is the estimated forest area in year (t). For descriptive comparisons among management-related periods, an exposure-weighted mean annual crime density was calculated as

$$D_p = \frac{\sum_{t \in p} Y_t}{\sum_{t \in p} F_t} \times 1000$$

where D_p denotes the exposure-weighted mean annual registered forest crime density per 1000 ha for management-related period (p); (p) denotes the relevant management-related period; (t) denotes an individual year included in period (p); and $\sum_{t \in p} Y_t$ denotes the total number of registered forest crimes across all years included in period (p); and $\sum_{t \in p} F_t$ denotes the total estimated forest-area exposure across all years included in period (p).

Statistical analyses were conducted using SPSS version 20 [115]. First, an independent-samples t -test was used as a preliminary parametric comparison of mean annual registered forest crime counts between election and non-election years. Homogeneity of variance was evaluated using Levene's test, and Hedges' g was calculated as an effect-size measure. Pearson product-moment correlation was used as the parametric bivariate procedure to examine pairwise linear relationships among registered forest crime counts, estimated annual forest area, population and real per capita income. Because election-year status was binary, its association with registered forest crime counts was expressed as a point-biserial correlation.

Potential multicollinearity among election-year status, population and real per capita income was assessed using variance inflation factors (VIFs) and tolerance statistics, with tolerance calculated as the reciprocal of VIF. A VIF greater than 5 or a tolerance value below 0.20 was considered indicative of potentially problematic multicollinearity [116]. Population was scaled in units of 10,000 persons, and real per capita income was scaled in units of USD 1000 to facilitate interpretation of the regression coefficients and incidence rate ratios.

Because the response variable consisted of non-negative annual count data, an initial Poisson regression model was fitted and overdispersion was evaluated using the ratio of the Pearson chi-square statistic to the residual degrees of freedom. A ratio substantially greater than 1 was interpreted as evidence of overdispersion. Because overdispersion was detected, negative binomial regression with a log-link function was used as the principal inferential approach [117].

The first negative binomial regression model tested whether election-year status, population and real per capita income were associated with annual registered forest crime counts after accounting for forest area exposure. The model was specified as follows:

$$\text{Log}[E(Y_i)] = \beta_0 + \beta_1 \text{Election}_i + \beta_2 \text{Population}_i + \beta_3 \text{Income}_i + \log(\text{Forest area}_i)$$

where Y_i represents the annual number of registered forest crimes in year i , Election_i is the election-year dummy variable, Population_i is the annual population, Income_i is real per capita income and $\log(\text{Forest area}_i)$ is the natural logarithm of the linearly interpolated forest-area estimate for year (i), included as an offset with its coefficient fixed at 1 [118]. In this study, the term "bivariate analysis" refers to the Pearson or point-biserial correlation between two variables, whereas "multivariable analysis" refers to the negative binomial regression model containing election-year status, population and real per capita income as simultaneous explanatory variables. No principal component analysis, factor analysis or other multivariate dimension-reduction procedure was performed.

To test whether forest crime density differed among management-related periods, a second negative binomial regression model was fitted using management period as a cat-

egorical predictor and the natural logarithm of forest area as an offset variable. The model was specified as follows:

$$\text{Log}[E(Y_i)] = \gamma_0 + \gamma_1 \text{Period2013–2023}_i + \gamma_2 \text{Period2024–2025}_i + \log(\text{Forest area}_i)$$

where Period2013–2023_i and Period2024–2025_i are dummy variables representing the second and third management-related periods, respectively. The 1981–2012 period was used as the reference category. The overall period effect was evaluated using a likelihood ratio test [119]. The significance level was set at $p < 0.05$.

Temporal dependence was assessed using the autocorrelation function of Pearson residuals and Ljung–Box tests at lags 1, 5 and 10. If meaningful residual autocorrelation had been detected, a negative binomial GEE model with an AR(1) working correlation structure would have been used. Because no meaningful residual autocorrelation was identified, the standard negative binomial models were retained.

The statistical outputs were interpreted together with the spatial LULC and landscape metric results. All statistical tests were two-sided, and statistical significance was evaluated at $p < 0.05$. H1a was evaluated using the election versus non-election comparison and the adjusted election-year coefficient in the multivariable negative binomial model. H1b was evaluated using the population and real per capita income coefficients in the same model. H2 was evaluated using the period-based negative binomial model with forest area exposure. H3 was evaluated descriptively by comparing period-based forest crime density with changes in landscape metrics, particularly number of patches and mean patch size. Because landscape metrics were available only for three reference years, H3 was interpreted as temporal correspondence rather than as an inferential statistical association or causal relationship.

3. Results

3.1. Registered Forest Crime Records and Statistical Outputs

After excluding the incomplete 2026 observation, the analyses included 45 complete annual observations covering the 1981–2025 period. Of these, 19 were classified as election years and 26 as non-election years. Annual registered forest crime counts ranged from 2 to 78, with a mean of 28.40 crimes per year ($SD = 16.47$) and a median of 24.

The mean annual number of registered forest crimes was 28.11 in election years ($SD = 17.91$) and 28.62 in non-election years ($SD = 15.69$). Levene's test indicated no evidence of unequal variances ($p = 0.909$). The independent-samples t-test showed no statistically significant difference between election and non-election years [$t(43) = 0.101$, $p = 0.920$, Hedges' $g = -0.030$]. Similarly, the point-biserial correlation between election-year status and registered forest crime counts was not significant ($r = -0.015$, $p = 0.920$). These results did not support H1a.

In the Pearson correlation analyses, registered forest crime counts were positively correlated with population ($r = 0.433$, $p = 0.003$). The correlations of registered forest crime counts with real per capita income ($r = -0.282$, $p = 0.061$) and estimated annual forest area ($r = 0.241$, $p = 0.111$) were not statistically significant. Variance inflation factors were 1.00 for election-year status, 1.83 for population and 1.83 for real per capita income. The corresponding tolerance values were 1.000, 0.546 and 0.546, respectively. Because all VIF values were below 5 and all tolerance values were above 0.20, the adjusted estimates were not considered to be materially affected by problematic multicollinearity.

The initial Poisson model showed substantial overdispersion, with a Pearson chi-square-to-residual-degrees-of-freedom ratio of 7.85. Negative binomial regression was therefore retained as the principal count-data model. The overall multivariable negative binomial model, including election-year status, population and real per capita income and

using estimated annual forest area as the offset, was statistically significant compared with the intercept-only model (likelihood-ratio test, $p = 0.038$).

