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Disentangling the drivers of deforestation and forest degradation in the Miombo landscape: A case study from Mozambique

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ABSTRACT

The fragmented and complex landscape in the Miombo landscape makes it a challenge to map and disentangle the various forest change drivers (FCD) associated with these changes and relate them to other underlying drivers. To overcome these challenges, we developed a method to spatially disentangle the drivers of deforestation (smallholder and commercial agriculture, mining, and clean-cutting charcoal), forest degradation (selective charcoal production, wildfires, logging), and forest growth (abandoned land, regrowth including plantations) in the Beira corridor, in central Mozambique. We identified ten potential FCD from the literature and created two land use and land cover (LULC) maps for 2000 and 2020 to identify areas of forest change. We used stratified random sampling based on the LULC change map, visually interpreted high-resolution satellite imagery, and NDVI time series to characterise and collected observation points of the FCD. We derived several potential underlying drivers as explanatory spatial variables. We used the random forest algorithm to evaluate their relative importance and generate a map of FCD. The forest loss due to deforestation and degradation accounts for 82.8 % (38,553.1 ha year^{-1}) and 5.2 % (2,399.1 ha year^{-1}), respectively, while the gain due to plantations accounts for 2.8 % (1,314.4 ha year^{-1}) and regrowth for 9.2 % (4,297 ha year^{-1}) of the total forest change area from 2000 to 2020. Smallholder agriculture (72.2 % of the total forest change), clear-cutting charcoal (9.1 %), abandoned land (5.4 %) and regrowth (5.7 %) were the main FCD in the study area. They are explained mainly by the intensity of change, altitude, population density and proximity to the main road. The results show a satisfactory accuracy for the LULC map (overall accuracy = 88 % and F1-score = 80 % for LULC 2000 and 90 % and 88 % for LULC 2020) and for the FCD map (overall accuracy = 79 % and F1-score = 73 %). This study provides a significant improvement in quantifying FCD by using spatially explicit data. The method could help decision-makers design land use policies better and monitor their impacts.

1. Introduction

Miombo woodlands, the most extensive savannah in the world (Pennington et al., 2018), are dry deciduous forests characterised by an open tree canopy and a continuous grass layer that burns down regularly (Ryan et al., 2016). These forests provide essential ecosystem services such as carbon storage (Pelletier et al., 2018), energy sources (International Energy Agency, 2014), non-timber forest products (Chirwa et al., 2008), and habitats for biodiversity (Linder et al., 2012). They are critical to the livelihoods of over 100 million people in rural areas (Ryan et al., 2016). However, due to deforestation and forest degradation, miombo woodlands are experiencing a decline in biodiversity (Tripathi et al., 2021) and are releasing carbon into the atmosphere at an alarming rate (Goetz et al., 2015). While this situation is expected to worsen due to the increasing demand for natural resources triggered by the unprecedented population growth in sub-Saharan Africa, which is predicted to reach 2 billion people by 2050 (United Nations, 2022), there are additional factors that can either exacerbate or mitigate this impact,

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for instance, dependence on local lands for subsistence. This challenge undermines the efforts of sub-Saharan African countries to achieve the Sustainable Development Goals (United Nations, 2015).

Deforestation and forest degradation are significant issues, with deforestation referring to converting natural forests into non-forested land (Pendrill et al., 2022). Forest degradation involves changes in forest structure and function without a change in land cover, resulting in reduced biomass and ecosystem services (Putz & Redford, 2010). Proximate drivers of deforestation in tropical and subtropical developing countries include agricultural expansion, urban growth, mining activities, and infrastructure development, while forest degradation is driven by logging, fuelwood extraction, charcoal production, wildfire, and livestock grazing (Hosonuma et al., 2012; Lapola et al., 2023). These drivers vary by region and over time (Rudel et al., 2009). Empirical evidence is crucial for understanding the significance of these drivers (Ryan et al., 2014). Analysing the relationship between forest change drivers (FCD) and LULC change patterns provides insights for informed decision-making in spatial planning (Aldwaik & Pontius, 2012; Oliveira & Meyfroidt, 2022). While deforestation can be readily detected and monitored through remote sensing, assessing, and understanding the drivers of forest degradation remotely is more challenging (Ahrends et al., 2021; Sasaki & Putz, 2009). Hence, poor quantification of forest degradation drivers leads to policy uncertainties (Ahrends et al., 2010; Gao et al., 2020). Direct measurement of forest degradation requires high-resolution optical imagery (Herold et al., 2012) or radar remote sensing data (Mitchard et al., 2011; Ryan et al., 2011), but their application is limited due to the sensitivity of the signal to surface roughness and humidity as well as limited availability of long-wavelength radar imagery (Joshi et al., 2015).

Despite advancements in forest monitoring systems, detecting degradation in tropical dry forests remains a complex challenging. Masolele et al. (2024), used an active learning approach and deep learning models to predict post-deforestation land use in African countries using Planet data. At the national level, Montfort et al. (2021) assessed land degradation in Mozambique by integrating climate data, anthropogenic factors, and MODIS data on NDVI as indicators of land productivity. In the context of tropical dry forests, Jiménez-Rodríguez et al. (2022) used multitemporal optical data from Landsat-8 and Sentinel-2 to model forest biophysical parameters and identify relevant biophysical and socioeconomic factors related to forest degradation. Several studies have also focused on specific local areas. Ryan et al. (2014) conducted a causal linkage assessment using radar data, a linear model, and reference data to detect changes in aboveground biomass. Sedano et al., (2016,2020) also investigated the local FCD. However, these earlier studies were limited to using very high-resolution imagery and focused mainly on the spatial estimation of drivers of deforestation. It is worth noting that some studies (e.g., Montfort et al., 2021) have used coarse-resolution imagery or radar data to assess forest degradation.

Nevertheless, there is a significant knowledge gap in quantitatively assessing FCD and underlying drivers at regional and local scales, specifically for dry forests in sub-Saharan Africa (Romijn et al., 2015; Ryan et al., 2014). Countries like Mozambique lack comprehensive information on the drivers contributing to deforestation and forest degradation. Smallholder agriculture and charcoal production have been identified as the primary proximate drivers of deforestation and forest degradation (CEAGRE & Winrock International, 2016; Ryan et al., 2014; Sedano et al., 2020). Previous research has primarily focused on quantifying the extent of cropland and charcoal production, overlooking other crucial drivers such as forestry plantations, commercial agriculture, and wildfires (Bey et al., 2020; Rufin et al., 2022; Sedano et al., 2020, 2021). This limited analysis restricts our understanding of FCD and may result in incomplete or ineffective policies. To address this gap, comprehensive research is needed to consider a wide range of drivers and their interactions, particularly at regional and local levels. This study introduced a nuanced analytical technique to enhance understanding of the underlying drivers of deforestation and forest degradation in miombo woodlands. This will inform the development of targeted and effective policies for sustainable forest management.

This study aims to quantify the extent of forest change and identify the proximate drivers that explain the forest change in Mozambique at the sub-national level over the last two decades. The study will be conducted in three steps: (1) quantifying and analysing the spatial distribution of LULC change and FCD between 2000 and 2020, (2) identifying the FCD and the underlying drivers that explain the spatial patterns of deforestation, forest degradation and regrowth through point sampling and visual interpretation, and (3) combining both analyses to assess the relative importance and spatial representation of the drivers of deforestation, forest degradation, and forest regrowth.

2. Methods

2.1. The study area

Our study focuses on the Beira corridor (BC), located in central Mozambique. This corridor encompasses six districts within the province of Manica and Sofala (Fig. 1). The total area of the corridor is approximately 61,836.64 km^2. Historically, the BC has served as a crucial transportation route, connecting Mozambique's second-largest city, Beira, with the port cities of the Mozambique Channel. For decades, smallholder agriculture has been considered the main driver of deforestation (Nhantumbo & Mausse, 2015) and the most important source of income for the rural population. More recently, charcoal production has emerged as another major driver of forest degradation (Gou, 2016; Nhantumbo & Mausse, 2015). After a vibrant history of land use, the post-2000 period saw rapid land change due to the expansion of smallholder farmers and large-scale agricultural investments (Gou, 2016).

2.2. Framework overview

We conducted the data collection and analysis in seven steps (Fig. 2). We performed all analysis routines and accuracy assessments using R software (R Core Team, 2022) and post-processing using QGIS software v. 3.28.

2.3. Step 1: Defining the classes of LULC and FCD

We used the national classification system (FNDS, 2018), which is consistent with the 2006 IPCC guidelines, to outline the LULC (step 1, Fig. 2). We selected 8 LULC classes: forest, mangroves, forestry plantation, cropland, grassland, wetland, settlement, and other land (Fig. 3A). We reviewed existing studies in Mozambique that have addressed FCD. We identified eight drivers from this review and added two from this study (abandoned land and forest regrowth, Table 1, and Fig. 3B). The inclusion of the two additional drivers provides insight into the drivers contributing to forest change in the study area.

2.4. Step 2: Data collection and pre-processing

Landsat images pre-processing for LULC.

