Improved land use change maps and annual change methodology

Initiative for Climate Action Transparency

Initiative for Climate Action Transparency – ICAT

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Deliverable # (Deliverable 1 of Activity 4)

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DISCLAIMER

PREPARED UNDER

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ABBREVIATIONS

AFOLU	Agriculture, Forestry and Land Use
CCDC	Continuous Change Detection and Classification
ESWADE	Eswatini Water and Agricultural Development Enterprise
GEE	Google Earth Engine
IPCC	Intergovernmental Panel on Climate Change
LULUCF	Land Use, Land Use Change and Forestry
SNL	Swazi Nation Land
TDL	Title Deed Land
USGS	United States Geological Survey

EXECUTIVE SUMMARY

The agriculture and forestry industry in Eswatini plays a very big role in the economy and the livelihoods of many Emaswati (Swazis). In the same vein, these sectors play a significant role in the country's greenhouse gas (GHG) budget as reported in the recent (2020) National Inventory Report where the AFOLU sector contributed almost half (48%) of the country's emission. The increases in emissions were largely attributed to activities such as deforestation through forest conversions, cropland expansion, and biomass burning, among others. Sugarcane and timber plantations are some of the biggest land uses in the country predominantly grown on Title Deed Land (TDL) and leased Swazi Nation Land (SNL). This makes these land uses key categories for GHG estimates and hence the need for better estimates using higher tier methods. In line with the country's NDC commitments, a detailed analysis of land use change was undertaken covering the period from 1990 to 2020 at 30m resolution. The analysis took advantage of the increasing availability of high-quality remote sensing data and advanced technologies characterizing land change.

An approach 3 was used wherein tracking of land use conversion was done on a spatially explicit basis to derive information on changes on each 30m grid or parcel of land. The analysis made use the Landsat satellite images archive and other ancillary data via the Continuous Change Detection and Classification (CCDC) to produce annual land use maps for Eswatini. The data was validated using a collection of over 6000 reference samples collected independently using Collect Earth and field validation. The overall agreement of the maps reached more than 90 %. The data and maps will be shared for public access. To our knowledge, this is the first set of published 30 m annual land change datasets that include land use and land use change spanning from the 1990s to the present for Eswatini. The data forms a basis for making better estimates of GHG dynamics within the AFOLU sector as well as providing useful information for land resource management. The data will also improve the understanding of terrestrial ecosystems and the complex land use dynamics of Eswatini.

The findings indicate that all land uses, with the exception of indigenous forest and grassland, are increasing. These changes can be attributed to a wide variety of factors such as deforestation for agricultural and human settlement expansion (including urbanization), large-scale forestry operations, among others. On the other hand, land use change is caused by both human and climate drivers. Decisions on land use are often based on short-term economic factors and are influenced by globalization, technological innovation, and policies at different levels (i.e. local, regional or national). For indigenous forests, the risk of conversion to other land uses is correlated with environmental, political, social, cultural, and economic factors. Therefore, understanding the trends and long-term demographic context for population change is critical in land carbon (C) dynamics and land use planning. Even though some C stocks may be increasing due to forest regrowth, bush encroachment or alien plant invasion, it is critical that Eswatini addresses the issue of forest conversion due to its significant contribution on the C budget. An analysis of the drivers of land use change in Eswatini assists in developing scenarios for future land use changes up to 2050. This will be primarily based on the trends and land use change matrices from the past 30 years.

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1. INTRODUCTION

The agriculture and forestry sectors are key economic sectors in Eswatini, collectively accounting for more than 13% of the country's Gross Domestic Product (GDP). Similarly, these sectors play a significant role in the country's greenhouse gas (GHG) budget. For instance, the recent National Inventory Report indicated that the AFOLU sector was a net emitter at 1551.14 Gg CO2e in 2018. This emission trend represented a 128.35% increase (excluding Land & HWP) compared to the levels reported in 1990, where Eswatini was a sink of 1090.61 Gg CO2e. Notably, almost half (48%) of Eswatini's emissions in 2018 came from the AFOLU sector (see Figure 1). The Forestry and Land Use (FOLU) sub-sectors, also jointly termed the Land Use, Land Use Change and Forestry (LULUCF) sector, is a source of significant emissions. The increases in emissions are largely attributed to activities such as deforestation through forest conversions, cropland expansion, and biomass burning, among others.

