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Vegetation Cover Changes and Drivers in Nzeeu River Catchment in Kitui County, Kenya

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Abstract

Vegetation cover change is a key indicator of ecosystem health, soil moisture availability, and land degradation at global, regional, and local levels. Assessment of these changes is crucial to ensuring the sustainability of terrestrial ecosystems such as the Nzeeu River Catchment. The study aimed to determine land use and land cover changes, as well as drivers, in the Nzeeu River catchment for the period 2000 - 2023. The study employed a remote sensing workflow to analyze vegetation dynamics using the complete Landsat archive (Landsat 5 - 9) and Sentinel imagery, processed in Google Earth Engine. Cloud-free monthly composites were generated using median reducers, while atmospheric and cloud masking were implemented using quality assessment bands and the CFMask algorithm. Vegetation changes were assessed through post-classification comparison of annual land-cover maps generated via supervised classification to quantify transitions between cover types, and through continuous NDVI time-series analysis. Classification accuracy was evaluated using error matrices to calculate overall accuracy, producer's/user's accuracies, and kappa statistics. Overall accuracy for the classifications ranged from 92.57% for the year 2000 to 92.8%, 94.4%, and 94.9% for the years 2010, 2020, and 2023, respectively. Higher values were reported for the Kappa coefficient corresponding to 0.825, 0.83, 0.866 in 2020, and 0.879 in the years 2000, 2010, 2020, and 2023, respectively. The results of the classification and analysis process established that forest cover reduced from 39.95% to 27.54%, agriculture increased from 27.40% to 32.44%, shrubs increased from 28.13% to 33.61%, bare ground increased from 3% to 4.44%, and urban land cover increased from 1% to 2%. The main drivers of land use and land cover changes identified were agricultural expansion, urbanization and demographic pressures, hydrological interventions, climate variability, and environmental drivers.

Subject Areas

Vegetation Cover Changes

Keywords

Land Use, Land Cover, Google Earth Engine, Landsat Imageries

1. Introduction

Research demonstrates that sand dams can enhance vegetation recovery in semi-arid regions by prolonging soil moisture availability (Lasage *et al.*, 2015 [1], Pringle, 2021 [2]). NDVI-based studies in Kenya's Kitui County show localized greening near SDs due to improved groundwater access (Mati *et al.*, 2008 [3]), though up-stream deforestation and farming often offset these gains (Ngigi *et al.*, 2020 [4]). Critically, SD effectiveness depends on sediment management—poorly maintained structures may exacerbate erosion downstream (de Trincheria *et al.*, 2015 [5]), while well-designed spillways sustain riparian ecosystems (Quilis *et al.*, 2009 [6]). The existing studies rarely disaggregate SD-induced vegetation changes from climate variability or land-use pressures. The study addressed this by pairing NDVI trends (2000-2023) with dam deployment timelines and climate data.

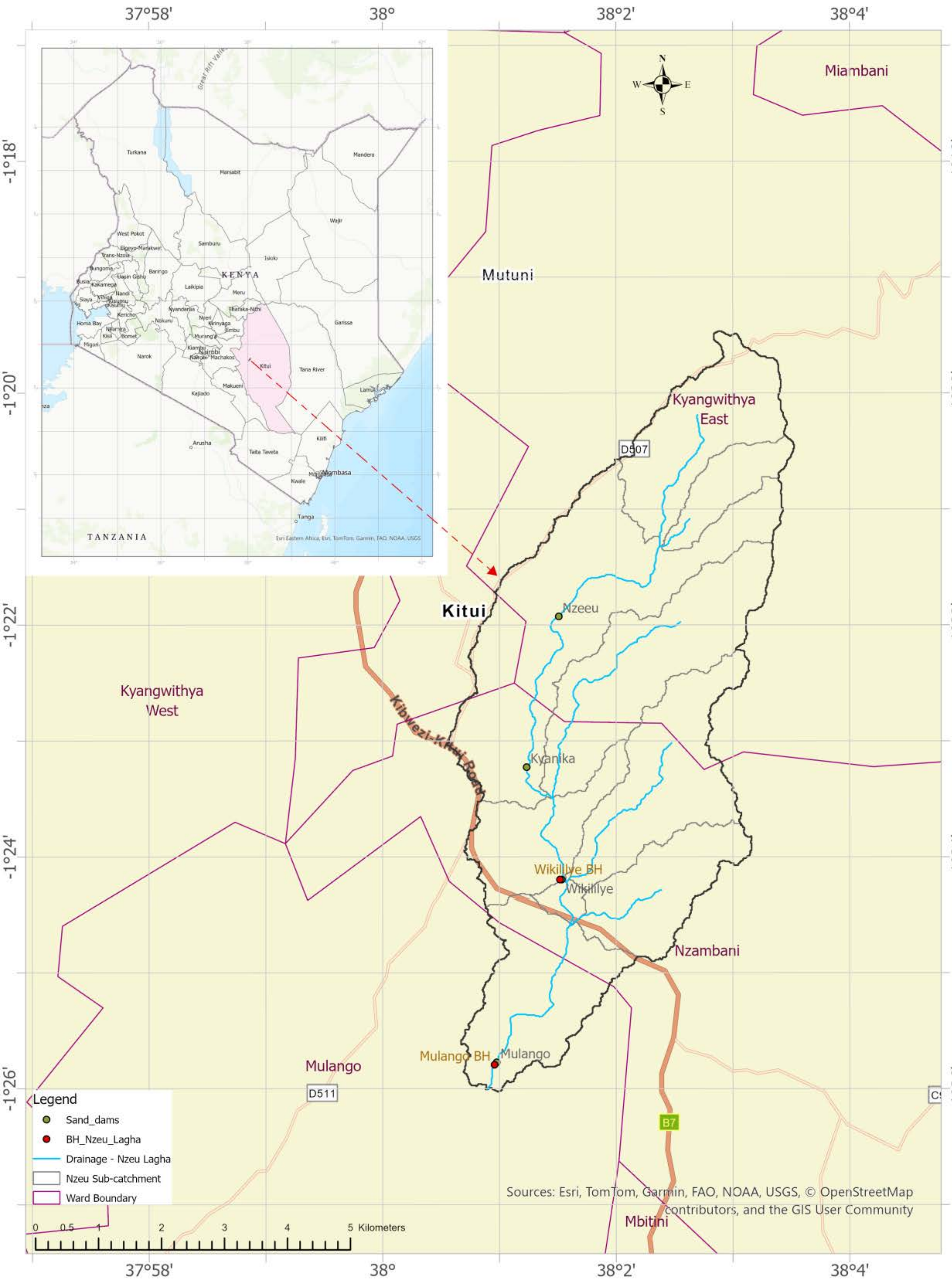
2. Materials and Methods

2.1. Description of Study Area

The Nzeeu catchment lies approximately 150 kilometers east of Nairobi, the capital city of Kenya, and is part of the country's larger arid and semi-arid lands. It covers an area of approximately 231 square kilometers across both Kitui Central and Kitui Rural sub-counties, characterized by gently sloping terrain and low-lying plains. The landscape is dominated by seasonal rivers, which flow during the rainy seasons but dry up for most of the year. These rivers provide opportunities for the construction of sand dams, which are widely used to harvest and store water. The catchment experiences a hot and dry climate and receives bimodal rainfall, with the long rains occurring between March and May and the short rains between October and December. The average annual rainfall ranges from 500 mm to 700 mm, which is insufficient to support year-round agricultural activities. The catchment is highly vulnerable to climate variability and change, characterized by: Prolonged dry spells and droughts are common, exacerbating water scarcity and food insecurity; unpredictable rainfall patterns with significant variations in timing, duration, and intensity; and land degradation ranging from soil erosion and loss of vegetation cover, further exacerbated by deforestation and sand harvesting, reducing the water retention capacity. **Figure 1** shows the study area, which constitutes part of the Nzeeu catchment.