To map LULC changes between 2000 and 2020, we utilised Landsat data acquired by the Thematic Mapper sensor on Landsat-5 and the Operational Land Imager sensor on Landsat-8. The analysis focused on images acquired during the dry season, from 8 April to 28 October, to minimise the impact of cloud cover. We employed the median composite method (Flood, 2013) to create composite images for 2000 and 2020. In addition to the composite images, we calculated three vegetation indexes: Normalised Difference Vegetation Index, Normalised Difference Water Index, and Normalised Burn Ratio, which are commonly used to assess vegetation health and density. Furthermore, we derived elevation data from the Shuttle Radar Topography Mission (SRTM) dataset

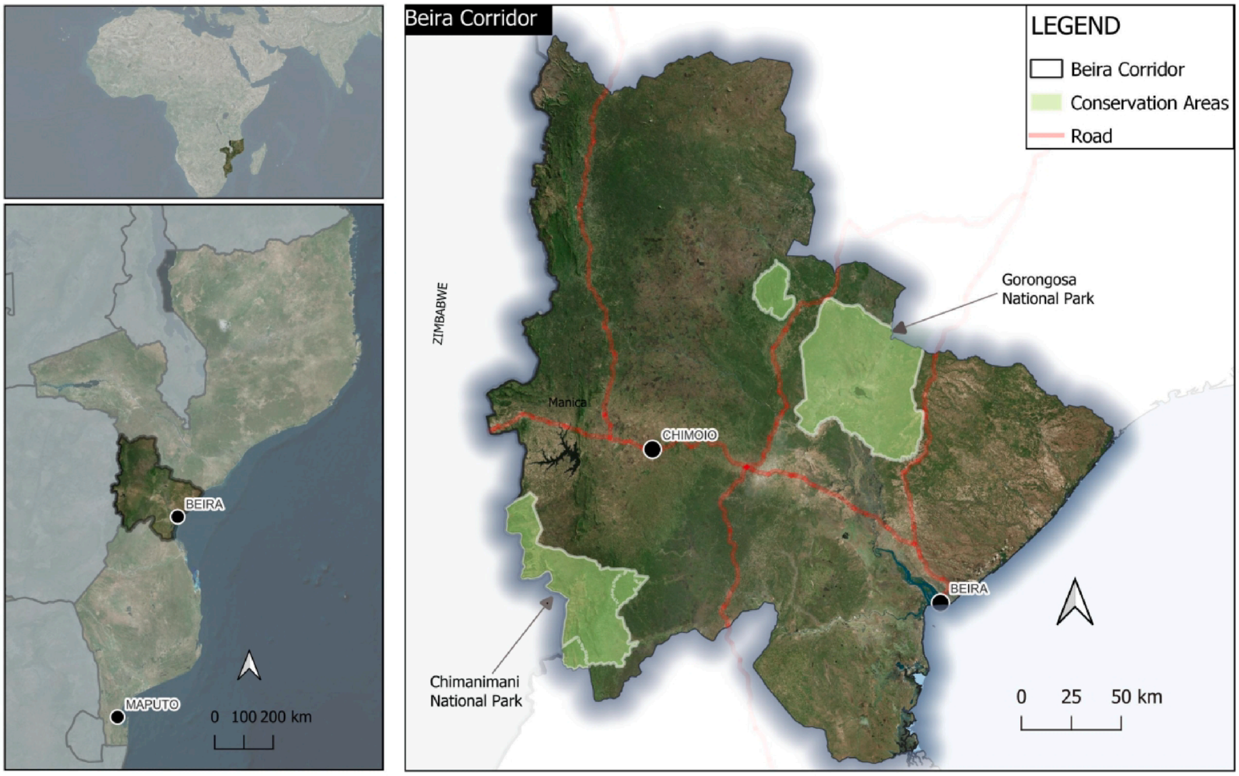

Fig. 1. Study site, Beira corridor in central Mozambique.

(NASA, 2013). Elevation data is a topographic feature that can influence LULC patterns, particularly in mountainous regions. The vegetation indexes and elevation data are valuable in classifying LULC and identifying small-scale agriculture (Bay et al., 2020). We used the Google Earth Engine platform (Gorelick et al., 2017) to perform all these data processing steps, including creating composite images, calculating vegetation indexes, and deriving elevation data.

Data of forest height gain and loss derived from the GLAD product.

We also utilised the publicly available forest height loss and gain dataset for 2000 and 2020 from the Global Land Analysis and Discovery (GLAD) program. This dataset, developed by Potapov et al. (2020), provides information on the changes in forest height over time. The dataset identifies areas where forest height has been lost or gained by comparing the canopy height measurements for different periods.

Reference data collection

We conducted field missions to collect reference data on-site. The field missions were carried out in July 2022, during the middle of the dry season, and in October 2022, at the end of the dry season. The main objective of the field visits was to observe and record the hotspots of deforestation, forest degradation, and commercial agriculture identified on the forest change map. We recorded 567 GPS points, representing the different LULC categories, such as croplands, forests, mangroves, etc.; and FCD, such as charcoal areas, logging, and abandoned land (Fig. 4).

The reference samples were expanded by collecting additional points using Collect Earth software. Collect Earth (CE) is a tool for collecting ground reference data using high-resolution satellite imagery (Bey et al., 2016). The sample size of the reference data for the LULC map was $n =$ 1215 (ranging from 16 to 560) and 1104 (24 – 347) for 2000 and 2020, respectively, while for FCD, the sample size was $n = 484$ (12 – 188) (Fig. 4).

2.5. Step 3: Classifying the LULC

To create LULC training data, a single interpreter used high-resolution images from Google Earth Pro and Bing Maps in QGIS. A total of 4,050 training polygons for the year 2000 and 3680 for the year 2020 were collected (Fig. 4). The Random Forest (RF) algorithm was used with 70 % of the training data to classify LULC with 100 trees and determine the number of variables using the tune function from the R randomForest package. All image features, including spectral bands, vegetation indices, and topographic features, were used in the RF classification. We computed overall accuracy and F1-score to assess the model robustness on the 30 % validation dataset. We performed a post-classification process to improve accuracy and remove isolated pixels, involving a majority filter with a 4 x 4 pixel sliding window. The settlement class was manually adjusted using data from Facebook High-Resolution Population Density Maps (CIESIN, 2016) in Google Earth in QGIS. Following the good practices recommendations proposed by Olofsson et al (2014), we used reference data collected in the field and computed indices such as users, producers, overall accuracy, and F1-score.

2.6. Step 4: Mapping the key forest change processes

In this step (step 4, Fig. 2), we aimed to map forest change processes accurately. We developed a simple decision tree classification to identify three main forest change processes: deforestation, forest degradation, regrowth, and plantation. We used the LULC maps produced for 2000 and 2020 to determine these processes. We also analysed forest height loss and gain dataset derived from the GLAD product for the same years. By combining the land cover and forest height datasets, we could identify forest degradation, which was impossible from the land cover maps alone. For example, a forest in 2000 that remains in 2020 but has a lower forest height as forest degradation. We applied ten threshold rules to classify forest change processes (Fig. 5). The resulting map, depicting the different forest change processes, was then used to define the sampling design for collecting FCD. This information also helped to inform the analysis and interpretation of the forest change drivers in the study area. This information also helped to inform the analysis and interpretation of the forest change drivers in the study area. We did not

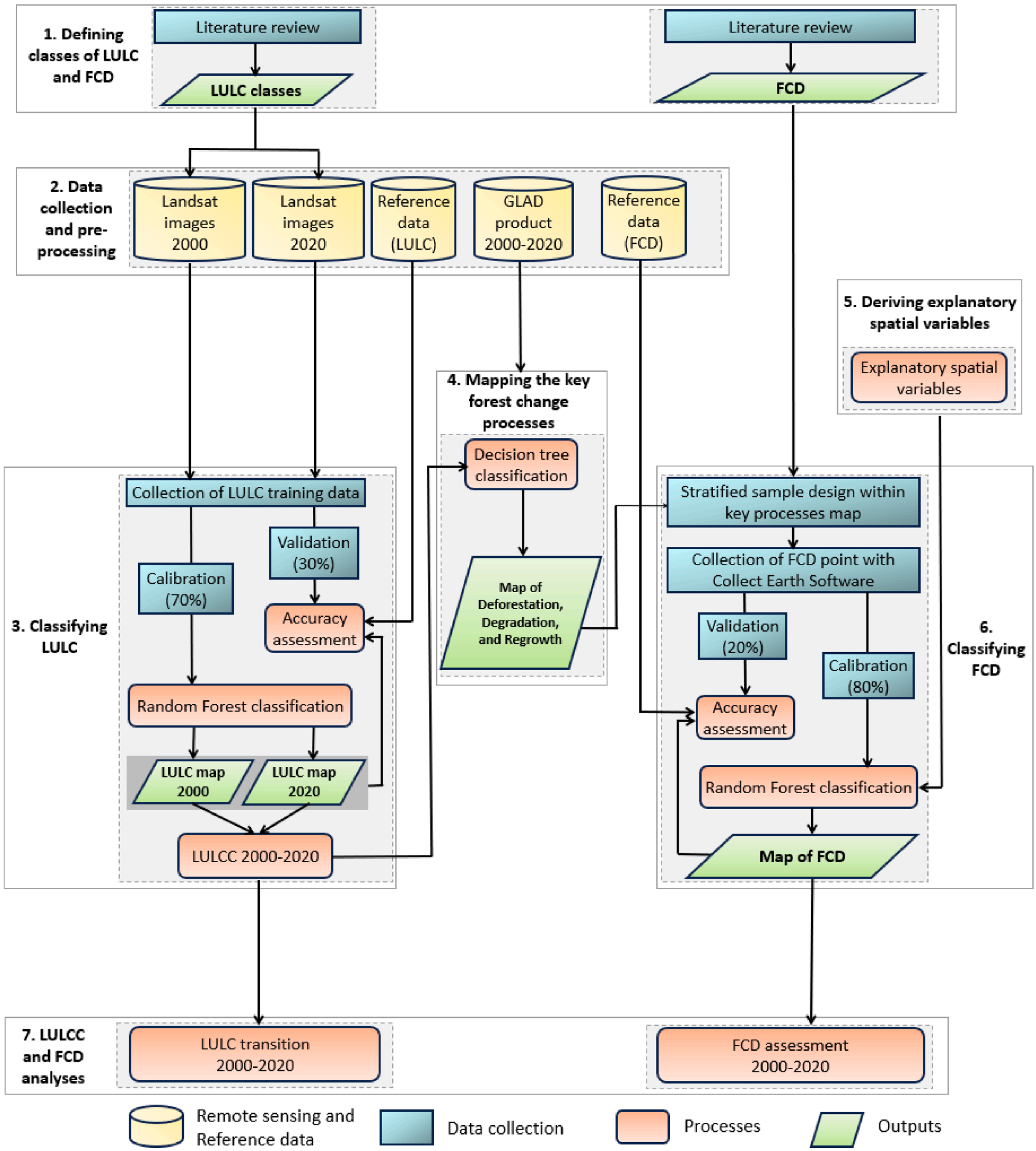

Fig. 2. Methodological framework for LULC change and disentangling of FCD in the Beira corridor, in central Mozambique.

encounter discrepancies such as cases where a transition from forest to cropland occurred without a corresponding decrease in forest height.