The LULUCF sector is one of the key sectors of the economy and covers the exchange of GHG between terrestrial ecosystems (land) and the atmosphere as a result of human activities. The majority of the high-value agricultural crops (sugarcane, forestry, and citrus fruits) in Eswatini are grown on Title Deed Land (TDL) and leased Swazi Nation Land (SNL) where there are high levels of investment and irrigation, and high productivity. However, most of the Eswatini population - approximately 75% (Central Statistical Office, 2018) - resides in rural Swazi Nation Land (SNL) and is engaged in subsistence agriculture. These socio-economic and land use dynamics have implications on the country's carbon budget, hence the need for continuous assessment and monitoring. There is, therefore, a need for ongoing efforts to improve the availability, collection and quality of data required for estimating emissions in the LULUCF sectors to enable Eswatini to meet its enhanced international reporting standard requirements. In the context of the UNFCCC, including its Paris Agreement (PA), Eswatini has the obligation to report its national GHG inventory of anthropogenic emissions by sources and removals by sinks of GHG. The periodic reporting and review of the national GHG s inventory provides the international community with complete, accurate, transparent, consistent and comparable information on the anthropogenic GHG emissions and removals at the national level. Furthermore, under the Paris Agreement, the GHG inventory provides a means of assessing whether the country is on track to meet its nationally determined contributions (NDCs).

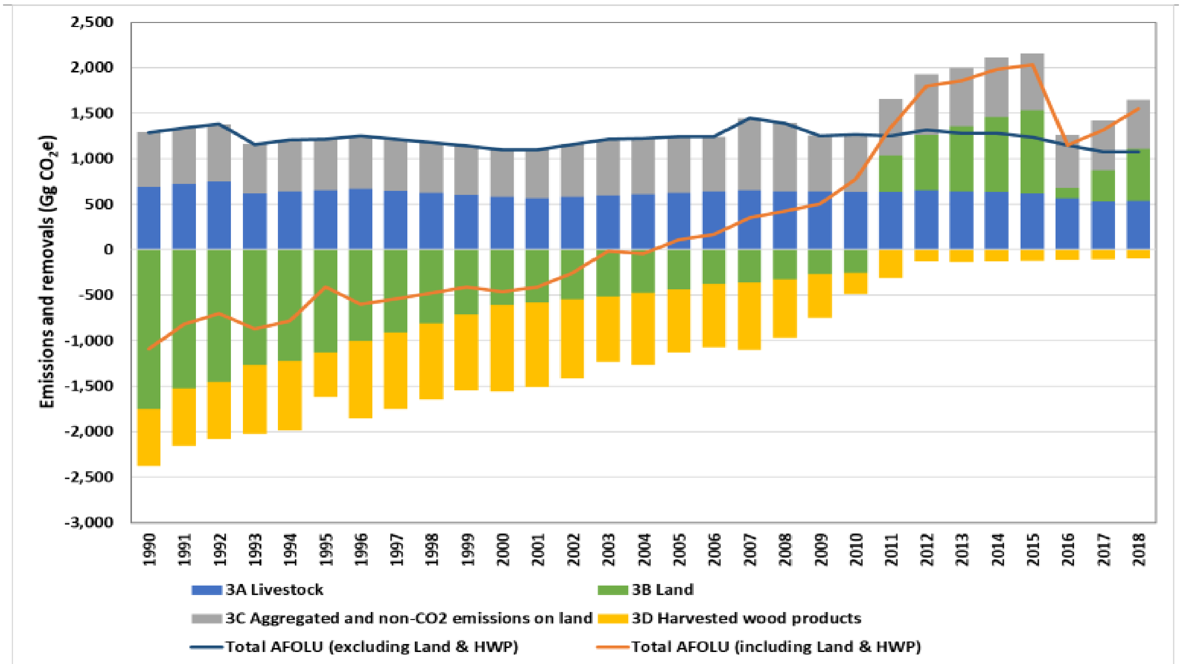


Figure 1: GHG emissions and removals as estimated during the national GHG inventory for the period 1990-2018.