2.2. Research Methodology

This study employed a robust remote sensing workflow to analyze vegetation dynamics in Nzeu Catchment using the complete Landsat archive (Landsat 5 - 9) and Sentinel imageries processed through Google Earth Engine (Gorelick *et al.*, 2017 [7]).



Source: Author.

Figure 1. Map of the Nzeeu catchment.

Cloud-free monthly composites were generated using median reducers, with particular focus on growing seasons (March-May, October-December), while atmospheric and cloud masking was implemented using quality assessment bands and the CFMask algorithm (Foga *et al.*, 2017 [8]). Vegetation changes were assessed through post-classification comparison of annual land cover maps generated via supervised classification (Random Forest algorithm) to quantify transitions between cover types, and continuous NDVI time-series analysis.

The Random Forest (RF) classification was trained using a consistent set of reference samples across all years analysed to ensure comparability of land use/land cover (LULC) classifications and minimize classification bias associated with changing training datasets. A total of 345 training samples were used, distributed among the five LULC classes as follows: Forest (101 samples), Shrubland (68 samples), Bareland (65 samples), Urban/Built-up Areas (57 samples), and Agriculture/Cropland (54 samples). The training samples were selected to adequately capture the spectral variability within each land cover class while maintaining a balanced representation of the dominant landscape characteristics within the study area.

Historical training labels were derived primarily from Google Earth high-resolution imagery, which provides a reliable and widely accepted source of reference data for remote sensing-based land cover classification. The historical imagery available through Google Earth's time-series archive enabled the identification and verification of stable land cover features corresponding to different periods of analysis. To ensure temporal consistency and facilitate robust change detection, the same land cover class definitions and classification scheme were applied across all years analysed. Each training sample was assigned to one of the five predefined classes (Forest, Shrubland, Agriculture, Urban/Built-up, and Bareland) using identical classification criteria throughout the study period. This standardized approach minimized inconsistencies arising from variations in class interpretation and enhanced the reliability of temporal comparisons and land cover change assessments.

Validation combined multiple approaches to ensure accuracy. Historical high-resolution imagery from Google Earth Pro provided temporal reference points, while field data from 50 stratified random locations (GPS-referenced photographs) were used for ground-truthing classifications (Muriuki *et al.*, 2023 [9]). These were supplemented by the Regional Centre for Mapping of Resources for Development (RCMRD) land cover maps for regional consistency. Classification accuracy was rigorously evaluated through error matrices, calculating overall accuracy, producers'/users' accuracies, and kappa statistics (Congalton & Green, 2019 [10]).

Although the overall study period extended to 2023, the NDVI and EVI analysis was intentionally limited to 2000, 2010, and 2020 for methodological and analytical reasons. The NDVI and EVI analysis aimed at evaluating long-term vegetation dynamics in relation to land use changes. The period was restricted to 2000, 2010, and 2020 so as to provide a more robust framework for assessing long-term vegetation change while minimizing the influence of short-term climatic variability. The year 2023 experienced relatively higher and more evenly distributed rainfall compared to the selected benchmark years. The improved rainfall conditions resulted in enhanced vegetation growth across much of the study area, producing vegetation index values that were strongly influenced by short-term climatic conditions rather than long-term land cover dynamics. The inclusion of 2023 could have masked or exaggerated underlying land degradation and vegetation change trends by reflecting temporary climatic responses rather than structural changes in land use and vegetation cover.

The drivers of land use/land cover (LULC) change were identified through an integrated analysis of multi-temporal LULC classifications, demographic trends, historical imagery interpretation, and field-based validation. The primary indicators of landscape change were derived from observed transitions among the major land cover classes, particularly the decline in forest cover, expansion of agricultural land, and increase in urban/built-up areas over the study period. A reduction in forested areas was interpreted as evidence of increasing pressure from agricultural expansion, fuelwood extraction, settlement growth, and other human activities. Similarly, the expansion of agricultural land indicated growing demand for cultivated areas driven by food production needs, while increases in urban and built-up areas reflected settlement expansion, infrastructure development, and economic growth within and around the study area.

To further explain these changes, LULC trends were compared with population census data from 1999, 2009, and 2019, which showed progressive population growth within the study area and its surrounding administrative units. Population increase was considered a key underlying driver of land transformation through its influence on agricultural expansion, settlement development, resource extraction, and increased demand for land and natural resources. The relationship between demographic growth and observed land cover changes provided additional evidence for attributing landscape transformations to anthropogenic pressures.

The identified drivers were subsequently assessed and validated through historical image interpretation using Google Earth time-series imagery, which provided a reliable archive for tracking changes in land use patterns, settlement expansion, vegetation cover, and agricultural development over time. Field observations and discussions with key informants during ground-truthing exercises further supported the interpretation of observed land cover transitions. Local community members, land managers, and other knowledgeable stakeholders provided valuable insights into historical land use practices, population dynamics, agricultural development, deforestation activities, settlement growth, and environmental changes within the study area. The integration of remote sensing analysis, demographic data, historical imagery, and local knowledge enhanced the reliability of the identification and interpretation of the major drivers of land use/land cover change.

3. Results and Discussion

3.1. Accuracy Assessment

The results from the accuracy assessment, determined using Overall Accuracy (OA), Kappa coefficient, Producer Accuracy (PA), and Consumer Accuracy (CA), confirmed a high degree of reliability in the land use and land cover (LULC) classifications and hence suitability for temporal change detection and analysis. Overall accuracy for the classifications ranged from 92.57% for the year 2000 to 92.8%, 94.4%, and 94.9% for classifications of the years 2010, 2020, and 2023, respectively. The high overall accuracies obtained exceeded the minimum widely accepted values of 85%, all of which indicated the robustness of the classifications (Congalton & Green, 2019 [10]; Olofsson *et al.*, 2014 [11]), so these maps hold up statistically. Higher values were also reported for the Kappa coefficient corresponding to 0.825, 0.83, 0.866 in 2020, and 0.879 in the years 2000, 2010, 2020, and 2023, respectively, indicating an almost perfect agreement. Typically, the high values for both Overall Accuracy and Kappa coefficient resulted in sharper images which depicted clearer differences between land cover types.

The Forest class gave the highest and most consistent accuracy, with Producer's Accuracy ranging 97.90% to 99.3% while the Consumer Accuracies ranged from 95.3 in 2000 to 99.3% in 2023. This indicated minimal omission and commission errors for the Forest Cover, which confirmed its clear separations from other classes, thereby enhancing confidence in subsequent analysis such as change detection (Gao *et al.*, 2020 [12]). The classification performance for Urban land cover depicted a moderate to strong reliability, with producer accuracy ranging from 78% in 2000 to 89% in 2023, while consumer accuracy reached near-perfect at 1.0 in both 2010 and 2023. Such patterns are common in rural catchments, where built-up areas are small, fragmented, and spectrally mixed with bare soil and cultivated land (Weng, 2012 [13]).