After adjustment for the other explanatory variables and forest-area exposure, the provincial population was positively associated over time with annual registered forest crime counts during the 1981–2025 study period. An increase of 10,000 persons in the provincial population was associated with a 7.5% increase in the expected registered forest crime rate (IRR = 1.075, 95% CI: 1.015–1.139, $p = 0.014$). Election-year status was not statistically significant (IRR = 0.984, 95% CI: 0.719–1.347, $p = 0.920$), and real per capita income was also not significant when expressed per USD 1000 (IRR = 1.010, 95% CI: 0.949–1.074, $p = 0.760$). Thus, H1b was supported only for the broader-scale population indicator and not for real per capita income.

The Pearson residuals of the multivariable negative binomial model showed no meaningful temporal autocorrelation. The lag-1 ACF coefficient was 0.162, and the Ljung–Box tests were not significant at lag 1 ($p = 0.261$), lag 5 ($p = 0.331$) or lag 10 ($p = 0.404$). Therefore, a GEE adjustment was not required for the primary multivariable model.

For the management-related period comparison, the mean annual registered forest crime count decreased from 30.44 in 1981–2012 to 23.27 in 2013–2023 and was 24 in 2024–2025. The corresponding exposure-weighted registered forest crime densities were 4.573, 3.602 and 3.811 crimes per 1000 ha-year, respectively (Table 4). The final period contained only two complete annual observations and was therefore interpreted cautiously.

Table 4. Registered forest crime counts and exposure-weighted crime density by management-related period.

Management Related Period	Number of Years	Total Registered Forest Crimes	Mean Annual Registered Forest Crimes (SD)	Mean Estimated Annual Forest Area (ha)	Exposure-Weighted Crime Density (per 1000 ha-Year)
1981–2012	32	974	30.44 (17.58)	6656.24	4.573
2013–2023	11	256	23.27 (13.68)	6461.14	3.602
2024–2025	2	48	24.00 (4.24)	6298.10	3.811

Note: Annual forest-area exposure was estimated by linear interpolation between the 1971, 2013 and 2024 reference-map values. The observed 2024 forest area was carried forward to 2025. Exposure-weighted crime density was calculated as the sum of annual registered forest crime counts divided by the sum of annual estimated forest-area exposure values, multiplied by 1000. The 2024–2025 period contains only two annual observations and should therefore be interpreted cautiously. The negative binomial model with management-related period as the categorical predictor showed that the overall period effect was not statistically significant (likelihood-ratio test, $p = 0.491$). Relative to the 1981–2012 reference period, the expected registered forest crime rate was not significantly different in 2013–2023 (IRR = 0.788, 95% CI: 0.531–1.170, $p = 0.237$) or in 2024–2025 (IRR = 0.834, 95% CI: 0.366–1.902, $p = 0.666$). No meaningful residual autocorrelation was detected in the period model; the lag-1 ACF coefficient was 0.270, and the Ljung–Box tests were not significant at lag 1 ($p = 0.061$), lag 5 ($p = 0.376$) or lag 10 ($p = 0.517$). Accordingly, H2 was not statistically supported.

3.2. Land-Use/Land-Cover Changes

The LULC analysis showed substantial changes in the Kümbet PU between 1971 and 2013. Degraded forest decreased from 1497.9 to 860.7 ha, open land decreased from 2273.0 to 1087.2 ha, and agricultural land increased from 637.3 to 1920.0 ha. The expansion of agricultural land originated from several land-cover classes. The largest gross conversion to agriculture occurred from open land (633.7 ha), followed by degraded forest (463.3 ha).

In addition, 273.6 ha of productive forest classes changed to agricultural land, comprising 237.8 ha of mixed forest, 14.6 ha of spruce forest and 21.2 ha of beech forest. These transitions indicate that agricultural expansion occurred primarily through the conversion of open land and degraded forest, although a smaller but non-negligible amount of productive forest was also converted to agriculture. Agricultural expansion should therefore not be interpreted as a direct one-to-one explanation of the net decrease in total forest area. During the same period, 723.8 ha of degraded forest changed into mixed forest, spruce stands increased from 1070.9 to 1257.4 ha, and mixed stands increased from 4139.6 to 4179.4 ha. Alder stands and settlement areas were recorded as separate classes in the 2013 map (Supplementary Table S1).

Between 2013 and 2024, degraded forests further decreased from 860.7 ha to 331.4 ha. Alder stands increased from 33.3 ha to 120.6 ha, and settlement areas increased from 54.0 ha to 63.3 ha. During this period, 206.1 ha of spruce stands changed into mixed stands, whereas 178.9 ha of mixed stands changed into beech stands (Supplementary Table S2).

Over the whole 1971–2024 period, spruce stands increased from 1070.9 ha to 1234.1 ha, and mixed stands increased from 4139.6 ha to 4283.0 ha. The largest changes occurred in degraded forests, open lands and agricultural lands. Degraded forests decreased from 1497.9 ha to 331.4 ha, open lands decreased from 2273.0 ha to 1118.9 ha, and agricultural lands increased from 637.3 ha to 2177.7 ha. Total forest area, defined as the sum of spruce, beech, alder, mixed and degraded forest classes, decreased from 6747.8 ha in 1971 to 6298.1 ha in 2024. Over the same 1971–2024 interval, the largest gross transitions to agricultural land originated from open land (641.8 ha) and degraded forest (616.4 ha), while 321.3 ha originated from productive forest classes. Because substantial bidirectional transitions also occurred among open land, degraded forest and productive forest classes, the net forest-area decrease of 449.7 ha cannot be attributed on a one-to-one basis to agricultural expansion. The results instead indicate a combination of agricultural conversion, forest structural transitions and landscape reorganization. Overall, 44.3% of the study area changed to another land-cover type during the 53-year period (Table 5; Figures 2 and 3).

Table 5. Tree species transition matrix between 1971 and 2024 in Kümbet PU (ha).