2.7. Step 5: Deriving explanatory spatial variables

We considered fifteen underlying drivers (hereafter called explanatory spatial variables) to assess the FCD in BC (Table 2). We selected these variables based on previous research in southern Africa, identifying them as significant explanatory spatial variables for FCD (Ryan et al., 2014; Sedano et al., 2016; Grinand et al., 2020). We categorised the explanatory spatial variables into four groups. The first group includes variables related to the time required to access land and transport goods to market. These variables were proximity to towns or villages and proximity to main or secondary roads. We calculated them using QGIS software. The second group represents potential agricultural productivity factors. These variables include soil fertility, measured by the carbon–nitrogen ratio, proximity to a waterbody, and terrain relative height. We used the SAGA tool to compute the terrain relative height. These factors can influence the suitability and productivity of agricultural activities in the study area.

The third group is demography, specifically the population density. We excluded urban areas i.e. pixels with more than 100 inhabitants per

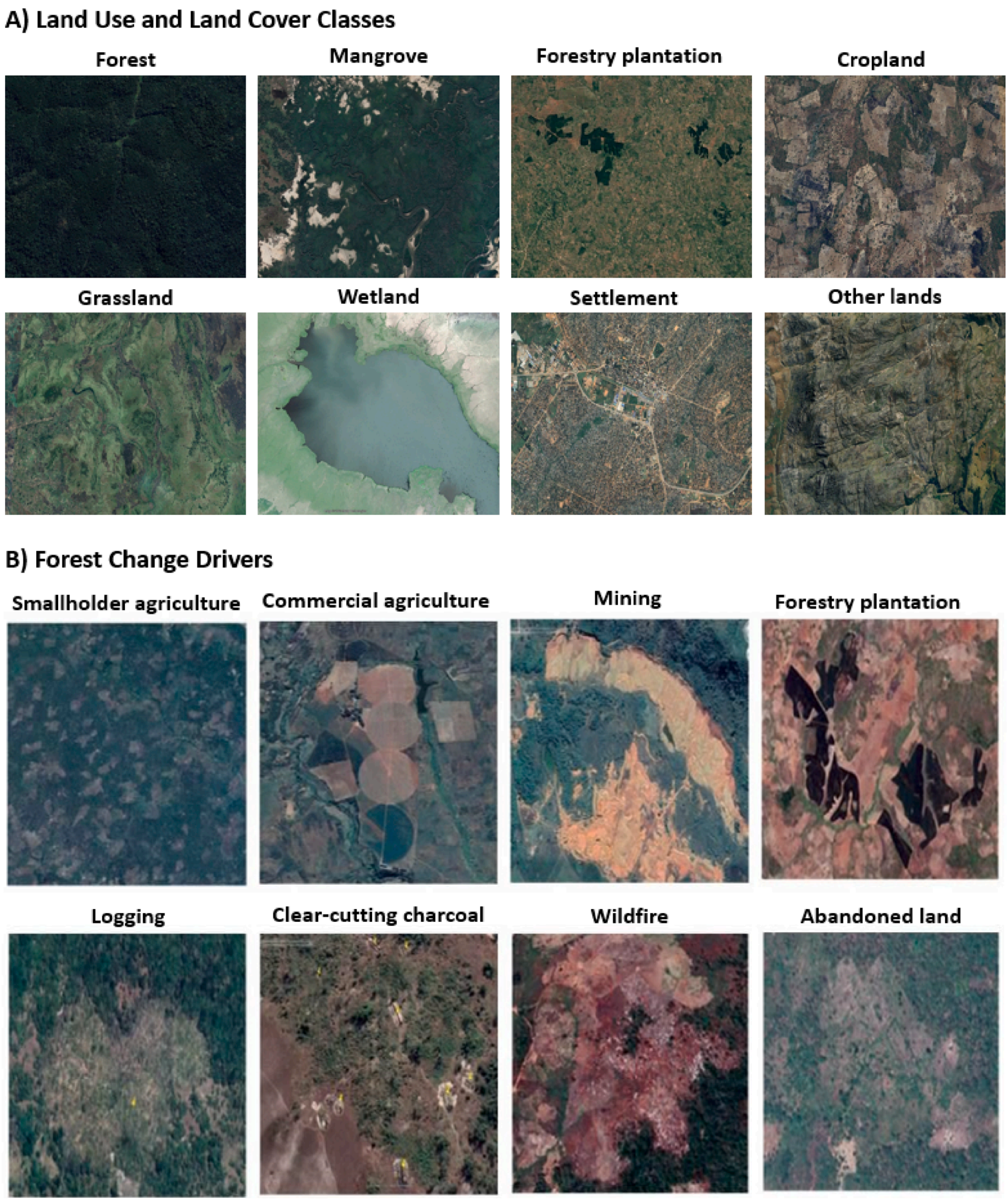

Fig. 3. Illustration of LULC classes (A) and FCD (B) on the Google Earth images in the Beira corridor in central Mozambique.

km^2 because our aim is to provide a more detailed and focused analysis of the interactions between rural land use practises and FCD.

The fourth group is the landscape metrics. The intensity of change was calculated by dividing forest height 2020 by forest height 2000 from GLAD data. We chose five landscape metrics based on their relevance to the specific research question and objectives of our study. We selected heterogeneity and fragmentation landscape metrics since we assumed that the level of heterogeneity and fragmentation of a landscape is directly related to the type of forest change drivers. We computed common landscape metrics, since it has demonstrated its importance, notably in the study of drivers of forest degradation in the Brazilian Amazon (Bourguoin et al., 2020). The study computed landscape metrics on the 2020 LULC map using a sliding window of 65 m. We selected this scale based on a 1,000-point sample and the method that Bourgoin et al. (2020) applied, which determined the scale at which the average curve of the landscape heterogeneity plateaued. We used Chloé software v.4.1beta6, designed explicitly for landscape analysis, to derive the landscape metrics and distance to the waterbody (Boussard and Baudry,

Table 1
Forest change drivers that led to deforestation, forest degradation, and regrowth in Beira Corridor, central Mozambique.

Process name	Driver name	Description	References studies in Mozambique
Deforestation	Commercial agriculture	Forest clearing for cropland, and pasture. Usually is a long-term, permanent conversion of forest and shrubland to non-forest land use such as agriculture.	Ryan et al. (2014); CEAGRE & Winrock International (2016)
	Smallholder agriculture	Refers to small-scale agriculture.	
	Clear-cutting charcoal	This includes charcoal production produced for both domestic and local market supply.	Ryan et al. (2014); Sedano et al., (2016; CEAGRE & Winrock International (2016)
	Mining	All types of surface mining, including artisanal and small-scale mining.	CEAGRE & Winrock International (2016)
Degradation	Logging	Logging is for commercial use and includes both legal and illegal logging.	
	Wildfire	All wildfires are defined as large-scale forest loss resulting from burning forest vegetation with no charcoal or agricultural activity afterwards.	Ribeiro et al. (2019); Ryan & Williams (2011)
	Selective-cutting charcoal	Charcoal is produced using specific tree species which are selectively picked up.	CEAGRE & Winrock International (2016)
Regrowth	Abandoned land	This applies to all croplands unused or neglected, not to fallow, for extended period, and the householders never returned, followed by subsequent forest regrowth.	This study
	Forestry plantation	Forestry plantation is defined for commercial purposes only as large-scale forestry operations. It includes both eucalyptus and pine plantations.	Bey & Meyfroidt (2021)
	Forest regrowth	Woodlands affected by fire, for instance, can immediately grow if the fire frequency is lower.	This study

2017).

2.8. Step 6: Classifying the FCD

We used the forest change processes map to locate 2959 training data points based on the stratified sampling design proportional to the area of key processes as described by Olofsson et al. (2014). Using Collect Earth (CE) software, we visually assessed the LULC status and history of each point using high-resolution data from sources like Google Earth. We split the training data for model calibration (80 %) and validation (20 %). We used the RF algorithm to classify the FCD. We also conducted a partial plot analysis and utilized variable importance analyses from RF to assess the impact of each explanatory variable on the FCD. To calibrate the RF model, we used 400 trees determined based on the out-of-bag (OOB) error for each driver. We used 20 % of the training data for internal validation and the reference data, which were not included in the model calibration, for external validation (Olofsson et al., 2014). This comprehensive approach helps to demonstrate the robustness and reliability of the model by showing how well it performs with both known and unknown datasets.

2.9. Step 7: LULC and FCD analyses

We used a transition matrix to assess LULC change between 2000 and 2020, following the approach described by Pontius et al. (2004). This allowed for a detailed analysis of land use components and spatial configuration. From the matrix, we calculated metrics including gross gain, gross loss, net change, total change, swap change, and persistence, as outlined by Pontius et al. (2004) and Braimoh (2006). We also analysed the vulnerability of land class transition using the gain-to-persistence ratio (*gp*) and loss-to-persistence ratio (*lp)*, following Braimah (2006). We also computed the deforestation rate using the formula proposed by Puyravaud (2003). Sankey diagrams were used to visualise and analyse the proportion and distribution of LULC change between 2000 and 2020 (Bellón et al., 2020).

3. Results

3.1. Land use and land cover change

The BC experienced significant landscape change from 2000 to 2020, with a total area of 53,748 km^2 (86.4 %) (Fig. 6). The annual deforestation rate was estimated at 1.72 % (365.3 km^2/year), accounting for 29.1 % of the net change (Table 3). Cropland saw a substantial increase in area, accounting for 72.9 % of the net change. Grassland had a slight net change increase of 5.3 %. Plantations and settlements experienced the largest net change, with increases of 163.8 % and 264.1 %, respectively. Cropland, plantations, and settlements had more gain than persistence ($gp > 1$), while forest, cropland, plantations, and other land classes tended to lose more than persist ($lp > 1$). Swap change accounted for 18,802.7 km^2 of the total change, with grassland having the largest area of swap change at 45 % (Table 3). Forest mainly was converted to grassland and cropland, with similar proportions of about 10 % each. The loss of cropland was primarily due to a 10 % increase in grassland and a 2 % increase in forest (Fig. 7). These changes were concentrated in the northern and southwest parts of the study area, along the main road, and in the western part for forest plantations.