Shrubland presented the greatest classification challenge, with producer accuracy remaining relatively low in 2010 (50.1%) and 2020 (50.5%) but improved to 0.70 in 2023. Consumer accuracy ranged from 62.5% (2020) to 1.0 (2023). The confusion matrices reveal that shrub pixels were frequently misclassified as forest, agriculture, or bare ground. This reflects the inherent spectral heterogeneity of shrub-dominated landscapes, particularly in semi-arid environments where vegetation structure is sparse and transitional (Ustin & Gamon, 2010 [14]). The shrubland cover often represents a dynamic interface between degraded vegetation, fallow cropland, and rangeland, which made the spectral discrimination complex.

Agriculture demonstrated strong but slightly variable performance. Consumer accuracy ranged from 80% - 94%, while producer accuracy remained relatively stable at approximately 80% - 85%. Errors were primarily associated with confusion between agriculture and forest or shrubs, reflecting mixed land cover conditions such as agroforestry, intercropping, and residual woody vegetation within croplands. In semi-arid catchments, cropland often includes scattered trees and shrub remnants, complicating spectral classification (Reed *et al.*, 2020 [15]). The classifications for Bare ground land cover performed well across all the years, reporting producer accuracy of 100% in 2020 and 2023, while consumer accuracy ranged 77% and 92% over the same period. The classification error matrix showed that bare ground occasionally got mixed up with shrubs since drylands often have bare dirt and patchy plants together. However, the high accuracy values show that bare surfaces stood out clearly in the imagery.

3.2. LULC Changes in Nzeeu Catchment

Figure 2 shows the land cover transformations for the Forest, Shrub, Agriculture, Urban, and Bare ground land use/covers between the year 2000 and 2023. The changes are characterized by forest decline, agricultural expansion, shrub dynamics, and gradual urban growth.

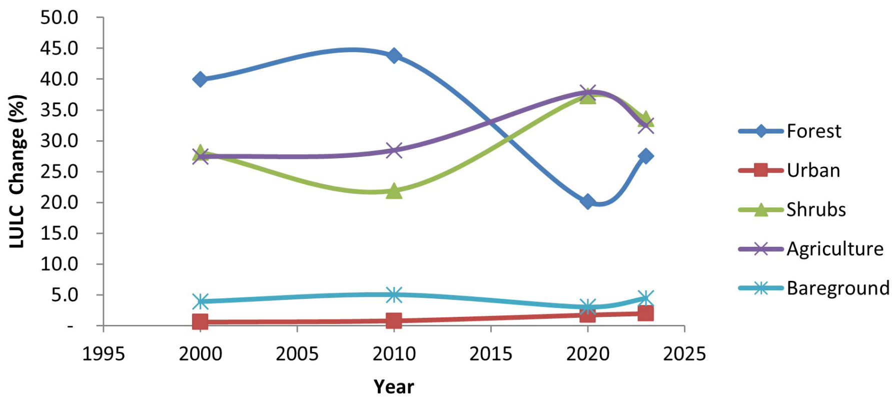


Figure 2. Land cover transformations.

The forest cover accounted for approximately 40% - 45% of the total catchment areas between 2000 and 2010. However, the forest declined sharply to about 20% by the year 2020 before partially recovering to roughly 28% in 2023. The decline could be attributed to extensive clearance of deep vegetation, similar to deforestation, possibly creating space for agriculture while making use of the cleared forest vegetation for charcoal and fuel wood, coupled with limited regeneration. Such patterns are consistent with global observations where forest loss is largely driven by agricultural expansion, settlement growth, and resource extraction (FAO, 2020 [16]; Hansen *et al.*, 2013 [17]). The partial recovery observed after 2020 may indicate efforts at localized reforestation initiatives, especially from Mango fruit trees.

The inverse relationship between forest and agriculture shows the existence of direct forest-to-cropland conversion. Similar patterns were observed from sub-Saharan Africa and other tropical regions, where agricultural expansion remains the dominant driver of deforestation (Gibbs *et al.*, 2010 [18]; Curtis *et al.*, 2018 [19]). The slight decline in area under agriculture after 2020 could most likely be associated with changes in weather, declining soil productivity, with little effort on soil regeneration, in addition to urban encroachment. These dynamics indicate that agriculture functions as the principal force shaping land cover/use change in the catchment.

The shrubs' land use/cover showed non-linear changes, with a decline observed between 2000 and 2010, followed by a significant increase up to 2020. A decline in the area under shrub was also observed between 2020 and 2023. The fluctuation in shrubland area reflects transitional vegetation dynamics. The increase in shrubland cover may indicate the presence of fallow systems, the abandonment of agricultural areas, or the emergence of woody vegetation influenced by rainfall variability (Archer *et al.*, 2017 [20]). In many semi-arid and sub-humid systems, shrub proliferation can indicate either ecological recovery or land degradation, depending on context. The simultaneous rise in shrubs and agriculture between 2010 and 2020 may be an indication of shifting cultivation, partial abandonment, and mixed land uses.

Urban land use covered the smallest proportion of the total catchment area. Though urban land cover/use occupies a limited spatial area, its systemic influence on land transformation may be substantial. An analysis of change in area showed a trend with steady growth from 1% to 2% throughout the study period. The observed changes were most likely associated with increased demand for agricultural and forest resources (Seto *et al.*, 2012 [21]). Urban growth often acts indirectly, stimulating peri-urban agricultural intensification and accelerating forest conversion.

The analysis established that Bare ground covered an area of 3% - 5% of the total catchment. Between the years 2000 and 2010, this land cover observed a 1.1% increase in area as a function of the total catchment before reporting a 2% decline in coverage by the year 2023. While this indicates the absence of significant expansion of bare ground cover, it does not necessarily imply ecological stability, since degraded shrublands or marginal agricultural areas may not appear as bare ground in classification outputs. Overall, the bare ground land cover increased by 3.2% between 2000 and 2023.

Urbanization trends in the catchment reveal aspects of both partial convergence and divergence from national patterns. National statistics indicate that rapid urban expansion in Kenya, particularly around Nairobi, Mombasa, and other major towns (Seto *et al.*, 2012 [21]), is influenced by demographic pressures, while urban growth within rural catchments such as Nzeeu is largely confined to small trading centres and rural settlements. This limited expansion suggests that land transformation in the catchment is driven more by rural livelihood strategies than by metropolitan sprawl. This diverges from rapidly urbanizing corridors such as Nairobi-Naivasha, where infrastructure and industrial growth are major drivers of LULC change.

The observed pattern resembles a forest transition framework where deforestation initially accelerates due to agricultural expansion before stabilization of partial recovery (Mather & Needle, 1998 [22]). Peak conversion was observed to take place in the period 2010 to 2020 and 2023. The increased construction of sand and subsurface dams within the catchment may have indirectly influenced forest recovery, as it increases water availability, which supports localized regeneration of tree cover, including mango production, in the surrounding area. At the same time, enhanced soil moisture recharge downstream of sand dams may promote riparian vegetation regeneration and shrub growth, partly explaining localized increases in shrub and woodland cover after 2020. The scale of influence of sand and subsurface dams is spatially limited to adjacent areas, which contributes to a micro-catchment land use intensification and vegetation recovery. However, broader LULC changes across the catchment would strongly be driven by agricultural expansion and demographic changes.