Land Cover	2024									
	L	Kn	Kz	Mixed	Degr.	Open L.	Agri.	Settle.	Total	
1971	L	684.6	0.3	0.6	262.8	44.7	60.4	15	2.6	1070.9
	Kn	-	-	-	15	0.8	-	23.7	-	39.4
	Mixed	324.3	282.4	49.5	3042.2	105.4	50.8	282.6	2.4	4139.6
	Degraded	14.2	22.6	65.2	679.1	76.5	23.8	616.4	-	1497.9
	Open Land	210.9	22.8	4.5	247.4	103.4	983.9	641.8	58.4	2273
	Agriculture	-	1	0.7	36.6	0.7	-	598.2	-	637.3
Total	1234.1	329.1	120.6	4283	331.4	1118.9	2177.7	63.3	9658.1	

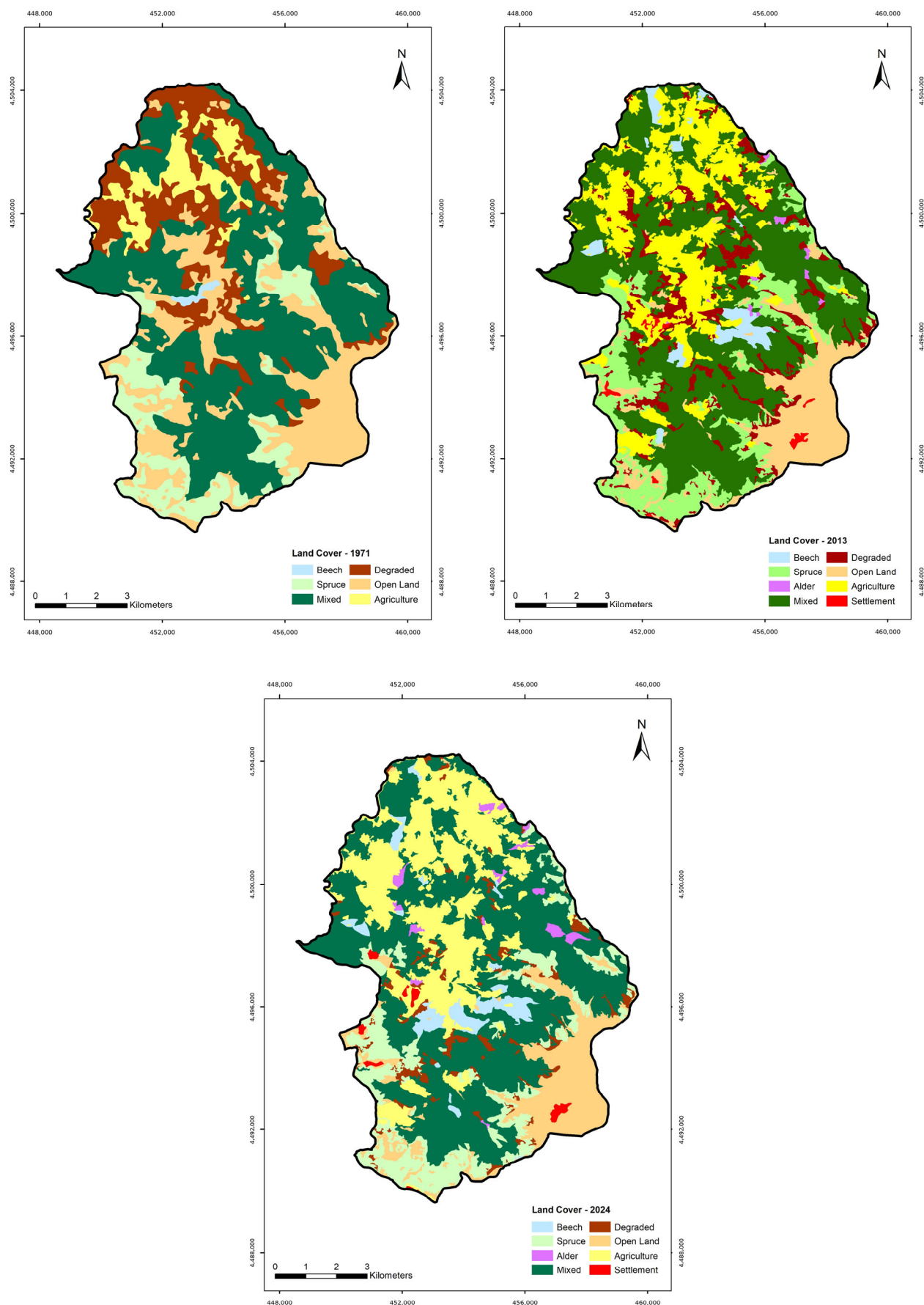


Figure 2. Land cover maps of Kümbet PU in 1971, 2013, and 2024.