3.2. Extent and importance of each driver in the forest change processes

Our study identified three key processes for FCD in BC: deforestation, forest degradation, regrowth (Figs. 8 and 9). Deforestation accounted for the largest proportion of forest change, covering 7,710.6 km^2 (82.8 %). This was followed by regrowth (859.4 km^2 or 9.2 % including plantation with 262.9 km^2 or 2.8 %), and degradation (479.8 km^2 or 5.2 %). The annual rates of forest change ranged from 13.1 km^2/year for plantation to 385.5 km^2/year for deforestation. Smallholder agriculture accounted for 6,719.7 km^2 of the forest change, followed by clear-cutting for charcoal production (850.9 km^2), while mining had a negligible impact. Logging was the primary driver of forest degradation (282.2 km^2), followed by selective charcoal production (102.5 km^2) and wildfires (95.1 km^2). Abandoned land contributed the most to forest regrowth (529.6 km^2), while natural regrowth accounted for 329.8 km^2. Plantation covered 262.9 km^2 of the total forest change.

3.3. Relationship between FCD and explanatory variables

Out of the 15 explanatory variables analysed (Appendix A), the following variables played a key role in determining FCD: intensity of change, elevation, population density, proximity to main road,

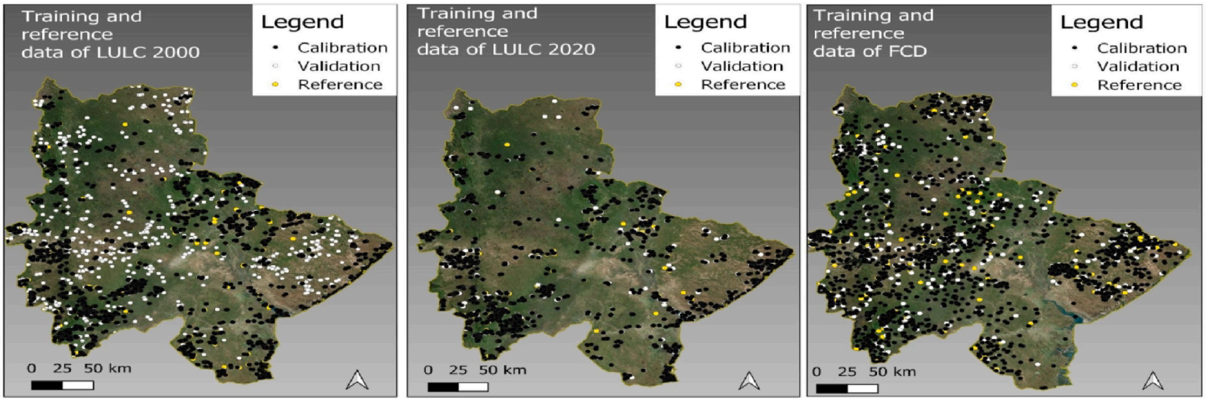

Fig. 4. The centroid of polygons of calibration and validation data and points of the reference data used for the LULC and FCD maps.

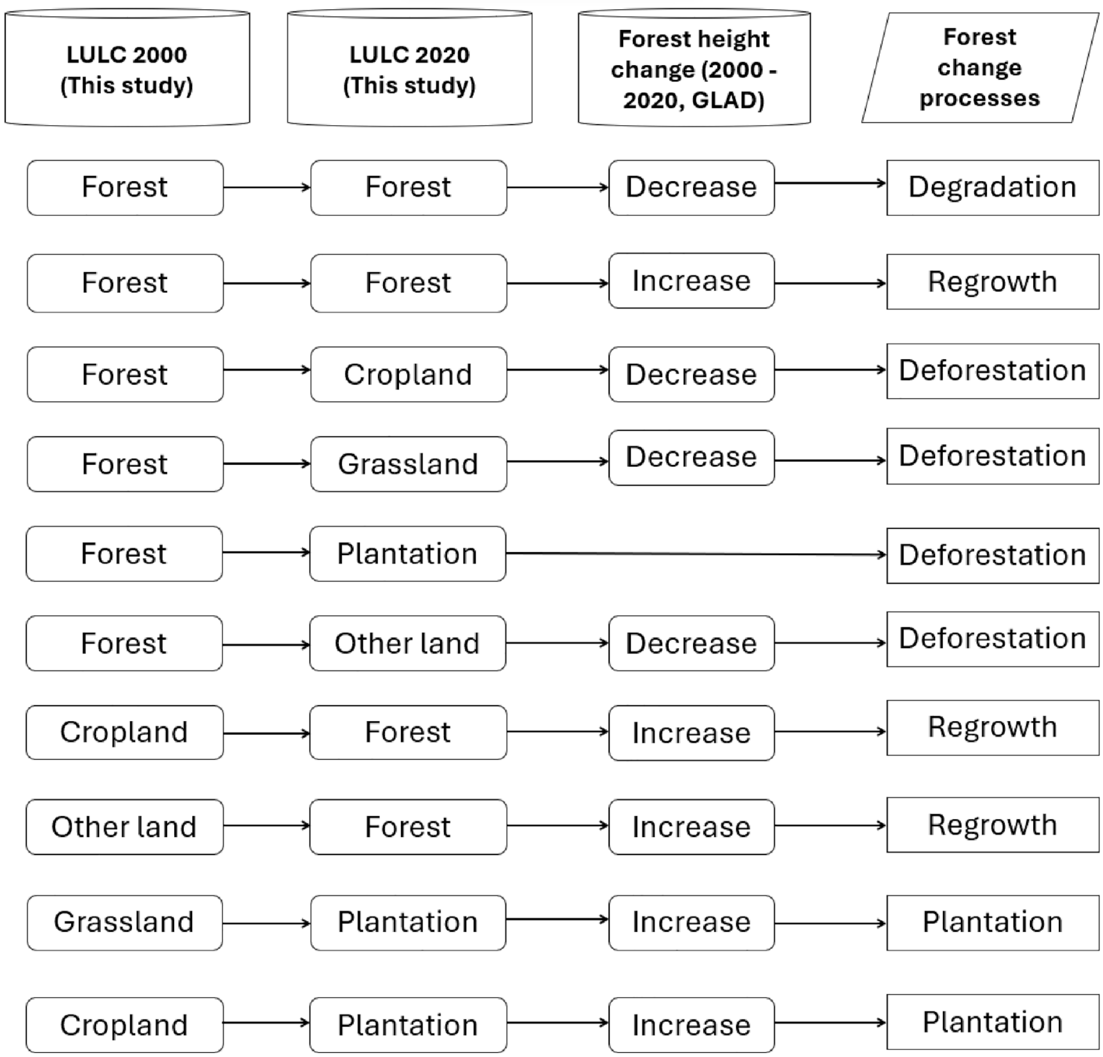

Fig. 5. Decision tree of the four forest change processes identification (deforestation, degradation, regrowth, and plantation).

proximity to the secondary road, and proximity to water bodies (Fig. 10). The partial plots (Fig. 11) showed that the intensity of change had a substantial linear decrease, influencing almost all drivers of forest change. Elevation had the strongest influence on the FCDs, indicating a linear probability increase up to a certain point and a slight decline. Distance to the main road steadily increased and decreased sharply, influencing specific drivers. Population density showed a slight decrease and then remained constant, playing a role in determining the probability of occurring certain drivers. Proximity to water increased sharply and then stayed constant, strongly influencing mining. Appendix B provides information on the relationships between the other explanatory variables with lower significance, such as landscape metrics.

Table 2
Forest change potential spatial explanatory variables calculated.

Group of variables	Name	Short name	Input data source & Resolution	Unit	Range (min–max)	Method of calculation and reference
Market and land accessibility factors	Proximity to the main road	mainRoad	National dataset	Meter	0.0 – 65,077	Euclidean distance
	Proximity to the secondary road	secRoad	National dataset	Meter	0.0 – 58,828	Euclidean distance
	Proximity to town	proxTown	National dataset	Meter	10 – 66,722	Euclidean distance
	Proximity to village	proxVillage	National dataset	Meter	0.0 – 37,228	Euclidean distance
Agricultural productivity factors	Soil fertility (C:N ratio)	fertility	Innovative Solutions for Decision Agriculture Ltd. (iSDA), 30 *m*	Unit less	3.6 – 19.8	NA
	Terrain relative height	relatHeight	SRTM, 30 *m*	Meter	0.0 – 1.0	Boehner and Selige (2006)
	Proximity to the watercourse	proxWater	Global Waterland	Meter	0.0 – 36,875	Euclidean distance
	Elevation	elevation	SRTM, 30 *m*	Meter	0.0 – 2,385	Extract altitude from SRTM
Demography factor	Population density	PopDens	WorldPop, 1 km	People/ km^2	0.0 – 99	NA.
Landscape metrics.	Intensity of change	intchangeDiv	GLAD, 2000–2020, 30 *m*	Percentage	0.0 – 8.7	The ratio of the forest height area in 2020 to the forest height area in 2000
	Distance to the forest edge	foresEdge	LULC 2020 map (this study)	Meter	0.0 – 15,866	Euclidean distance
	Mean of patch area	areaChange	LULC 2020 map (this study)	Hectare	3.9 – 288.8	McGarigal et al. (2012).
	Largest Patch Index	LPI	LULC 2020 map (this study)	Hectare	14.6 – 288.8	McGarigal et al. (2012).
	Shannon diversity index	SHDI	LULC 2020 map (this study)	Unit less	0.0 – 1.7	McGarigal et al. (2012).
	Heterogeneity structure index	HET-Frag	LULC 2020 map (this study)	Unit less	0.0 – 0.7	McGarigal et al. (2012).