Further divergence was observed in the relative stability of bare ground in Nzeeu. In parts of northern Kenya and Somalia, increasing bare surfaces have been linked to recurrent drought and land degradation. The comparatively stable bare ground proportion in Nzeeu suggests that vegetation transitions are occurring mainly between woodland, shrubs, and agriculture rather than progressing toward widespread soil exposure. This highlights the spatial heterogeneity of dryland systems across East Africa, where rainfall gradients, soil characteristics, and land management practices produce distinct land change trajectories even within similar climatic zones. The LULC dynamics in the catchment largely converge with regional evidence identifying agricultural expansion as the primary driver of woodland decline in Kenya and East Africa. Figures 3-6 show LULC maps for the period between 2000 and 2023.

3.3. LULC Change and Transitions

Table 1 gives the land use/cover transitions between 2000 and 2023. The land use and land cover changes in the catchment between 2000 and 2023 tell a story of a landscape in flux. Back in 2000, forests covered almost 40% of the area, making it the dominant land cover. Shrubs and agriculture followed closely behind, each taking up just over a quarter of the land. Urban areas barely registered, while bare-ground made up only a small slice.

From 2000 to 2010, something interesting happened. Forest cover actually went up by nearly 4%. This growth hints at woodland regeneration or perhaps some successful afforestation projects. Maybe there was less pressure on the forests during those years. At the same time, shrubland shrank by over 6%, while agriculture and bare ground crept up a bit. It looks like some of the shrubland might've been converted into either new forest or farmland, which is pretty typical in semi-arid places where climate and human activity keep the landscape shifting.

The real shake-up came between 2010 and 2020. Forest cover plummeted by more than 21 percentage points. That's the biggest single shift in any class over the whole period. Meanwhile, shrubs and agriculture surged, together taking over as the main land cover types by 2020. The numbers tell a clear story: forests gave way to farmland and expanding shrubland. This kind of change usually means more agriculture, more fuelwood cutting, growing settlements, and maybe even the effects of a hotter, drier climate. Urban areas also started to spread out—doubling in size, though they still cover a small part of the whole area. Interestingly, bare ground actually decreased a bit, which suggests that as forests disappeared, people put the land to use rather than leaving it exposed.

Between 2020 and 2023, the landscape shifted again. Forest cover bounced back by about 5%, which could point to natural regrowth, new planting efforts, or just better land management. Still, forests in 2023 covered much less ground than they did at

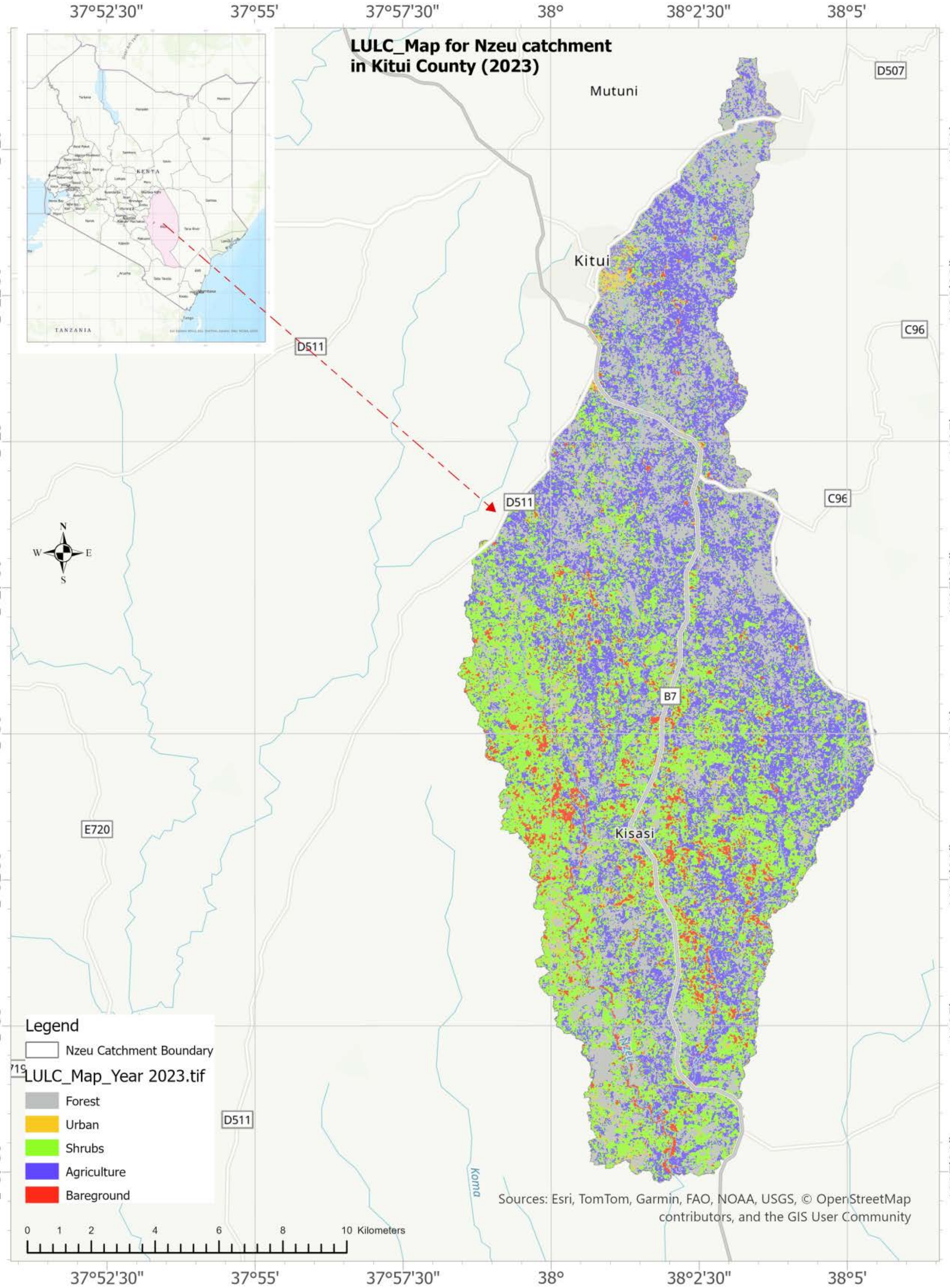


Figure 3. LULC map for the year 2023.