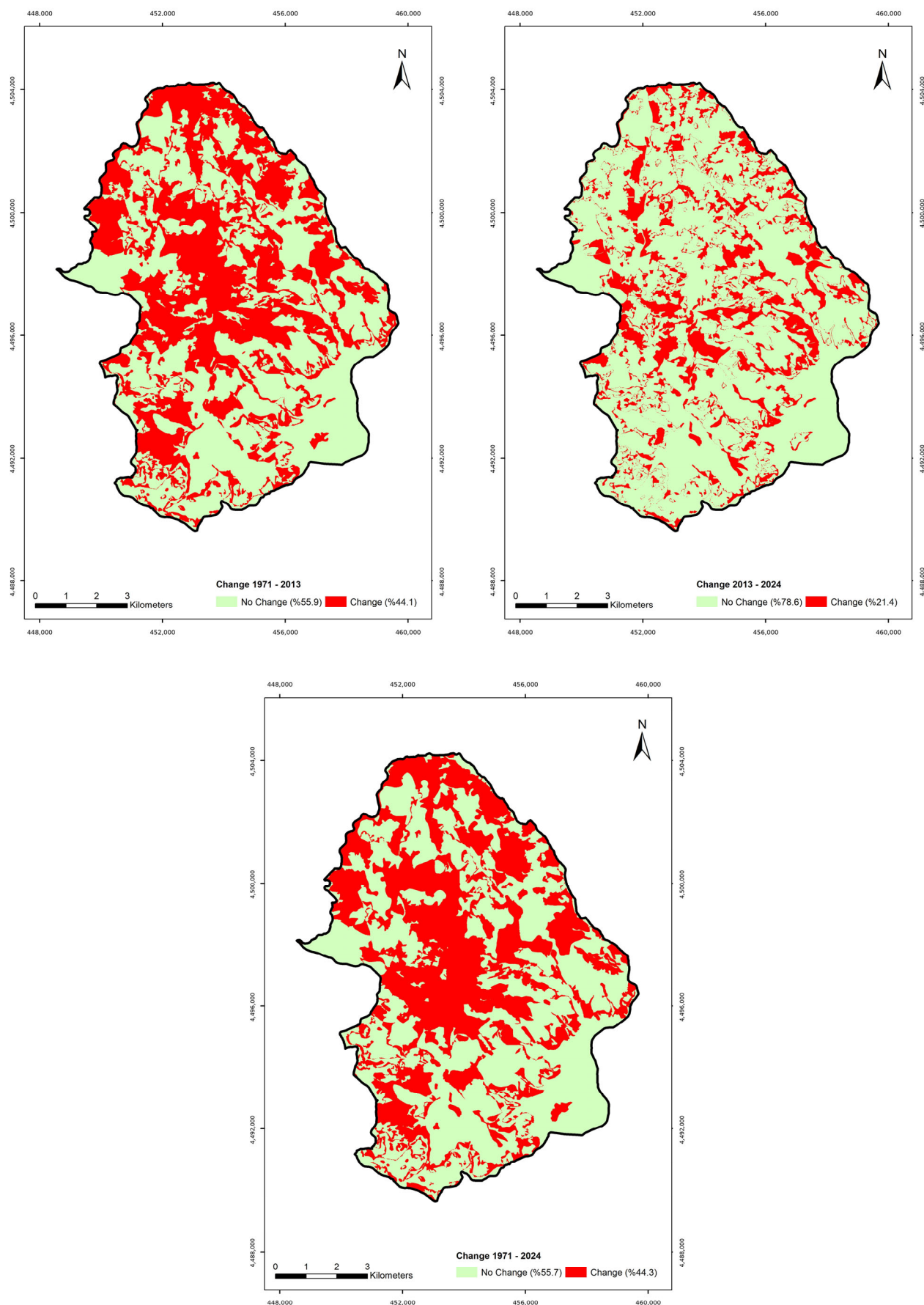


Figure 3. Land cover change maps of 1971–2013, 2013–2024, and 1971–2024 in Kümbet PU.

3.3. Changes in Stand Developmental Stages

Changes in stand developmental stages were analyzed for the same reference years. Between 1971 and 2013, the area mapped as medium-tree stage decreased from 4443.9 to 1397.8 ha. Most of the area mapped as medium-tree stage in 1971 shifted to younger developmental-stage classes by 2013, while substantial areas of degraded forest were mapped as productive developmental-stage classes (Supplementary Table S3; Figure 4). The transitions from the medium-tree stage to juvenile or sapling–pole stages do not indicate that individual mature trees became smaller. Rather, they represent changes in mapped stand condition over the 42-year interval and may reflect stand-replacing harvesting, severe natural disturbance followed by regeneration, or the establishment of a new cohort after removal of the previous stand. Differences in interpretation and polygon delineation between the analogue 1971 map and the digital 2013 map may also have contributed to some apparent developmental-stage transitions. Because event-level harvesting and disturbance records were not available for the entire period, the relative contribution of these mechanisms could not be determined.

Between 2013 and 2024, sapling–pole stage stands increased from 652.9 ha to 1119.5 ha, and medium-tree stage stands increased from 1397.8 ha to 2136.3 ha. In contrast, small tree–large pole stage stands decreased from 3461.6 ha to 2359.2 ha. Multi-story stands appeared as a new developmental-stage class in 2024. The main transitions included 196.6 ha from juvenile to sapling–pole stage and 1154.8 ha from small tree–large pole to medium-tree stage. A total of 76.2 ha of productive forests changed into degraded forest, whereas 394.0 ha of degraded forest changed into productive forest developmental-stage classes (Supplementary Table S4; Figure 4).

Over the whole 1971–2024 period, sapling–pole stage stands increased from 806.0 ha to 1119.5 ha, whereas medium-tree stage stands decreased from 4443.9 ha to 2136.3 ha. The transition matrix showed that 417.7 ha of sapling–pole stage stands changed into small tree–large pole stands. In total, 150.9 ha of productive forest changed into degraded forest, while 781.3 ha of degraded forest changed into productive forest developmental-stage classes. In addition, 321.3 ha of productive forest changed into agricultural land, 4.9 ha into settlement areas and 111.2 ha into open lands (Table 6; Figure 4).

Table 6. Developmental stage transition matrix between 1971 and 2024 in Kümbet PU (ha).

Develop. Stage	2024										
	a	b	c	d	Multi- Story	Degr.	Open Land	Agri.	Settle.	Total	
1971	b	0.2	143.9	417.7	133.4	21.8	18.4	9	60.1	1.5	806
	d	140.2	462.2	1452	1723.7	166.5	132.5	102.2	261.2	3.4	4443.9
	Degr.	2.2	390.9	285.1	102.7	0.4	76.5	23.8	616.4	-	1497.9
	Open	10.3	94.4	196.6	173.9	10.2	103.4	983.9	641.8	58.4	2273
	Agri.	-	28	7.8	2.6	-	0.7	-	598.2	-	637.3
Total		152.9	1119.5	2359.2	2136.3	198.9	331.4	1118.9	2177.7	63.3	9658.1