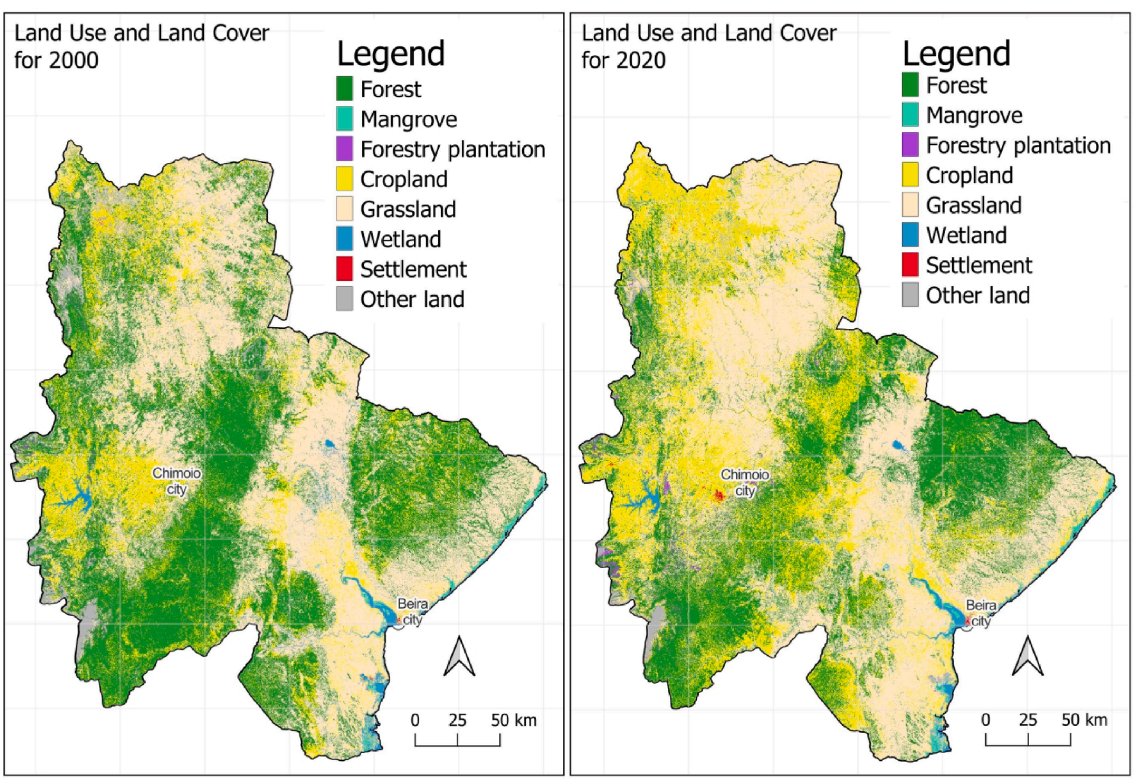

Fig. 6. Land use and land cover map for 2000 and 2020 of Beira corridor, central Mozambique.

3.4. Validation of LULC and FCD maps

Both maps exhibited high overall accuracy rates, with an accuracy of 87.8 % for 2000 and 89.9 % for 2020. Additionally, they displayed strong F1 values, with an overall F1-score of 80.3 % for 2000 with individual class F1-score ranging from 48.3 to 98.9 %. In 2020, the overall F1-score was 88.3 %, with F1-scores for each class ranging from 70 % to 99.2 %. Wetlands had the highest values in the 2000 map, while settlements had the lowest. A similar trend was observed in the 2020 map. Overall, the 2020 map performed better with validation data than the 2000 map, with the forest class performing better than grassland and cropland. With reference data, the OA was 94 % in 2000 and 92.3 % in 2020. UA showed no commission errors for certain categories in 2000, while in 2020, plantations, wetlands, and settlements had the highest

Table 3
Land use and land cover changes between 2000 and 2020 in BC using the confusion transition matrix calculated by pixel counting.

LULC classes	*LULC 2000 Km^2*	*LULC 2020 Km^2*	*Gross gain (Gg) in km^2*	*Gross loss (Gl) in km^2*	*Net Change in km^2 (% of change)*	*Total change km^2 (% of total area)*	*Swap change in km^2 (% of total swap change)*	*No change (NC) in km^2*	*gp*	*lp*
Forest	25,130.4	17,826.8	5,073.7	12,380.4	−7,306.6 (−29.1)	17,454.1 (28.1)	10,147.5 (27)	12,750.1	0.4	1.0
Grassland	25,646.4	26,994.7	9,709.8	8,361.5	1,348.3 (5.3)	18,071.3 (29.1)	16,723.1 (45)	17,284.9	0.6	0.5
Cropland	8,843.9	15,290	11,214.4	4,768.3	6,446.1 (72.9)	15,982.7 (25.7)	9,536.5 (25)	4,075.6	2.8	1.2
Other land	1,493.1	865.5	389.7	1,017.3	−627.6 (−42)	1,407 (2.3)	779.5 (2)	475.8	0.8	2.1
Wetland	677.7	540.2	98.4	235.9	−137,5 (−20.3)	334.3 (0.5)	196,9 (0.5)	441,7	0.2	0.5
Mangrove	312.1	377.6	128.8	63.3	65,6 (21)	192.1 (0.3)	126.5 (0.3)	248.8	0.5	0.3
Plantation	52.5	138.5	124.4	38.4	86 (163.8)	162.8 (0.3)	76.9 (0.2)	14	8.6	2.6
Settlement	47.6	173.3	134.9	9.2	125.7 (264.1)	144.1 (0.2)	18.4 (0)	38.4	3.5	0.2
Total	62,203.5	62,203.5	26,874	26,874	8,071.7	26,874	18,802.7	35,329.3		

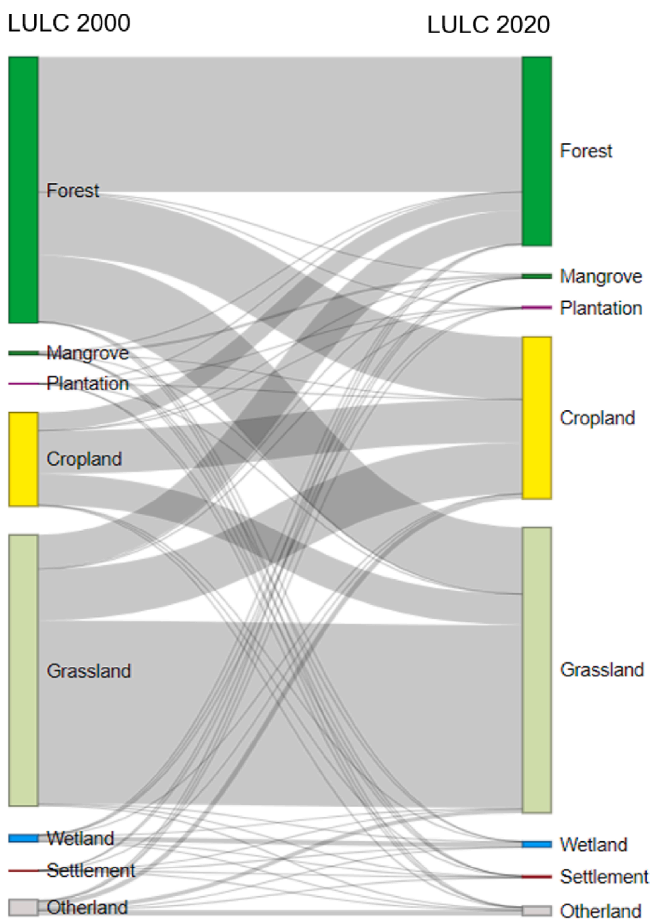

Fig. 7. Sankey diagram showing the total area covered by each LULC class in 2000 and 2020.

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The FCD map had an OA of 79.3 % and an F1 score of 73.5 % (ranged from 14 to 96.6 %) from validation data. Specific categories showed high OA and PAs, indicating good performance, while others had notable commission and omission errors. The FCD map achieved an OA of 76.2 % with reference data with F1-score ranging from 7.1 to 96.9 %, showing user and producer accuracy variations across categories. Omission errors affected the overall accuracy, particularly for selective charcoal and wildfire.

4. Discussion

4.1. Land use change and forest change drivers

Our study provides crucial insights into LULC change and the processes and drivers of forest change in the Miombo landscape. Approximately 30 % of the forest in BC has been converted to cropland and grassland between 2000 and 2020, suggesting the potential disappearance of the original forest within 50 years if the actual trend continues. Urgent implementation of conservation and land management strategies is necessary to protect the remaining forest cover in the corridor. The Sankey diagram showed that the proportion of forest conversion to cropland is nearly equal to grasslands. Logging and charcoal production have contributed significantly to forest loss in low-population-density regions, while smallholder agriculture drives forest conversion in high-population-density areas (Fig. 12). The expansion of grasslands is observed in sparsely populated regions engaged in charcoal production and logging. Notable grassland losses to cropland and settlements occur within the cropland hotspot, resulting in a decline in grassland in one area and an increase in another. The swap change analysis further supports the complexity of land cover change, with grassland being the primary affected class. The swap change observed for forest and cropland suggests that forest regrowth and land abandonment processes contribute to forest cover accumulation and cropland reduction. The dynamics of land cover change in the region involve the expansion of croplands and the swap of grasslands.