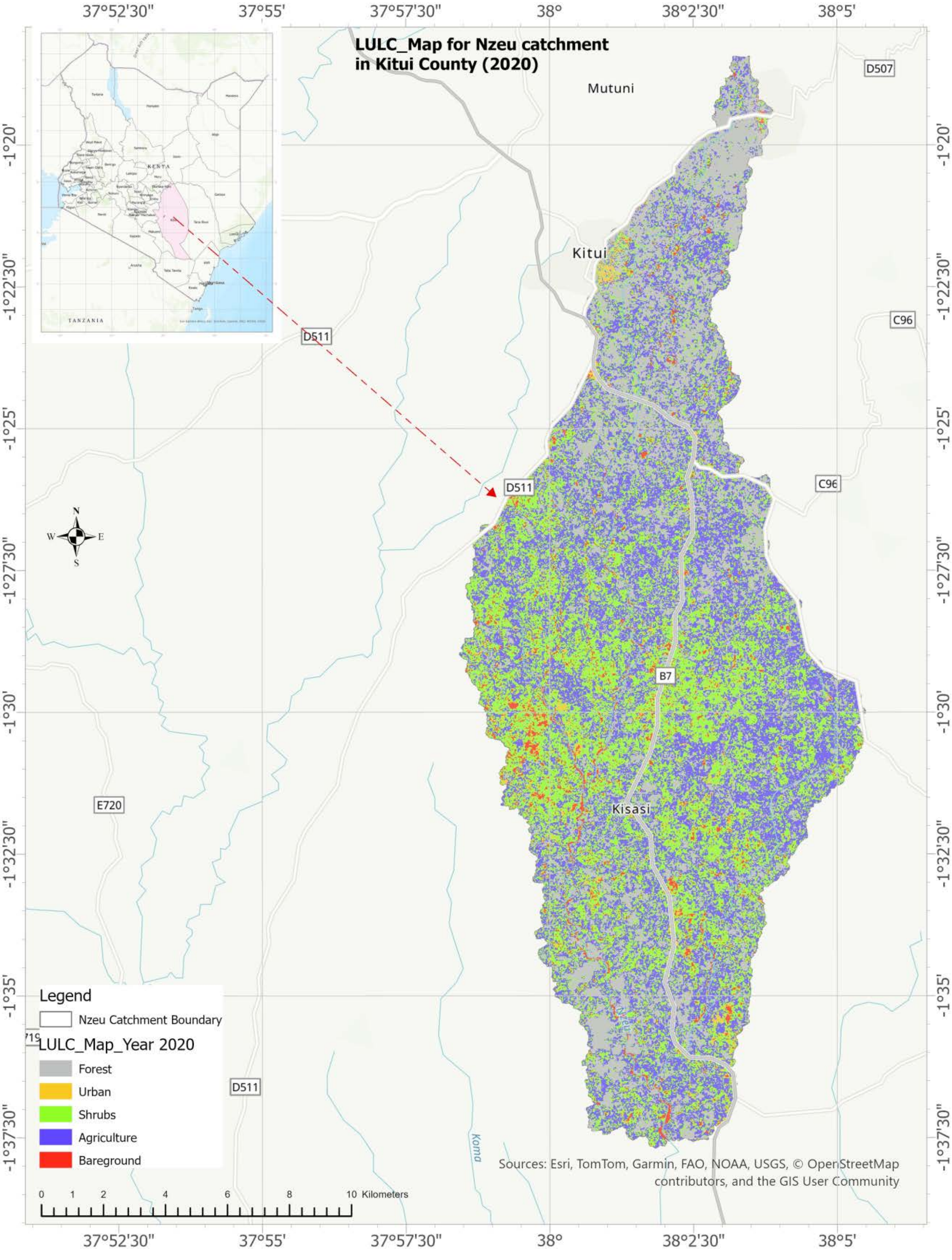


Figure 4. LULC map for the year 2020.

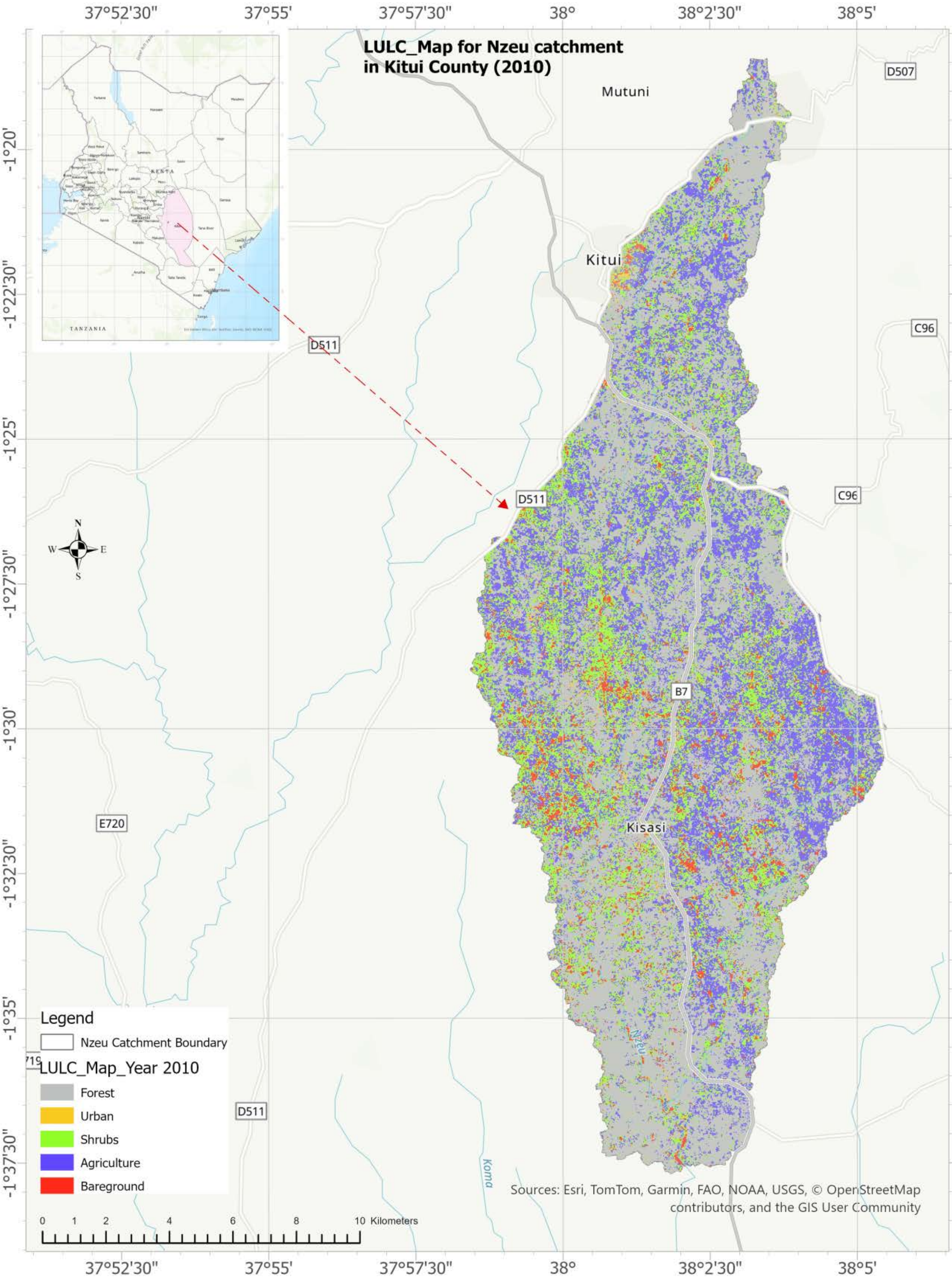


Figure 5. LULC map for the year 2010.