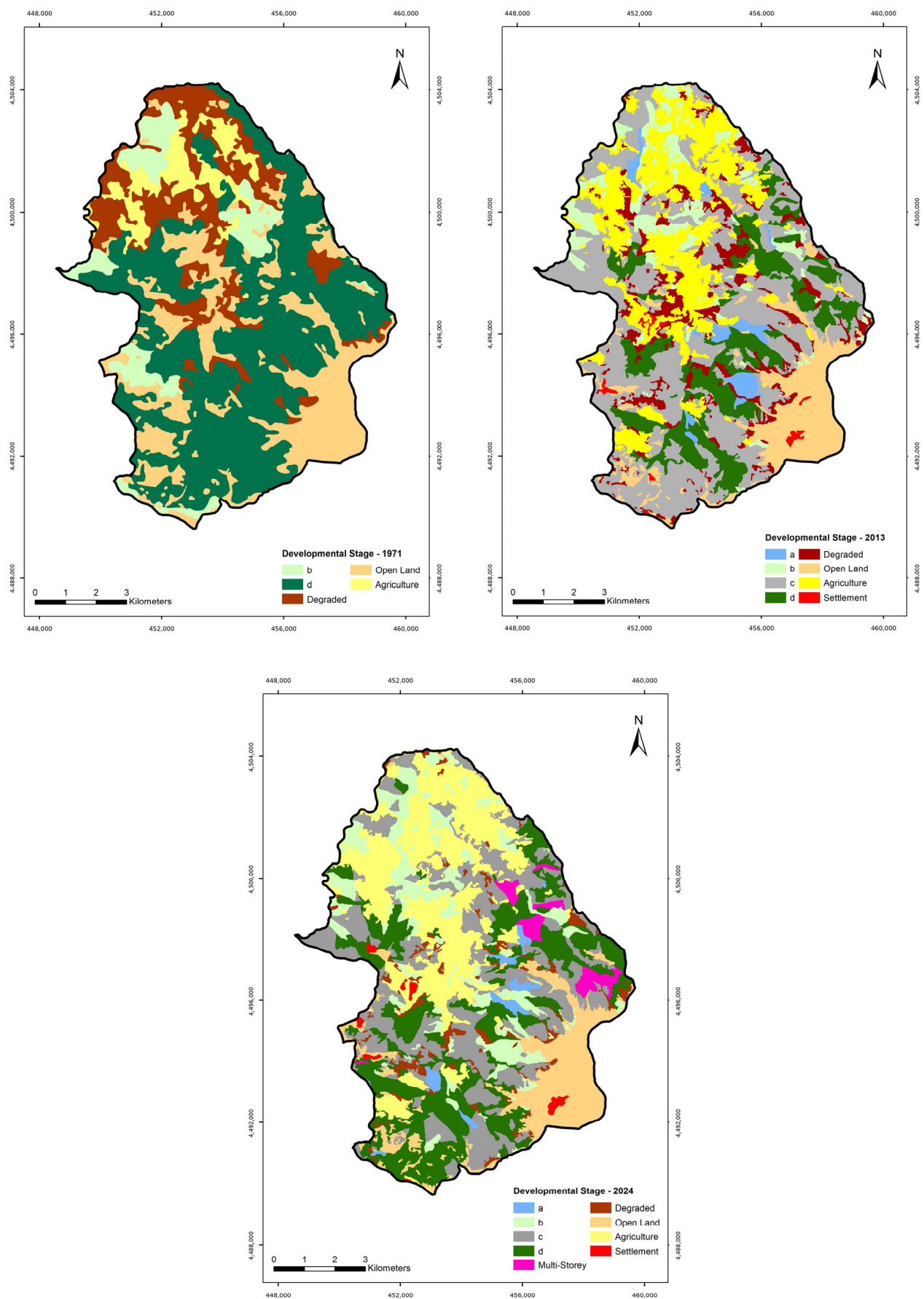


Figure 4. Development stages maps of Kümbet PU in 1971, 2013, and 2024.

3.4. Changes in Crown Closure

Crown closure classes were analyzed to evaluate changes in canopy structure. Between 1971 and 2013, degraded forests decreased from 1497.9 ha to 860.7 ha. During this period, substantial areas of degraded forest, open land and middle-covered forest shifted to denser crown-closure classes. Nevertheless, the total area of dense-covered forest decreased from 3873.0 ha to 2627.4 ha, indicating that canopy densification in some locations occurred alongside canopy reduction or land-cover conversion elsewhere (Supplementary Table S5; Figure 5).

Between 2013 and 2024, degraded forests further decreased from 860.7 ha to 331.4 ha. Dense-covered forests increased from 2627.4 ha to 3322.6 ha, while dispersed forests decreased from 859.8 ha to 461.6 ha, and middle-covered forests decreased from 2249.0 ha to 2182.5 ha. The transition matrix showed extensive bidirectional exchanges among dispersed, middle-covered and dense-covered forest classes, with an overall increase in dense-covered forest during the later period (Supplementary Table S6; Figure 5).

Over the whole 1971–2024 period, middle-covered forests increased from 1377.0 ha to 2182.5 ha, while dense-covered forests decreased from 3873.0 ha to 3322.6 ha. The long-term transition matrix showed extensive bidirectional exchanges between middle- and dense-covered forest, together with substantial shifts from degraded forest to productive crown-closure classes (Table 7; Figure 5).

Table 7. Crown closure transition matrix between 1971 and 2024 in Kümbet PU (ha).

Crown Closure		2024							
		1	2	3	Degraded	Open Land	Agri.	Settl.	Total
1971	2	134.7	555.3	517.1	36.6	19.2	111.7	2.4	1377
	3	257	1100.2	2097.4	114.2	92	209.7	2.6	3873
	Degr.	37	380.3	363.9	76.5	23.8	616.4	-	1497.9
	Open	33	133.1	319.5	103.4	983.9	641.8	58.4	2273
	Agri.	-	13.7	24.7	0.7	-	598.2	-	637.3
	Total	461.6	2182.5	3322.6	331.4	1118.9	2177.7	63.3	9658.1

3.5. Landscape Metrics and Descriptive Comparison with Forest Crime Density

Changes in LULC classes were accompanied by changes in landscape configuration. The total number of patches increased from 112 in 1971 to 415 in 2013 and then decreased to 299 in 2024. The mean patch size value considering the whole landscape reported in the Landscape Level row decreased from 86.2 ha in 1971 to 23.3 ha in 2013 and then increased to 32.3 ha in 2024. The area-weighted mean shape index changed from 4.2 in 1971 to 5.9 in 2013 and slightly decreased to 5.8 in 2024. At the class level, the number of patches increased between 1971 and 2013 in spruce, beech, mixed forest and degraded forest classes. Spruce patches increased from 14 to 53, beech patches from 1 to 11, mixed forest patches from 6 to 47, and degraded forest patches from 17 to 149. Between 2013 and 2024, the number of patches decreased from 53 to 45 in spruce stands, from 47 to 36 in mixed forests, and from 149 to 83 in degraded forests (Table 8).

Forest crime density was compared descriptively with landscape-metric changes to evaluate H3. The highest exposure-weighted registered forest crime density occurred during 1981–2012, while the largest increase in patch number occurred between 1971 and 2013. Registered forest crime density decreased to 3.602 crimes per 1000 ha-year in 2013–2023 and then increased slightly to 3.811 in 2024–2025. During the 2013–2024 landscape-change interval, the number of patches decreased from 415 to 299 and mean patch size increased, indicating partial spatial consolidation. This broad temporal correspondence

provides limited descriptive support for H3; however, it was not evaluated through inferential statistical testing and should not be interpreted as evidence of causality.