Our study highlights the significant impact of unplanned drivers, such as smallholder agriculture, charcoal production, and logging, on forest change compared to planned drivers like plantations and commercial agriculture (Ryan et al., 2014). It is important to note that unplanned drivers are not inherently harmful, as their importance in forest change is influenced by various factors such as low-input agriculture (Chirwa and Adeyemi, 2020), low energy efficiency (International Energy Agency, 2014), population density, and the absence of sustainable forest management practices. This aligns with previous research conducted in the western part of our study area (Ryan et al., 2014). Smallholder agriculture and clear-cutting charcoal emerge as the primary drivers of extensive forest conversion in BC, challenging the perception that small-scale agriculture alone is the main driver of deforestation. The complex relationship between subsistence farming practices and the demand for charcoal as an income and energy source is evident (Zorrila-Miras et al., 2018). Our research reveals the significant contributions of emerging factors like charcoal production, logging, and

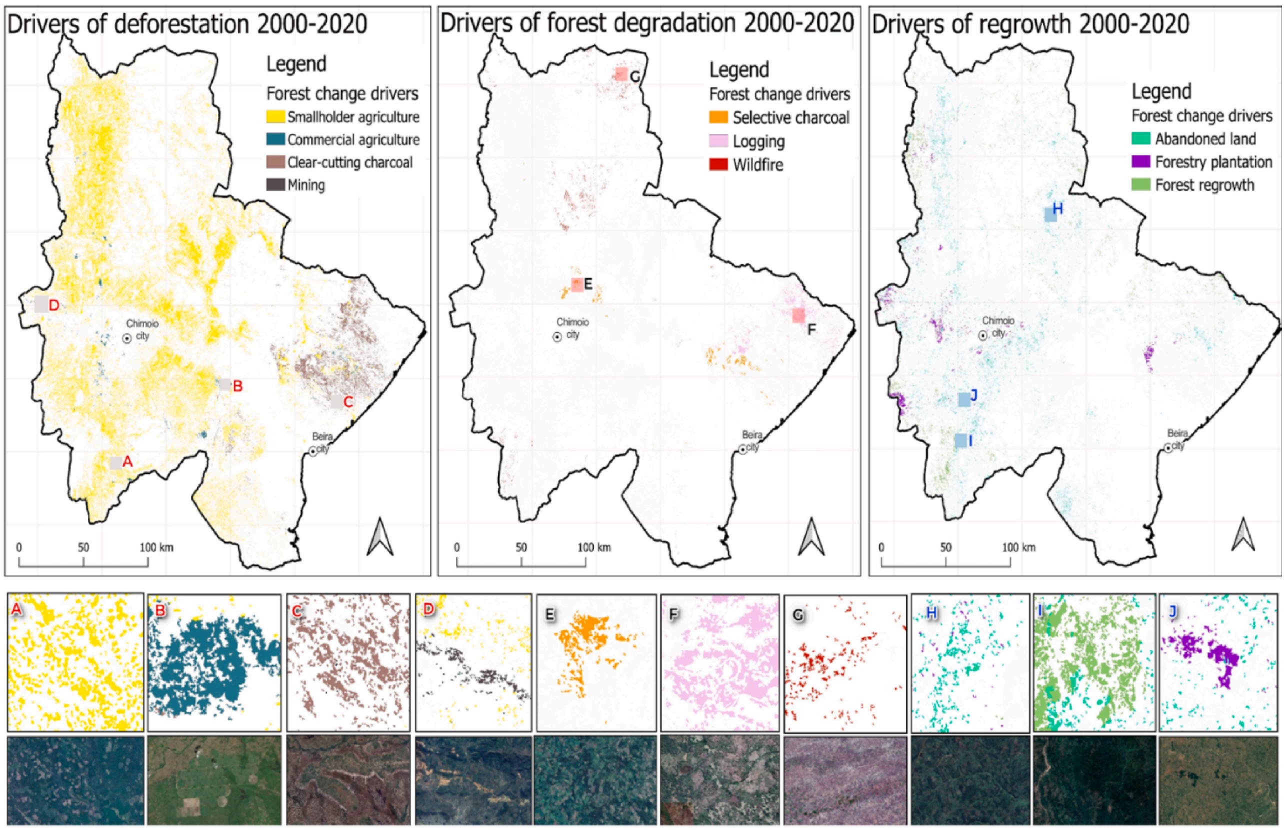

Fig. 8. Mapping and quantification of FCD of deforestation, degradation, and forest regrowth in Beira corridor, central Mozambique.

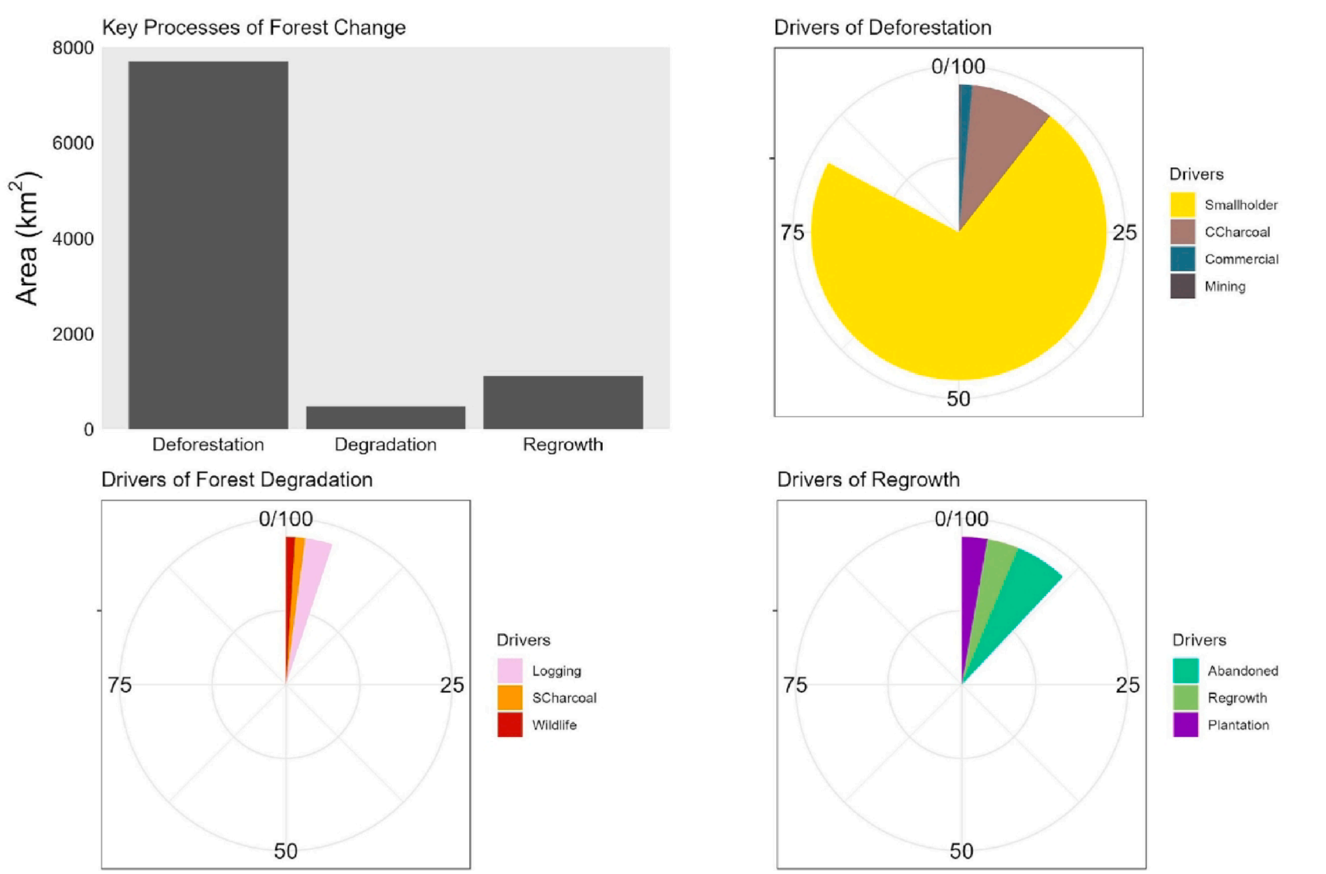

Fig. 9. Area and share of each FCD identified in Beira corridor, central Mozambique. The percentages of the three pie plots represent percentages of the total change.

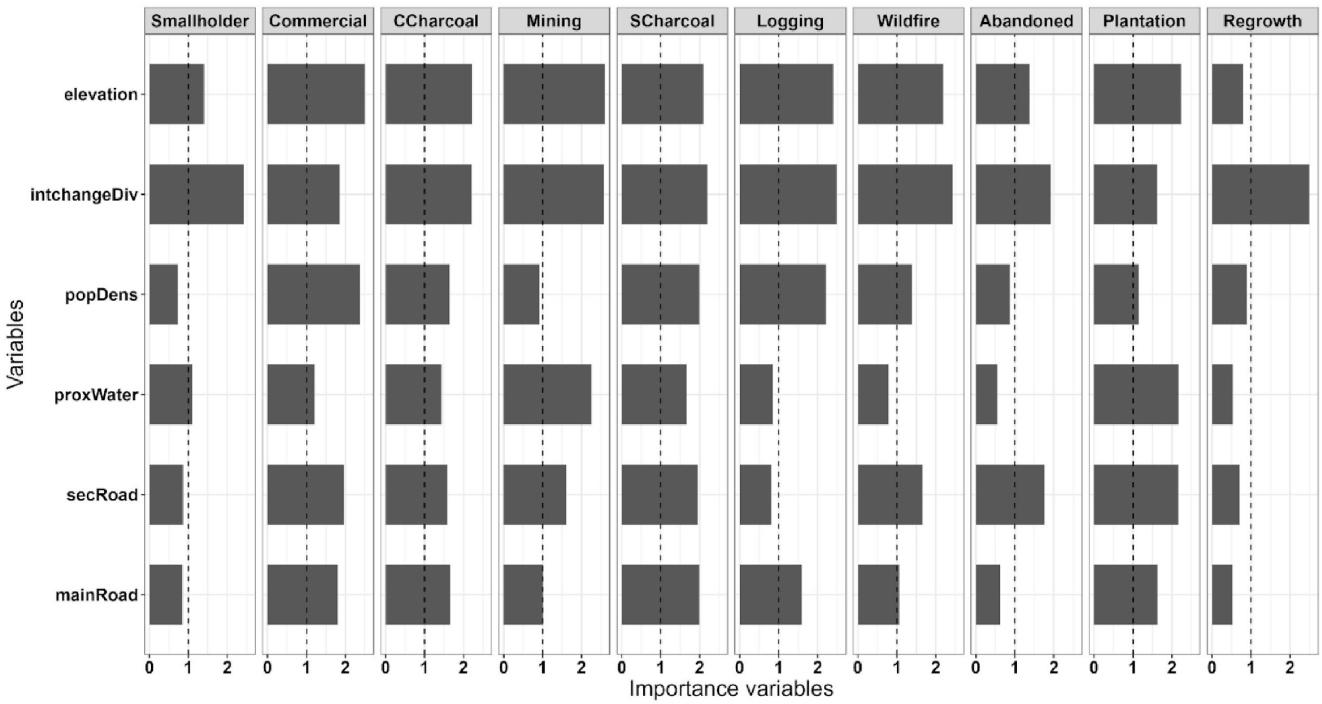

Fig. 10. Important explanatory variable of each FCD in Beira Corridor, central Mozambique.