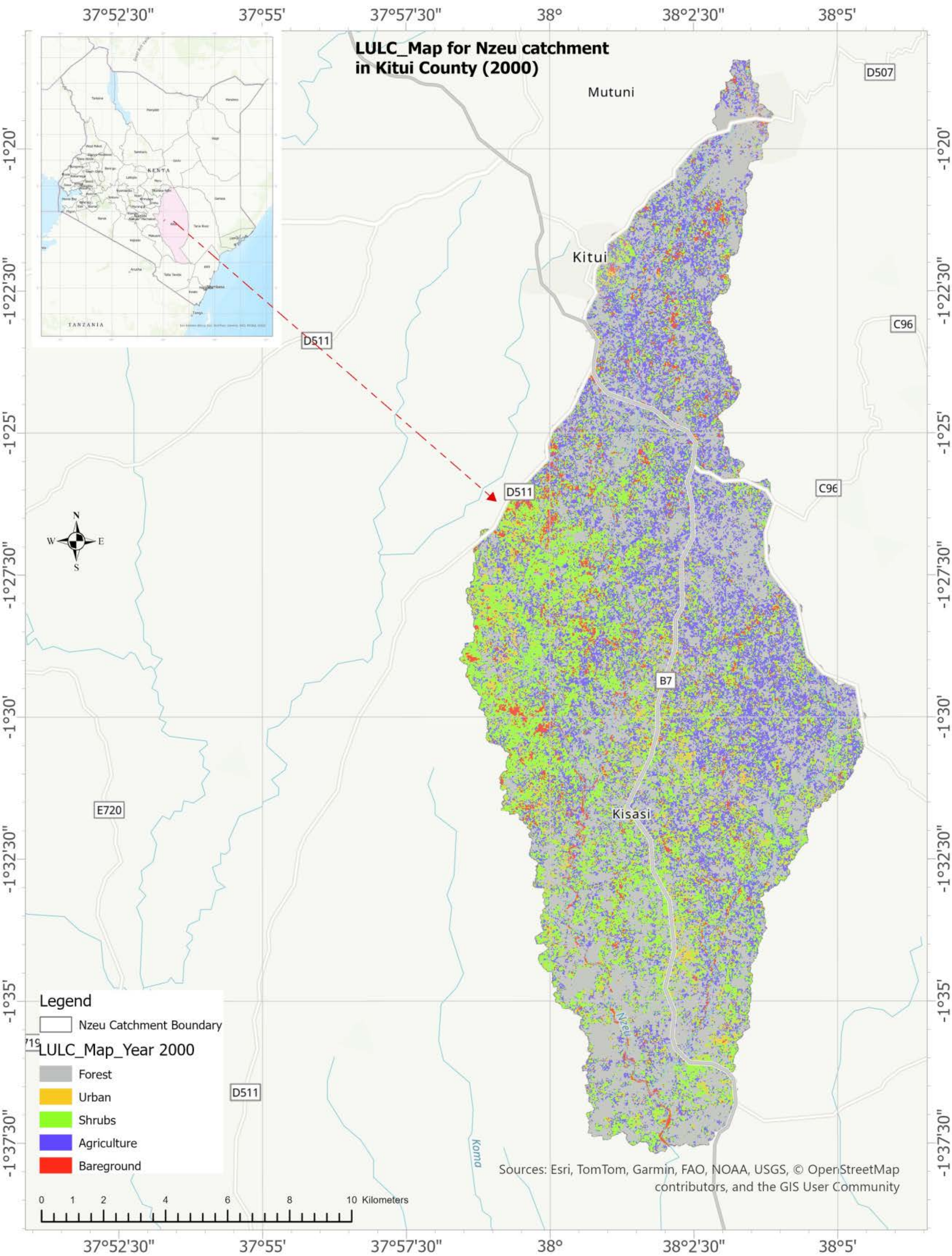


Figure 6. LULC map for the year 2000.

Table 1. Observable changes between 2000 and 2023.

	2000 (%)	2010 (%)	Δ2000 - 2010 (%)	2020 (%)	Δ2010 - 2020 (%)	2023 (%)	Δ2020 - 2023 (%)	Δ2010 - 2023 (%)	Δ2000 - 2023 (%)
Forest	39.95	43.80	3.84	22.36	−21.44	27.54	5.18	(17.60)	(12.42)
Urban	0.60	0.80	0.21	2.03	1.23	1.97	−0.07	1.44	1.37
Shrubs	28.13	21.91	−6.21	36.35	14.43	33.61	−2.74	8.22	5.48
Agriculture	27.40	28.46	1.05	35.60	7.14	32.44	−3.16	8.20	5.04
Bareground	3.92	5.03	1.11	3.66	−1.37	4.44	0.78	(0.26)	0.52

the start of the study. During these years, both agriculture and shrubland have declined, which could mean some of that land is slowly turning back into woodland or at least more mixed vegetation. Urban land more or less leveled off, and bare ground ticked up slightly, maybe because of some local land degradation or construction.

Looking at the whole 23-year stretch, a few trends stand out. Forests lost ground, while shrubs and agriculture expanded. Urban areas grew too, but from a tiny base. The increase in shrubland, paired with forest loss, points to gradual woodland degradation rather than a straight conversion to bare land. Agriculture's steady growth shows people are putting more pressure on the catchment, probably because of more mouths to feed and changing livelihoods. The recent uptick in forest cover is a good sign, but it doesn't undo the big drop from earlier years. All in all, the catchment has gone through some big changes due to deforestation, expanding farms, more shrubland, and slow but steady urban growth with just a hint of recovery at the end. These shifts matter. They affect watershed health, biodiversity, and how sustainably people can manage the land going forward.

From 2010 to 2020, forests kept shrinking while agriculture and shrubland crept in, and towns grew a little. Similar changes have been reported in other semi-arid places in Kenya and across East Africa. The Upper Tana Basin or eastern Kenya farmers push into forests, woodland gets chipped away, and this often turns into shrubland before disappearing further (Muriuki *et al.*, 2011 [9]; Maitima *et al.*, 2009 [23]). In the Mau Forest Complex, people have cleared huge sections for settlements and farms, breaking up the forest and replacing it with cropland and secondary growth (Were *et al.*, 2013 [24]). Landsat images tell a similar story: closed-canopy forests keep shrinking, small farms pop up everywhere, and shrub or bushland cover goes up and down, mostly because of growing populations and shifts in climate (Brink & Eva, 2009 [25]). However, between 2020 and 2023, forest cover started to bounce back a bit in this area. This agrees with what's happening in some other parts of Kenya, where reforestation, new policies, and patches of natural regrowth have slowly started to heal the land after years of damage.

3.4. Classification Uncertainty and Limitations

Despite the overall satisfactory classification performance, some degree of classification uncertainty remains, particularly within the shrubland class, which exhibited comparatively lower classification accuracies than the other land cover classes. This uncertainty is common in Arid and Semi-Arid Lands (ASALs) where shrub vegetation undergoes pronounced seasonal changes in canopy cover and spectral reflectance. During prolonged dry periods, many shrub species partially or completely shed their leaves, resulting in spectral characteristics that closely resemble bare land, sparse grassland, or degraded agricultural fields. Consequently, distinguishing shrubland from other sparsely vegetated surfaces can be challenging, leading to increased commission and omission errors. However, the achieved accuracies indicate that the classification provides a reliable representation of overall land cover patterns and trends within the study area.

3.5. NDVI Responses across Land Use/Cover Changes

Figure 7 shows the spatial and temporal variation in NDVI across the catchment. The NDVI analysis reveals significant changes in vegetation cover and condition across the Nzeeu Catchment between 2000 and 2020. Visual interpretation of the NDVI maps indicates a marked reduction in areas characterized by moderate to high vegetation density and a corresponding expansion of low-NDVI zones. In 2000, the catchment exhibited relatively extensive areas of moderate and high NDVI values, particularly within the central and southern portions of the watershed, suggesting healthier vegetation cover, higher biomass accumulation, and greater photosynthetic activity. By 2020, these areas had become increasingly fragmented and replaced by lower NDVI classes, indicating a decline in vegetation vigor and overall ecosystem productivity.