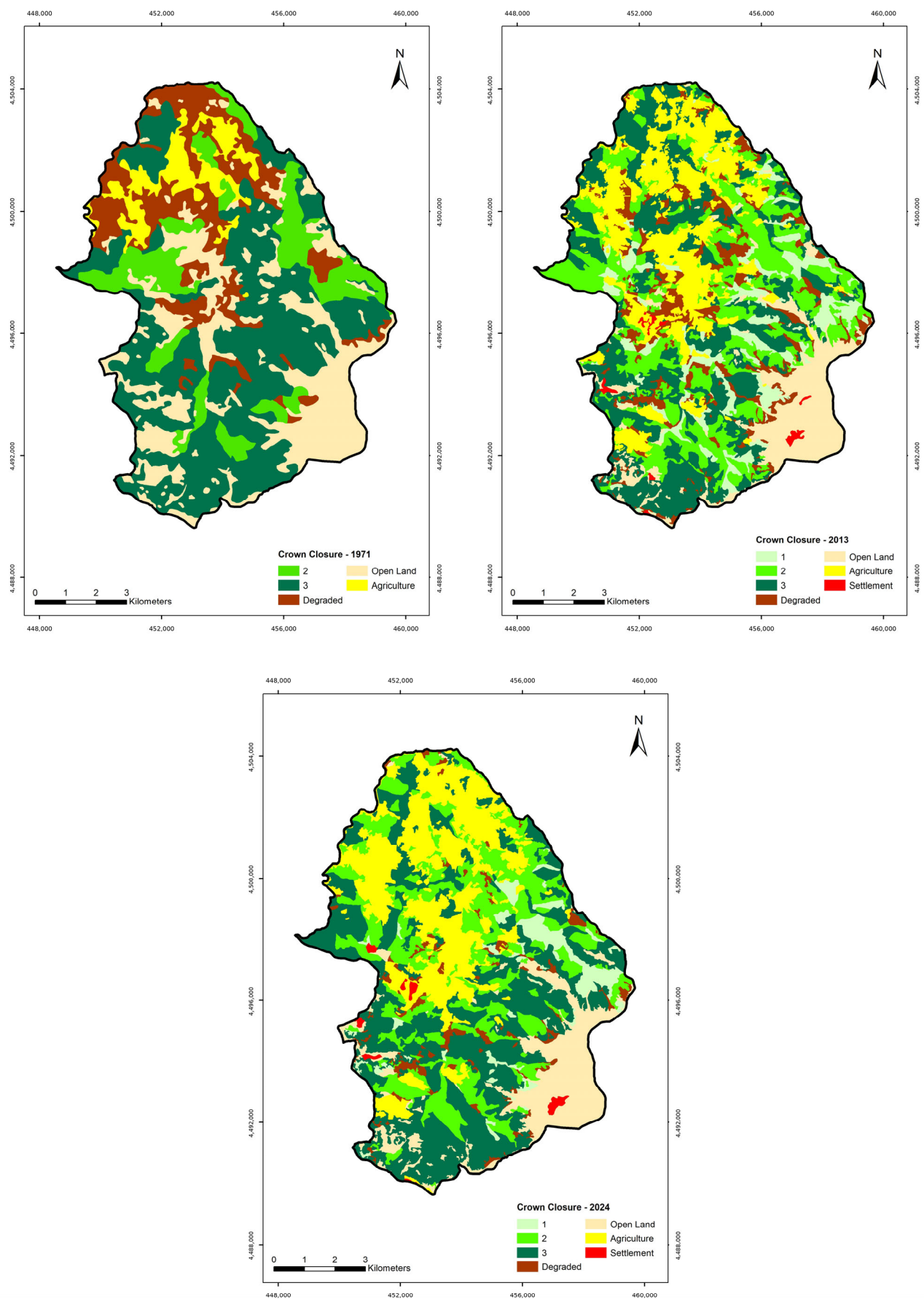


Figure 5. Crown closure maps of Kümbet PU in 1971, 2013, and 2024.

Table 8. Change in landscape pattern in Kümbet PU.

LULC Classes	NP			MPS			AWMSI		
	1971	2013	2024	1971	2013	2024	1971	2013	2024
L	14	53	45	76.5	23.7	27.4	2.9	3.5	3.3
Kn	1	11	16	39.4	24.2	20.6	2	2.2	2.1
Kz	-	11	14	-	3	8.6	-	1.5	1.6
Mixed	6	47	36	689.9	88.9	119	5.4	8.3	7.3
Degraded	17	149	83	88.1	5.8	4.	4	2.3	2.1
Open Land	69	74	58	32.9	14.7	19.3	2.9	3.9	4
Agriculture	5	60	40	127.5	32	54.4	4.2	5.7	6.6
Settlement	-	10	7	-	5.4	9	-	1.8	1.5
Landscape Level	112	415	299	86.2	23.3	32.3	4.2	5.9	5.8

Taken together, H1a was not supported because election-year status was not associated with registered forest crime counts. H1b received partial support because the provincial population showed a significant positive association, whereas real per capita income did not. H2 was not statistically supported by the management-period negative binomial model. H3 received only limited descriptive support based on the temporal correspondence between registered forest crime density and landscape configuration.

4. Discussion

The revised analyses distinguish between short-term election-year effects and broader demographic and economic associations. Accordingly, the primary contribution of this study is the documentation of long-term forest landscape transformation and agricultural expansion. The forest-crime component provides a complementary assessment of administratively recorded pressure and its broader contextual associations rather than a general explanatory model of landscape change. Election-year status was not associated with annual registered forest crime counts in either the unadjusted comparison or the multivariable negative binomial model. Therefore, H1a was not supported. This finding indicates that the presence of at least one national or local election within a calendar year did not correspond to a detectable change in annual registered forest crime counts. However, because national and local elections were combined into a single binary indicator, the analysis does not exclude more specific political or administrative effects that could not be represented by the available data.

The provincial population showed a positive temporal association with registered forest crime counts during the 1981–2025 study period in both the Pearson correlation analysis and the multivariable negative binomial regression model. After accounting for election-year status, real per capita income and annual forest-area exposure, an increase of 10,000 persons in the provincial population was associated with an approximately 7.5% increase in the expected registered forest crime rate. In contrast, real per capita income was not significantly associated with registered forest crime counts. Thus, H1b received partial support for the broader-scale population indicator but not for real per capita income. This result is broadly consistent with previous studies emphasizing the relevance of demographic conditions, rural livelihood structures and forest–community relations to registered forest offences [12,83]. However, because the population series represented Giresun Province rather than the Kümbet Planning Unit, the observed relationship should be interpreted as a broader-scale temporal association within the study period rather than as evidence of a direct local demographic effect.

Exposure-weighted registered forest crime density did not show a uniform decline across the three management-related periods. It decreased from 4.573 crimes per 1000 ha-year in 1981–2012 to 3.602 in 2013–2023 and then increased slightly to 3.811 in 2024–2025.

The negative binomial period model showed no statistically significant difference among the periods; therefore, H2 was not supported. Although Özden and Ayan [86] reported temporal decreases in several forest-crime categories in another regional context, the present aggregate dataset did not provide sufficient evidence for either a systematic long-term decline or a distinct management-period effect. Moreover, the 2024–2025 estimate was based on only two complete calendar years and was less precise than the estimates for the preceding periods. The observed variation may reflect changes not only in underlying forest-related activities but also in detection effort, enforcement capacity, reporting intensity and administrative recording practices. In particular, the lower registered forest crime density observed after 2012 occurred within a broader period in which agricultural land continued to expand. This apparent divergence indicates that a decline in officially registered cases should not automatically be interpreted as a decline in actual land-use pressure. Some forest-related activities may not have been detected or formally recorded, while other land-cover conversions may have occurred through legally authorized land-use decisions, administrative reclassification or changes in land status that would not necessarily generate a forest-crime record. However, the available dataset does not contain information on enforcement effort, prosecution outcomes, legal authorization or changes in cadastral and forest status; therefore, these mechanisms could not be evaluated directly. Registered forest crime records should consequently be interpreted as indicators of detected and administratively recorded cases rather than as complete measures of all legal and illegal processes contributing to agricultural expansion or forest-landscape transformation. Except for the population association, the largely nonsignificant crime-related results may reflect stable enforcement and recording practices, limitations of registered crime counts as a proxy for actual human pressure, and the spatial and temporal mismatch between the datasets; they should not be interpreted as evidence that human pressure was absent.