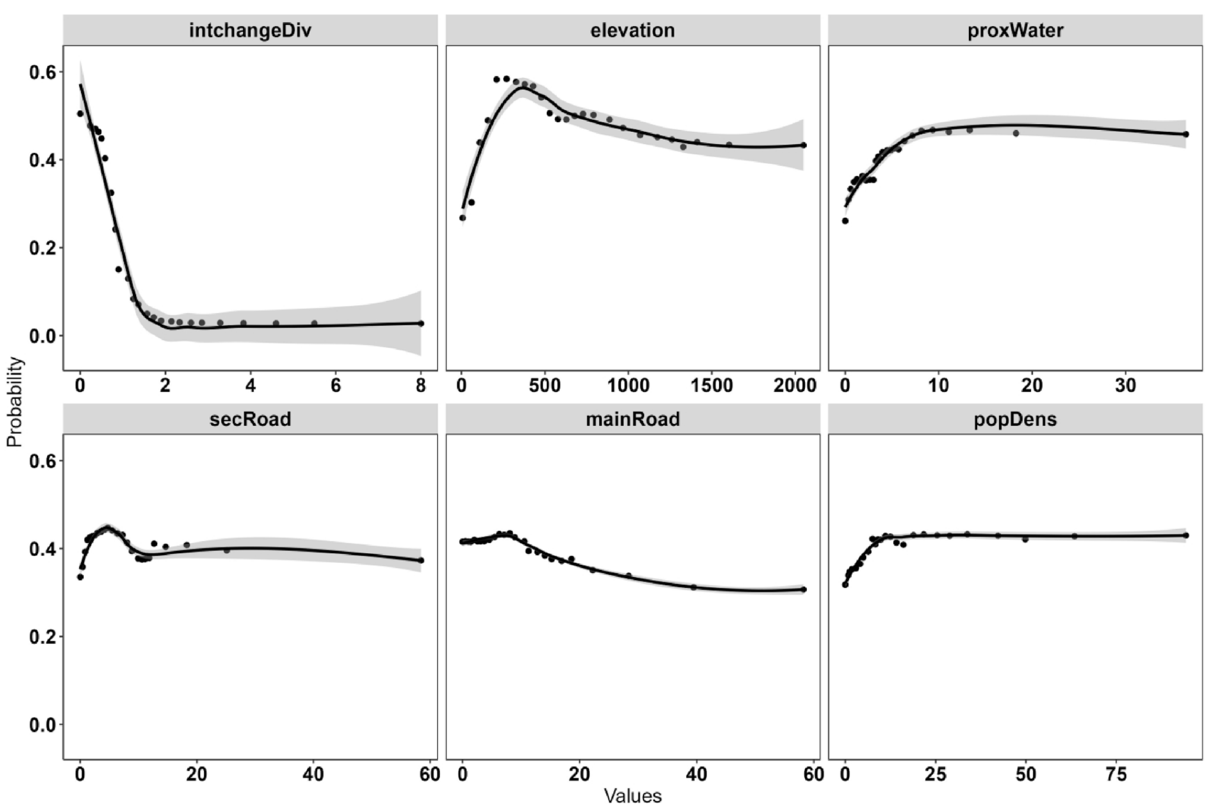

Fig. 11. Probability distribution of drivers of forest change in the Beira corridor for all drivers (full model).

plantations to forest change alongside small-scale agriculture. This highlights the need for comprehensive approaches that address multiple FCDs to prevent further degradation. Interestingly, our study uncovers a positive aspect of landscape dynamics in the BC. Abandoned land contributes to forest regrowth, indicating the potential for natural restoration of Miombo woodland. This finding aligns with previous research (McNicol et al., 2018). However, further ecological assessments are necessary to evaluate biomass recovery and floristic composition in these abandoned areas.

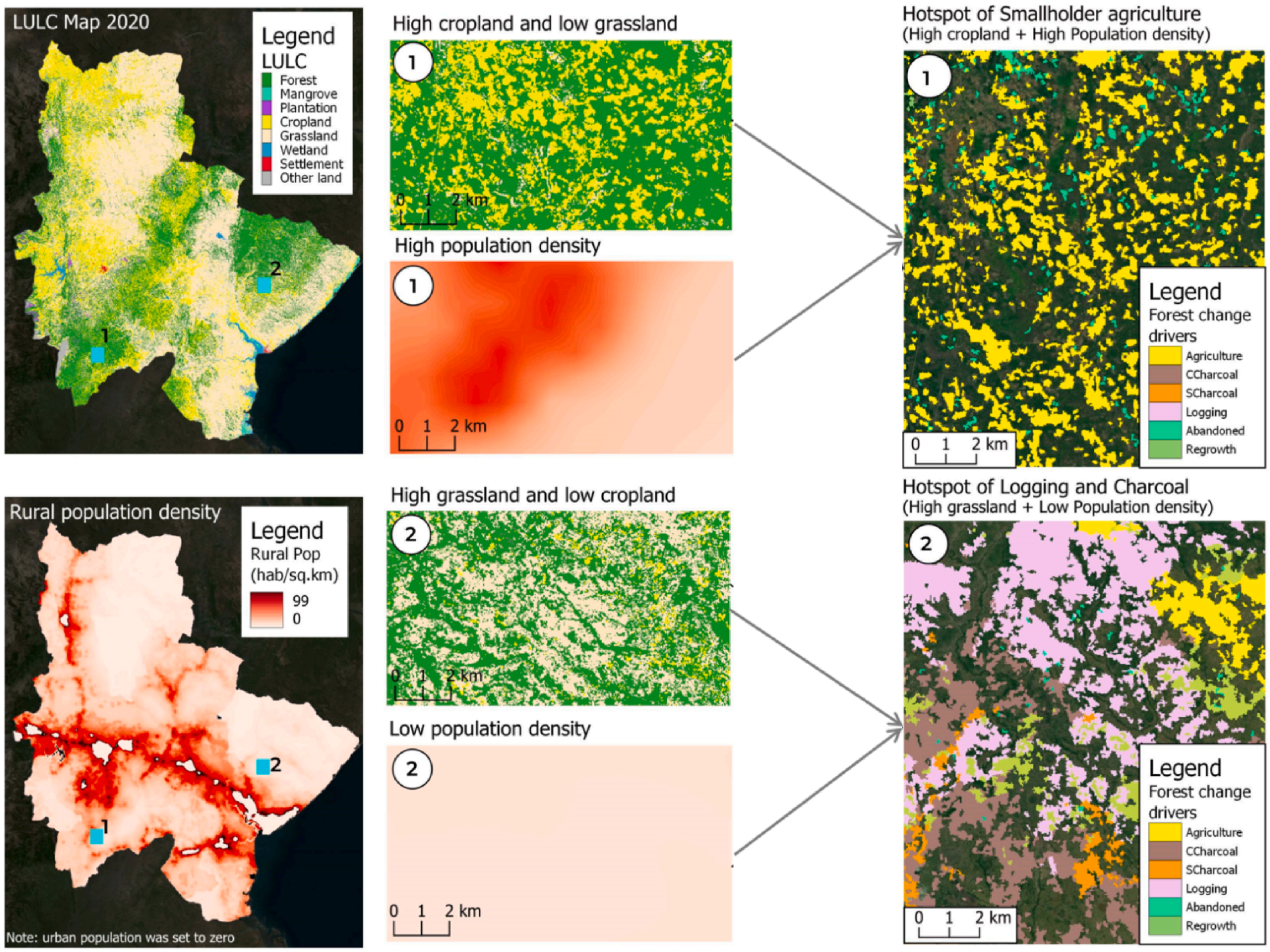

Fig. 12. Distinct landscapes influenced by specific FCD. Site 1 is a hotspot where forests have been converted into croplands and smallholder agriculture due to the high population density and dominance of cropland. Site 2 is a hotspot where forests have been converted into grasslands following logging and charcoal production, characterised by a low population density.

4.2. Influence of explanatory variables on the drivers of forest change

The intensity of change was the most important explanatory variable influencing forest change, capturing the combined effects of multiple drivers in the landscape. It identified regions with high driver activity and distinguished areas of persistent forest change from sporadic to temporary (Ryan et al., 2014). Population density and proximity to roads were not significantly correlated with smallholder agriculture but were associated with commercial agriculture, selective charcoal production, and logging. These results align with previous studies suggesting that local populations and markets are not underlying drivers of deforestation in tropical regions (Defries et al., 2010). However, it is important to acknowledge that the exclusion of urban population density in our study may limit the generalisability of the findings to the entire study area, as the dynamics of urban areas could also play a role in shaping land use patterns and FCD in the region. Topography was the most influential underlying factor for clear-cutting charcoal, particularly in low-lying areas. Secondary roads played a role in land abandonment, while road access did not explain clear-cutting charcoal, which contradicts previous studies (Ahrends et al., 2010; Sedano et al., 2016). Charcoal production in the study area was mainly carried out by local professionals who transported the charcoal by bicycle to the villages and then to the main markets in Beira and Chimoio cities. Proximity to water influenced artisanal and seasonal mining. Landscape metrics indicated that a highly heterogeneous landscape configuration was associated with more abandoned lands, offering alternative livelihood options. Surprisingly, forest conversion to cropland was not explained by soil fertility, possibly due to: (i) limitations of the low spatial resolution data used, and (ii) access to highly fertile soils can be restricted by land tenure, leading some sectors to cultivate their lands regardless of the suitability for specific crops, although this is unlikely to be the primary factor. Broadly, these findings provide insights into the main drivers of forest conversion in Miombo woodlands and highlight the complex interactions between variables.