Land-use maps primarily derived from remotely sensed (satellite) data are the main source of activity data for land category inventory. In the recent GHG inventory, the land areas were represented using the IPCC Approach 2 (total land-use area, including changes between categories) for the six identified IPCC land use categories or sub-categories per ecological zone. The IPCC Approach 2 provided an assessment of both the net losses or gains in the area of specific land-use categories and what these conversions represented (i.e., changes both from and to a category). The main dataset for the land categories were derived from processing of four sets of wall-to-wall raster data derived from supervised classification of 30m resolution Landsat 5 TM and Landsat 8 OLI imagery covering the years 1990, 2000, 2010 and 2015. The change detection analysis on the land use data were undertaken for three change pairs: 1990-2000, 2000-2010, and 2010-2015. Due to the lack of data for last year of the GHG estimates (2018), the period between 2015 and 2018 was extrapolated based on trends from the previous epochs. All matrices were linearly interpolated/ extrapolated to obtain annual land use change data for all individual years within these periods. There was therefore a need to replace or supplement all the extrapolated and interpolated data by measured data. As such continuous improvement in the collection of activity data and institutional arrangements for the LULUCF sector is key in ensuring that Eswatini meets the accelerated reporting requirements under the Paris agreement. This was also undertaken in lien with the country's commitment enshrined in the Nationally Determined Contributions (NDC) which entails moving from Tier 1 to Tier 2 GHG inventory for the AFOLU sector and improving data collection and institutional arrangements by 2030. Furthermore, the country commits to reducing land degradation (including in mountain ecosystems) through restoration including tree planting and improving livelihoods through better livestock management. The country also aims to plant 10 million trees during the same period.

This report, therefore, reports on the research conducted to generate new and improved land use maps for Eswatini covering the period from 1990 to 2020 as well as incorporating an enhanced land stratification (focusing on the inclusion of timber and sugarcane plantations).

2. SCOPE OF WORK

2.1. Objectives

The project focused on building capacities for key stakeholders in Eswatini, in developing a robust sustainable data collection process, including institutional arrangements, and improved Tier 2 data for future inventory compilation. Specifically, for the LULUCF sector, the project aimed at achieving the following:

- Updating land use change maps to incorporate an enhanced land stratification (focusing on the inclusion of timber and sugarcane plantations) covering the period from 1990 to 2020.
- Creating and updating a database of country specific LULUCF emission factor database.
- Identification of drivers of land use change to develop an improved projected baseline for LULUCF.

2.2. Expected outcomes and deliverables

The expected outcome for this exercise is an improved transparency and accuracy of emission estimates for the LULUCF sector through inclusion of timber and sugarcane plantations in the LULUCF inventory and projections. This will be achieved through:

a) Incorporating timber and sugarcane plantation data into land use maps and current inventory land use matrix, and provide annual areas for land remaining and land conversion categories;

b) Holding a capacity building workshop with trainers (GHGMI) on land representation and annual land area calculations;

c) Drawing up a list of required data for LULUCF inventory for each land type identified in the land maps;

d) Undertaking a literature review and develop a database of activity data, incorporating as much country specific data as possible and identify data gaps;

e) Updating the LULUCF inventory;

f) Holding a capacity building workshop (supported by GHGMI) to identify drivers of land use change (including policies) and to discuss projections for the LULUCF sector;

g) Developing an improved LULUCF projected baseline which can be utilised for tracking the impacts of renewable energy NDC targets on the AFOLU sector;

h) Uploading and managing the files and templates through the existing inventory archiving system.

The deliverables will be as follows:

1. Report on improved LULUCF LU matrix and annual area changes (including detailed methodology);
2. Database of activity data for LULUCF sector;
3. Updated LULUCF inventory and projected baseline.