The LULC findings indicate a complex landscape transformation pattern. Total forest area decreased and agricultural lands expanded markedly, while degraded forests and open areas declined. This pattern suggests that agricultural expansion and partial structural improvement in forests occurred simultaneously, rather than a one-way process of forest degradation. Similar to Kılıç and Karahalil [120], important changes in developmental stages and crown closure classes were observed in the Kümbet PU. However, the distinctive feature of the present case is that these structural changes occurred together with strong agricultural expansion.

These results are partly consistent with Khan [121], Kaptan [122,123], Bozali [124], Sauti and Karahalil [125], and Yel et al. [126], who reported forest structural improvement, rehabilitation, afforestation, natural regeneration and land-use transformation in different forest landscapes. The decline in degraded forests and open areas in the Kümbet PU is consistent with the broader literature. However, the marked increase in agricultural lands shows that improvements in forest quality do not necessarily mean that land-use pressure has disappeared. Similarly, Karahalil et al. [127] showed that declines in degraded and open areas may occur together with increases in agricultural or urban areas and landscape fragmentation. The present study extends this framework by evaluating structural forest change together with registered forest crimes and socioeconomic indicators.

The stand-type maps identify where agricultural land expanded, but they do not reveal the specific processes responsible for this expansion because the agricultural class does not distinguish among crop or plantation types. In the Kümbet context, hazelnut production, seasonal livestock grazing and highland tourism are locally relevant land-use activities that may have influenced demand at the forest–agriculture interface [19,98]. Rural out-migration and agricultural land abandonment may also produce contrasting land-cover trajectories by facilitating natural regeneration in some locations while allowing ag-

gricultural land to be maintained or reorganized elsewhere [11,19,47]. However, the individual contributions of these processes could not be quantified using the available spatial and socioeconomic data. They are therefore considered plausible contextual mechanisms rather than demonstrated causes, and the mapped agricultural class should not be interpreted as synonymous with hazelnut cultivation.

The results on developmental stages and crown closure support the interpretation of partial structural recovery within some parts of the forest landscape. The decline in degraded forest and the transition of some areas from dispersed or middle crown-closure classes to dense crown closure may reflect crown expansion of residual trees, stand maturation, recruitment into upper canopy layers, natural regeneration and silvicultural improvement. Reduced cutting or repeated canopy disturbance could theoretically allow these processes to proceed for longer periods without renewed opening of the stand. However, the present data do not demonstrate that changes in registered forest crime pressure directly caused the observed crown-closure transitions.

This ecological interpretation is particularly relevant to Oriental spruce (*Picea orientalis*) and Oriental beech (*Fagus orientalis*), which are major components of the Kumbet forest landscape. Both species can persist and regenerate under partially shaded forest conditions, although their regeneration and growth responses depend on gap size, light availability, stand structure and site conditions [128,129]. Where disturbance is limited, lateral crown expansion, ingrowth of younger cohorts and continued diameter and height growth may gradually increase canopy occupancy and shift stands from dispersed or intermediate closure toward denser canopy classes. For *Fagus orientalis*, shade tolerance and successful regeneration under closed or semi-closed canopy conditions may support the maintenance and gradual infilling of canopy cover. For *Picea orientalis*, persistence under partial shade and recruitment within mixed or multilayered stands may similarly contribute to increasing crown closure. Nevertheless, these species-specific pathways should be interpreted as plausible ecological mechanisms rather than as effects directly demonstrated by the forest-crime dataset. The observed structural changes may also reflect planned silvicultural treatments, natural stand development, regeneration following earlier disturbance and differences between the analogue 1971 map and the later digital maps. Therefore, improvement in canopy density cannot be attributed exclusively to reduced registered forest crime pressure.

Landscape metrics indicated marked changes in spatial configuration, but the decrease in patch number after 2013 should not be interpreted as uniformly positive or negative. At the class level, the number of spruce patches decreased from 53 to 45 while mean patch size increased from 23.7 to 27.4 ha, and the number of mixed-forest patches decreased from 47 to 36 while mean patch size increased from 88.9 to 119.0 ha. These changes suggest partial spatial consolidation within some productive forest classes, although number of patches and mean patch size alone do not demonstrate that ecological connectivity was fully restored. This pattern is broadly consistent with the importance of evaluating fragmentation through multiple landscape attributes rather than patch number alone [130,131].

At the same time, the number of agricultural patches decreased from 60 to 40, while their mean patch size increased from 32.0 to 54.4 ha and total agricultural area increased from 1920.0 to 2177.7 ha. This indicates that the reduction in patch number also reflected the enlargement or amalgamation of agricultural areas, which represents continuing land-use pressure rather than ecological recovery. Changes in degraded forest were also complex because the decline in both its total area and number of patches may reflect transitions to productive forest, agriculture or other land-cover classes. Therefore, the post-2013 decrease in patch number represented a mixed landscape process involving partial con-

solidation of some forest classes together with the expansion and amalgamation of agricultural land.

The highest exposure-weighted registered forest crime density occurred during 1981–2012, which partly overlapped with the 1971–2013 interval characterized by a marked increase in patch number. During the 2013–2024 landscape-change interval, class-level metrics indicated partial consolidation in some productive forest classes, particularly spruce and mixed forest but also enlargement and amalgamation of agricultural patches. The later decrease in the overall number of patches should therefore not be interpreted as uniform ecological recovery. Instead, it reflected different and partly opposing land-cover processes occurring within the same landscape. This broad temporal pattern provides only limited descriptive support for H3. The temporal intervals were not perfectly aligned because forest crime records began in 1981, whereas the first landscape-change interval began in 1971. Moreover, landscape metrics were available for only three reference years, and the 2024–2025 crime period contained only two annual observations. The observed correspondence therefore cannot be interpreted as an inferential association or as evidence that registered forest crimes caused fragmentation, forest consolidation or agricultural expansion.