4.3. Reproducibility and caveats of the framework

Our study was designed with reproducibility, utilising open-source tools and products throughout the analysis process. Using the R script to run the RF algorithm ensures that others can easily replicate and adjust the model. Furthermore, using QGIS for sample collection, mapping, and area extraction, combined with Collect Earth for point sample classification through high-resolution image interpretation, promotes transparency and repeatability in the classification process. We also relied on the Google Earth Engine platform for Landsat image pre-processing to enhance reproducibility. Integrating these open-source tools ensures transparency, facilitates collaboration, and encourages the scientific community to build upon our work. While our framework offers significant potential for reproducibility, it is essential to acknowledge certain caveats and limitations. Firstly, dry season imagery was used in our study to produce LULC maps, improving forest mapping precision but potentially limiting data on seasonal changes and vegetation patterns. However, the methodology we used for defining training polygons minimized misclassification risks, especially distinguishing miombo woodland from deciduous vegetation. Secondly, the accuracy of the classification results heavily relies on the quality and resolution of the input data and the accuracy of the collected training sample. While efforts were made to ensure the reliability of our training sample, some level of inherent subjectivity and uncertainty may persist. Challenges in assessing forest degradation compared to mapping changes in forest area. For instance, the categorisation of charcoal production and logging as drivers of deforestation and forest degradation led to difficulties in capturing degradation drivers and resulted in lower accuracy compared to the drivers of deforestation and regrowth. This challenge can be associated to the Landsat data, which indicates that not every driver can be mapped in detail. For instance, the complex relationship between charcoal production and smallholder agriculture also made disaggregation difficult. Additionally, the performance of the framework might vary across different landscapes and regions, as the drivers of forest change and their impact on the landscape can differ significantly. Researchers applying our framework to other geographic locations should exercise caution and consider the specific context and characteristics of the study area. Our methods have been shown to work well for all FCDs except selective charcoal production and wildfire. We encourage fellow researchers to build upon our work, refine the framework, and explore alternative approaches to advance further our understanding of the drivers of forest change in complex landscapes such as Miombo in southern Africa.

4.4. Implications for policy and national monitoring activities

Mozambique's participation in REDD + efforts and its national monitoring activities can benefit from the findings of this study. The drivers of forest change identified, particularly smallholder agriculture and charcoal production, should be targeted in the REDD + strategy. Other unplanned drivers like logging and wildfires, as well as planned drivers such as plantations and commercial agriculture, should also be addressed. Forest regrowth is a crucial aspect to consider under REDD + as well. Reporting removals from abandoned land management can present an opportunity for Mozambique in its REDD + efforts. The implications of these findings emphasise the need for an integrated REDD + landscape approach in the BC (Sitoe et al., 2022). This approach can address the complex challenges of forest change while promoting sustainable land use practices. It should incorporate strategies such as sustainable forest management, community engagement, alternative livelihood options, and reforestation initiatives. Sustainable agricultural policies, land use planning, and food security strategies should address the emerging frontiers of forest change. These findings can guide decision-makers and land managers in developing effective strategies and interventions to reduce forest change in the Miombo ecoregion. Scaling up the approach presented in this study to nationwide monitoring and the National Forest Monitoring System (NFMS) in Mozambique is feasible, as the country already has a robust Monitoring, Reporting and Verification (MRV) system and technical capacities in place. Clear-cutting charcoal should be the focus at the national level, as it has a more significant impact on forest areas than selective charcoal. These implications highlight the importance of integrating multiple strategies and addressing various FCDs to achieve successful REDD + implementation and sustainable land use practices in Mozambique.

5. Conclusion

This study represents a pioneering attempt to investigate processes and FCD, focusing on the complex and fragmented Miombo landscape. We specifically study the Beira corridor in central Mozambique, known for its dynamic and complex characteristics. Our framework builds on recent scientific advances in mapping and quantifying the drivers of deforestation and forest degradation using publicly available data and tools. By employing multiple methods and data sources, we can effectively analyse land-use change and identify the underlying drivers of forest change in the Miombo landscape. Our results confirm that smallholder agriculture remains the main driver of deforestation, but we also observe new drivers, such as charcoal clear-cutting and forest plantations in the study area. In addition, we find that forest regrowth is significant and largely influenced by abandoned land, highlighting the impact of FCD on the resilience of Miombo woodlands. The main factors influencing forest change were the intensity of change, population density, altitude, distance from the main road and proximity to water bodies. Overall, our approach successfully maps the drivers of deforestation and highlights the associated challenges in mapping the drivers of forest degradation. This scalable, reproducible approach improves our understanding of LULC dynamics and the underlying drivers of forest change. It facilitates the establishment of robust reporting and verification systems to achieve country-level climate targets.

CRediT authorship contribution statement

Sá Nogueira Lisboa: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Clovis Grinand:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Funding acquisition, Conceptualization. **Julie Betbeder:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Frédérique Montfort:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Lilian Blanc:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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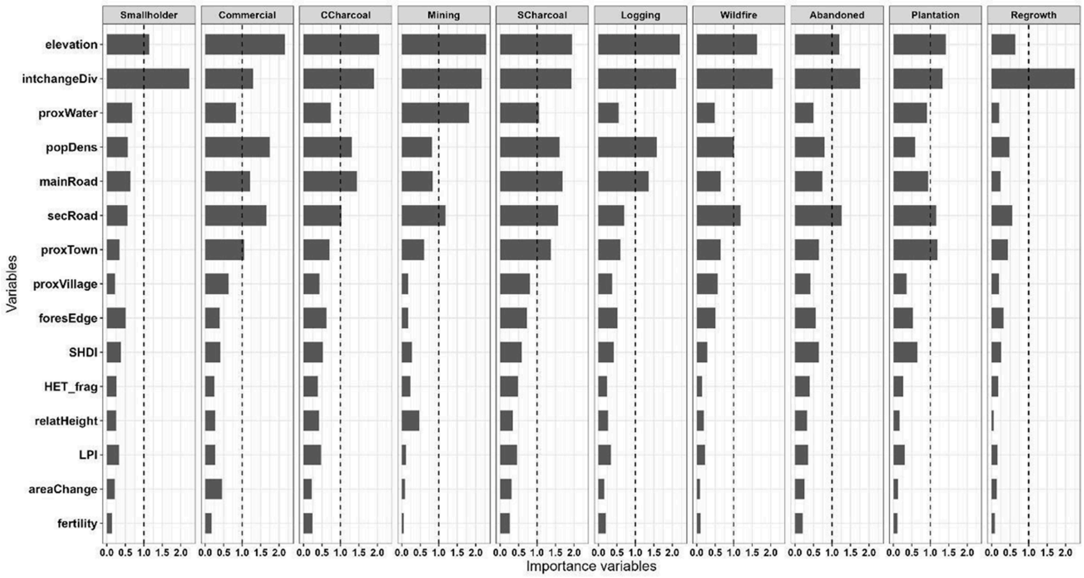
Appendix

Appendix A:. Influence of all explanatory variables on forest change drivers



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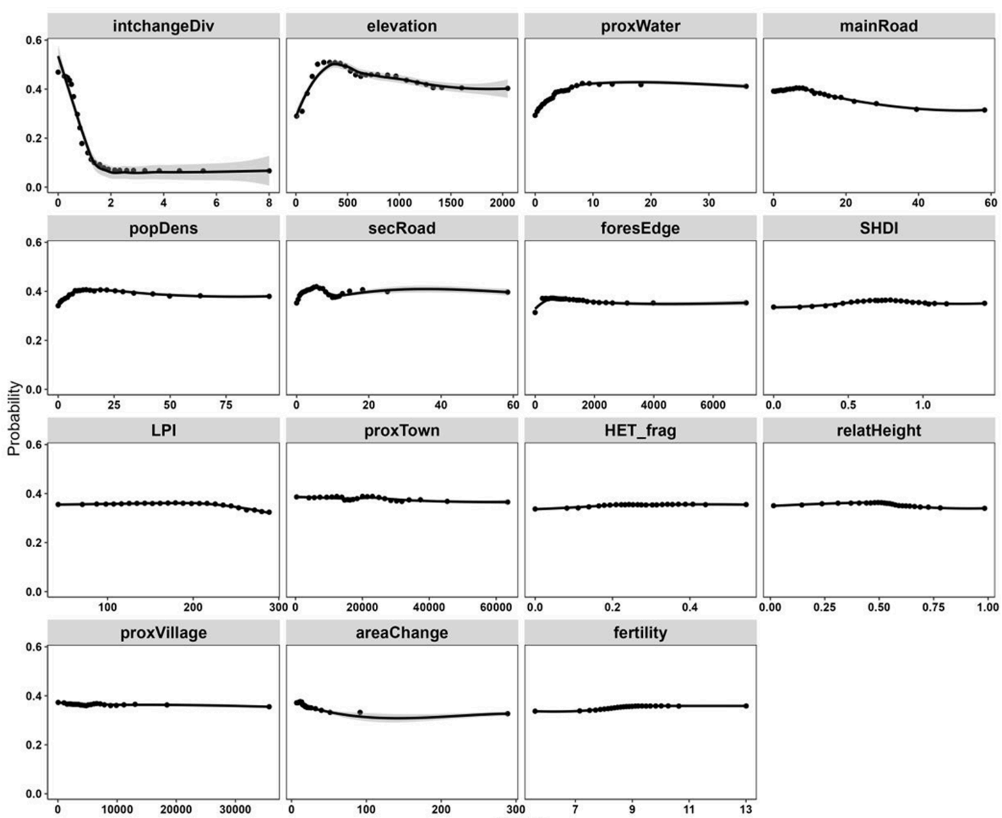
Appendix B:. Partial plot of all explanatory variables



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