3. METHODOLOGY

3.1. Collect Earth sampling

This study implemented the Approach 3 which requires spatially explicit observations of land use and land-use change. Land use, changes in land use, and land management practices may either be “sources” of GHGs or “sinks” of GHGs (sinks remove CO_2 from the atmosphere). The IPCC set out specific quality indicators, which implement the fundamental reporting principles established under the UNFCCC (e.g. UNFCCC decisions 24/CP.19, 17/CP.8, 12/CP.17) that countries must adhere to when compiling their reports: transparency, accuracy, consistency, completeness, and comparability (TACCC). However, estimating GHG emissions/removals from the LULUCF or FOLU sector remains a complex task due to the biophysical phenomena involved, which require the stratification of land according to several variables including vegetation, climate zone, soil type, and management type and intensity, as well as disturbances. To that end, the availability of transparent, accurate, consistent and complete land representation is of the utmost importance, requiring a robust and comparable methodology for classification that can be used across time and across space by a number of different stakeholders.

Various methods and approaches are used by different countries to collect area data for land-use classification, including but not limited to maps, censuses, surveys, ground sampling and remote sensing techniques. As part of the Open Foris initiative (Open Foris, 2021), the FAO and Google LLC recently released Collect Earth (Bey et al., 2016), an open-source software program featuring a number of powerful tools to assists countries in collecting, managing and analyzing landcover and land-use information, through an augmented visual interpretation of remotely sensed data based on a sampling approach. Collect Earth is increasingly being used by a number of developing countries as one of the tools needed to prepare their reports to the UNFCCC.

In a land-classification system, the categorical response variable can take on *k* different values. For an IPCC land-use representation, the number of categories samples was 36, covering the six land-use categories (i.e. forest land, cropland, grassland, wetlands, settlements, other land), and changes between these categories, namely 6x5. Such a multinomial response is quantified in the sample proportions that estimate each category in the population. Various authors have provided functions to determine ex ante the sample size in the case of multinomial proportions. Here, Thompson’s equation is proposed for the quantification of the sample size, n, for a first land classification survey using CE:

$$n = \frac{2z^2_{\frac{\propto}{k}}}{9d^2}$$

where *k* is the number of categories; *d* is the tolerable error (e.g. 1%); *α* is the risk we accept that the error is larger than the one we tolerate for each category; and the z value. The statistical analysis was based on data shown in Table 1. Based on this equation, approximately 6233 randomized plots are proposed within the Eswatini territory. Other assessment information, such as the survey structure and any information collected, are reported in detail in an additional "Cards" file.

Table 1: Summary of the sample size estimation parameters.

Elements	Expansion factor
A - Survey area (ha) (area of EK)	1 736 400
B - Number of plots (total)	6233

The size of the sample and its design (i.e. the spatial distribution of the plots) were defined during the preparation phase, based on the variability within the country. The plots were randomly distributed to ensure that the full range of variability of the study area is sampled (Figure 2). This sampling design corresponds to random squares where the plot is taken either randomly within the unit in order to ensure that the inclusion probability is known and identical for each sampling unit, and that the inclusion probabilities of all units in the population are non-zero. This sampling strategy in line with the IPCC guidelines in ensuring that the data are unbiased and can be scaled up where necessary. The number and location of the sampling units is such that they are adequately representative of the land uses of interest over time.