International studies demonstrate that relationships between forest offences and forest loss vary across institutional and geographical contexts. Bolton [80] and Sobko et al. [88] reported that illegal logging and deforestation may increase under weak governance, enforcement constraints or organized criminal activity. In the Kümbet Planning Unit, registered forest crime density was lower in 2013–2023 than in 1981–2012 and increased slightly in 2024–2025, although the overall management-period effect was not statistically significant. During the broader study period, agricultural land expanded and landscape configuration changed substantially. The findings of Abebe et al. [132] and Clerici et al. [81], which emphasize agricultural expansion, population pressure and contextual socio-economic conditions, therefore show a closer parallel with the land-use changes observed in the Kümbet Planning Unit. This comparison reinforces the distinction between administratively registered offences and the broader land-use processes affecting forest landscapes.

Overall, forest landscape transformation in the Kümbet Planning Unit reflected the combined occurrence of agricultural expansion, partial improvement in forest structure, landscape reconfiguration and broader demographic conditions. Income-based explanations, including reduced dependence on forest resources at higher income levels, have been discussed in previous research [12]. However, the present study found no statistically significant association between real per capita income and registered forest crime counts in either the Pearson correlation analysis or the multivariable negative binomial regression model. Therefore, the current findings do not provide direct support for an income-based or Environmental Kuznets Curve interpretation. Moreover, because the demographic and economic indicators were measured at the provincial level, they should be treated as contextual covariates rather than as direct local drivers of landscape transformation within the Kümbet Planning Unit.

These findings also have implications for forest conservation, landscape restoration and non-market ecosystem benefits. Although this study did not conduct an economic valuation of ecosystem services, the observed changes in forest area, stand structure, crown closure and fragmentation are directly related to the biophysical basis of non-market forest benefits [133,134]. Forests in mountainous rural landscapes support biodiversity habitat, soil and water protection, carbon storage, recreation, cultural landscape values and rural well-being [135,136]. Therefore, long-term spatial evidence on forest degradation, structural improvement, agricultural conversion and fragmentation can support future assessments of conservation value and restoration needs [137,138]. In this respect,

combining stand-type maps, landscape metrics, registered forest crime records and socioeconomic indicators provides a practical evidence base for identifying where conservation and restoration actions may be most relevant.

The study has several limitations. First, the forest crime dataset consisted of annual aggregate administrative records and did not include consistently comparable offence-type information or incident-level geographic coordinates. Registered counts may also have been influenced by changes in detection effort, enforcement capacity and reporting practices [80–82]. Second, population and real per capita income were provincial indicators and did not directly measure demographic or economic conditions within the Küm-bet Planning Unit. Third, national and local elections were combined into a single binary election-year variable, preventing the separate evaluation of election types or specific institutional mechanisms. Although the analytical dataset contained 45 complete annual observations and the primary model was restricted to three explanatory variables, the modest time-series length limited statistical power to detect small associations and reduced the precision of some estimates. Fourth, annual forest-area exposure values were estimated by linear interpolation between the 1971, 2013 and 2024 reference maps, and the observed 2024 value was carried forward to 2025. Fifth, LULC and landscape metrics were available for only three reference years, while the final crime period contained only two complete annual observations. The landscape-configuration assessment was restricted to number of patches, mean patch size and area-weighted mean shape index and therefore did not directly quantify edge effects, core habitat, isolation, contagion or functional connectivity. Future studies should incorporate these complementary metrics where historical map quality and temporal comparability permit. Comparisons involving the analogue 1971 map may retain residual positional and classification uncertainty because formal positional-accuracy statistics, a consistently documented minimum mapping unit and a reproducible georeferencing RMSE were not available for all reference dates [139]. These limitations restrict causal interpretation and the direct spatial or annual linkage of registered forest crimes with landscape change. Because the analysis was conducted within a single planning unit, the findings should be interpreted as site-specific evidence and should not be generalized to mountainous forest landscapes elsewhere in Türkiye without supporting comparative multi-site research. Future studies should use georeferenced and offence-specific crime records, planning-unit- or village-level socioeconomic indicators, separate measures of political and enforcement conditions, and more frequent LULC observations.

5. Conclusions

This study documented substantial long-term landscape transformation in the Küm-bet Planning Unit. Agricultural land expanded markedly, while total forest area, degraded forest and open land declined. At the same time, transitions toward productive developmental stages and denser crown-closure classes indicated partial structural recovery in parts of the forest landscape. The observed pattern therefore reflected simultaneous agricultural conversion, forest structural change and spatial reorganization rather than uniform degradation or recovery. More specifically, the long-term decline in forest area was driven by a combination of gross conversions from degraded and productive forest classes to agricultural land and bidirectional transitions among productive forest, degraded forest and open land, rather than by a single one-way process. These transformations were not fully captured by conventional registered forest-crime records because such records include only detected and administratively recorded cases and do not account for undetected activities, legally authorized land conversions, administrative reclassification or changes in cadastral and forest-land status.

The crime-related analyses provided limited support for the proposed relationships. Election-year status, real per capita income and management-related period were not significantly associated with registered forest crime counts, whereas the broader-scale population indicator showed a positive temporal association within the study period. The correspondence between registered crime density and landscape configuration was descriptive, and registered crime records should be interpreted as administrative indicators of detected cases rather than as causal explanations of landscape change.

Forest management should combine georeferenced offence records with regularly updated spatial observations, land-status and cadastral information, permits and field verification. More specifically, the GDF should establish a near-real-time monitoring system for the forest–agriculture interface by integrating frequently updated satellite imagery, forest management boundaries, cadastral parcels, land-use permits and georeferenced forest-offence records. Automated change-detection alerts should be used to identify new agricultural clearings or potential hazelnut-plantation expansion along degraded forests, productive forest edges and structurally recovering stands. Each alert should be linked to the relevant parcel and rapidly verified through field inspection. Following verification, the GDF should determine whether the detected change is legally authorized and initiate enforcement, restoration or boundary-recovery measures where unauthorized conversion is confirmed. Monitoring results should also be recorded in a common spatial database to support repeated inspections and long-term evaluation of high-risk forest–agriculture boundaries.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/land15071261/s1>, Table S1: Tree species transition matrix between 1971 and 2013 in Kümbet PU; Table S2: Tree species transition matrix between 2013 and 2024 in Kümbet PU (ha); Table S3: Mapped developmental-stage transition matrix between 1971 and 2013 in the Kümbet PU (ha); Table S4: Developmental stage transition matrix between 2013 and 2024 in Kümbet PU (ha); Table S5: Crown closure transition matrix between 1971 and 2013 in Kümbet PU (ha); Table S6: Crown closure transition matrix between 2013 and 2024 in Kümbet PU (ha).

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Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request. Some datasets are not publicly available because they include official forest management maps and administrative forest crime records obtained from institutional sources.

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