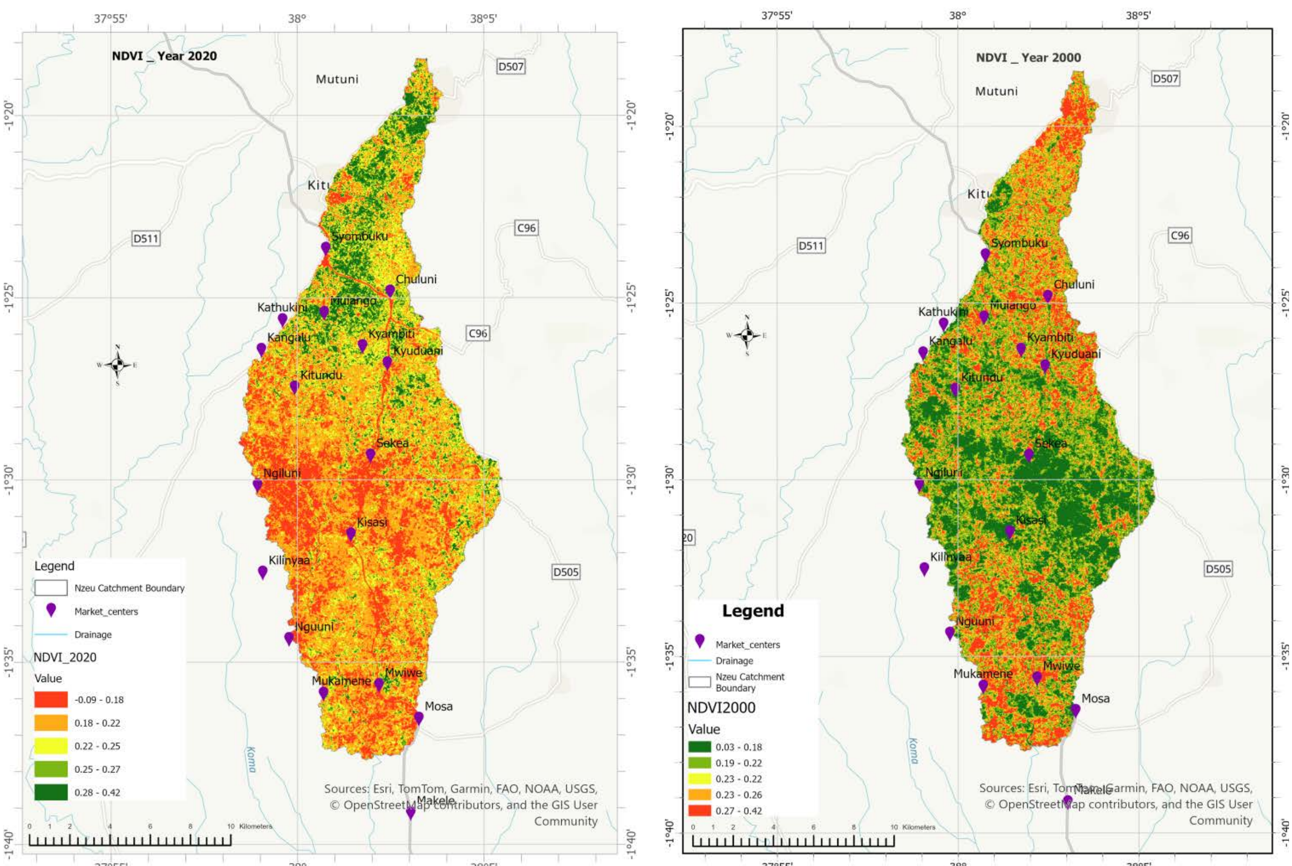


Figure 7. Spatial-temporal variation of NDVI between the years 2000 and 2020.

The observed NDVI decline may indicate a reduction in ecosystem resilience. Healthy vegetation enhances soil structure, carbon sequestration, biodiversity conservation, and watershed stability. Declining vegetation cover can therefore reduce the capacity of the catchment to withstand future climatic extremes, including droughts and intense rainfall events. Recent studies (Hou *et al.*, 2025 [26]) have shown that watersheds experiencing persistent vegetation decline are more vulnerable to land degradation, reduced water availability, and ecological instability. Overall, the NDVI results suggest that the Nzeeu Catchment has undergone substantial vegetation degradation between 2000 and 2020. The reduction in vegetation density, increasing fragmentation of vegetated areas, and expansion of low-NDVI zones indicate growing environmental pressure on the watershed. These findings are consistent with broader regional trends reported across East Africa (Nkinda *et al.*, 2025 [27]), where land-use change and increasing anthropogenic activities have contributed to declining vegetation productivity and ecosystem health.

3.6. EVI Responses across Land Use/Cover Classes

Figure 8 shows the EVI results across the catchment. The results show a clear decline in vegetation cover within the Nzeeu Catchment between 2000 and 2020. In 2000, moderate to high EVI values were more widespread and continuous, especially in the central, southern, and drainage-associated parts of the catchment.

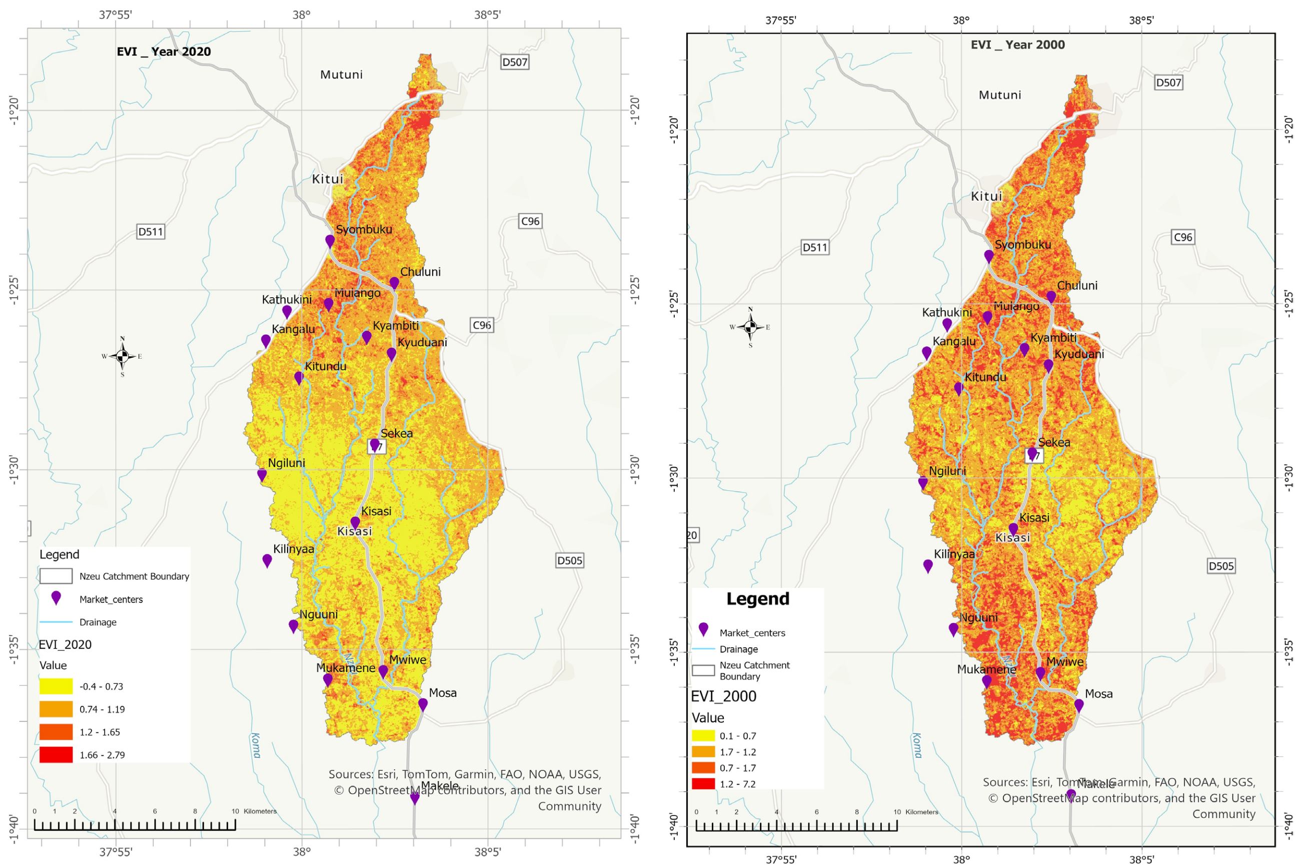


Figure 8. Spatial-temporal variation of EVI.

These areas likely represented zones with relatively better canopy development, higher vegetation biomass, and improved moisture availability. By 2020, the catchment was dominated by lower EVI classes, indicating reduced vegetation vigor, lower photosynthetic activity, and declining biomass. This pattern suggests that vegetation cover became more sparse and fragmented over the two decades.

The decline in EVI values across the Nzeeu Catchment suggests a reduction in vegetation biomass and canopy development, which may be attributed to both climatic and anthropogenic factors. Recent investigations of vegetation dynamics between 2000 and 2020 have demonstrated that human activities can influence vegetation productivity and landscape degradation. Similar studies conducted in semi-arid and sub-humid catchments have shown that long-term declines in vegetation indices are commonly associated with agricultural expansion, deforestation, overgrazing, and increasing human pressure on natural ecosystems (Hou *et al.*, 2025 [26]). The spatial pattern of EVI decline observed in the catchment is particularly evident in upland and agricultural areas, where moderate vegetation cover in 2000 transitioned into lower EVI classes by 2020. Such transitions are consistent with findings from East African and tropical watershed studies, which have reported progressive conversion of natural vegetation into cultivated land and settlements, resulting in declining vegetation density and increasing landscape fragmentation.

Despite the overall decline, relatively high EVI values remain concentrated along drainage channels and riparian corridors. These areas continue to benefit from enhanced soil moisture and shallow groundwater availability, allowing vegetation to persist even during dry periods. Similar observations have been reported by Rohde *et al.* [28] in a study of dryland environments, where riparian ecosystems function as a hydrological refuge, maintaining vegetation productivity and biodiversity under conditions of water stress and increasing climate variability. Riparian vegetation is often sustained by shallow groundwater and subsurface moisture, enabling greater resistance to drought than surrounding upland ecosystems (White *et al.*, 2021 [29]). However, the fragmentation of these riparian vegetation zones between 2000 and 2020 suggests increasing pressure from cultivation, grazing, fuelwood extraction, stream bank disturbance, and changing hydrological regimes. Such fragmentation can reduce ecological connectivity, increase channel instability, accelerate erosion processes, and diminish the resilience of riparian ecosystems to future climatic and anthropogenic stresses.

The EVI analysis provides strong evidence of progressive vegetation degradation within the Nzeeu Catchment over the last two decades. The reduction in vegetation productivity, increasing fragmentation of vegetated areas, and persistence of only localized riparian vegetation indicate a landscape undergoing significant ecological change. Related findings were reported by Nkinda *et al.* [27], showing consistency with broader regional studies that link declining vegetation indices to land-use transformation and increasing anthropogenic pressure on watershed ecosystems.

4. Drivers of LULC Change in the Nzeeu Catchment

4.1. Agricultural Expansion

This was identified as a key driver of LULC change in the catchment, as deduced from an inverse relationship between forest and agricultural land cover, where forest was observed to decline from 39.95% in year 2000 to 22.36% in the year 2020, while agriculture increased from 27.45% to 35.6% during the same period. Globally, agricultural expansions have been reported as a dominant driver of deforestation in most tropical regions (Gibbs *et al.*, 2010 [18]; Curtis *et al.*, 2018 [19]; FAO, 2020 [16]).

Between 2010 and 2020, forest cover experienced the sharpest decline at 21.44%, while agriculture increased by 7.14% for the same period, suggesting direct forest-to-cropland conversion. Similar findings were documented by Hansen *et al.* [17] in sub-Saharan Africa, where smallholders' agricultural expansion accounted for the majority of the loss of forest cover. In most rural catchments similar to the Nzeeu catchment, forest vegetation is cleared to create space for farming and to provide firewood and charcoal as a livelihood and energy strategy for rural communities (Muriuki *et al.*, 2023 [9]). However, between 2020 and 2023, agricultural land cover was observed to have declined from 35.6% to 32.44%. Similar findings have been reported in the past (Reed *et al.*, 2020 [15]). Agricultural contraction has been attributed to emerging challenges such as declining rainfall and soil fertility loss, contributing to farrowing cycles.

4.2. Urbanization and Demographic Pressures

The urban land cover/use in the Nzeeu catchment increased from 0.60% in 2000 to 1.97% in 2023. While the coverage appears small, it has the potential to affect the surrounding area by stimulating peri-urban agricultural intensification and accelerating the conversion of forest cover to other uses. The expansions were observed in the upstream part of the catchment near Kitui town and in other small, emerging centers such as Kisasi, Chuluni, and Kwa Mosa. In parts of Kenya, the urban areas are growing much faster, especially around big cities like Nairobi (Seto *et al.*, 2012 [21]).

The urbanization trend in the Nzeeu catchment differs greatly from that in other catchments with large towns like Nairobi, Mombasa, and Nakuru, where expansion is largely influenced by infrastructure development and demographic pressures, for rural catchments such as Nzeeu, urban expansion is normally confined to the growth of small trading centers and rural settlements. While urban area and growth remain significantly small in the Nzeeu catchment, the limited expansion can be attributed to livelihood strategies rather than urban sprawl (Seto *et al.*, 2012 [21]).

4.3. Hydrological Interventions

The analysis observed an increase in forest and shrub cover in 2020, mostly in patches along the Nzeeu Lagha. This pattern of localized increase in riparian vegetation and regeneration could be attributed to enhanced soil moisture, a factor most possibly attributed to the increased construction of sand and subsurface dams within the catchment. This is a case of a positive environmental contribution of the dams on the land use and land cover through the recovery of land and the regeneration of vegetation. Site verification and ground truthing revealed increased vegetation cover from mango production and shrubs near the dams. However, the impact is limited to areas around the sand and sub-surface dams. While the sand and sub-surface dams contribute to the micro-catchments' land cover and to intensification of land use and vegetation recovery, a larger part of the LULC changes in the catchment is influenced by agricultural expansion, which, in turn, is influenced by socioeconomic changes. Similar findings were reported by Gao *et al.* [12], who deduced that localized water management interventions rarely reverse regional-scale deforestation trends unless supplemented with appropriate policy and livelihood interventions.

4.4. Climate Variability and Environmental Drivers

Changes in weather patterns and declines in soil fertility may be contributing to the decrease in agricultural land cover after 2020, which remains a common constraint in semi-arid agricultural systems (Reed *et al.*, 2020 [15]). The bare ground land cover, which corresponded to areas with no vegetation, remained relatively stable, increasing by only 3.2% over the 23-year period. This suggests that vegetation transitions mainly occur between agricultural, forest, and shrub land uses/cover types, with limited widespread soil exposure. This diverges from patterns in other parts, such as northern Kenya and similar ASAL areas in East Africa, where bare surfaces are increasing due to drought and land degradation.

Conflicts of Interest

The authors declare no conflicts of interest.

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