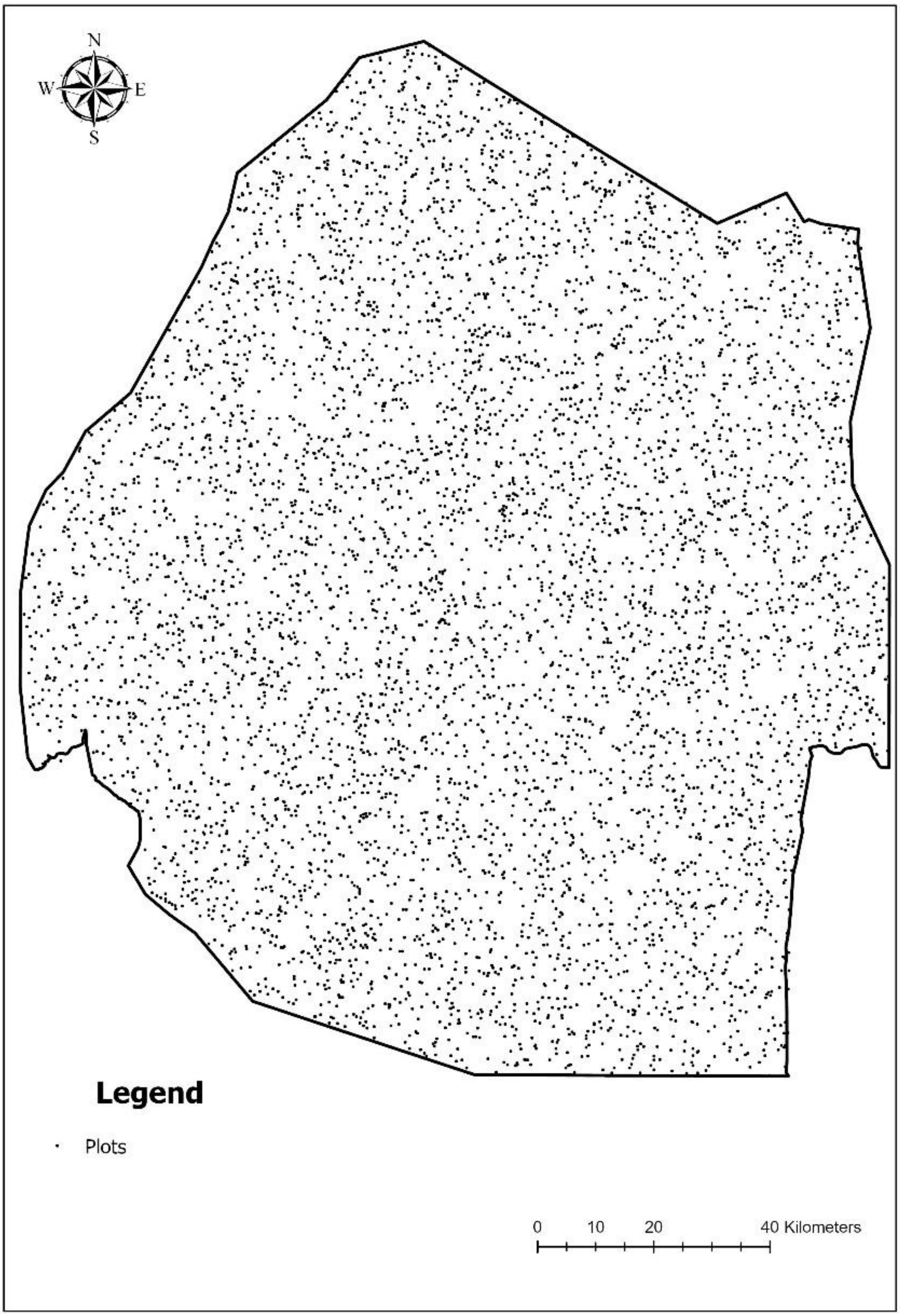


Figure 2: Map showing sample plots used in the Collect Earth data collection and analysis.

3.2. Land use mapping

The activity data was prepared using the following steps (Tzamtzis et al., 2019) in order to ensure a consistent land representation, and ultimately estimate GHG emissions and removals for all land-use categories in line with

the relevant IPCC guidelines:
Step 1. Determined the country-specific stratification scheme and define any strata (land-use categories, subcategories and subdivisions)
Step 2. Identified the land-cover elements and their distribution pattern.
Step 3. Collected information on coverage of the land-cover elements in the scenes.
Step 4. Applied the two-logic approach within the plot mask to determine the land-use category.
Step 6. Calculated and assigned cover density of the woody vegetation to each plot.
Step 7. Applied the same procedure to historical years.
Step 8. Documented of the entire process.

Land use stratification

For Eswatini, emissions and removals from the LULUCF were estimated from the following source and sink categories. Based on the IPCC 2006 Guidelines, the following categories were included in the emission estimates: Land

- Forest land (IPCC Section 3B1)
- Cropland (IPCC Section 3B2)
- Grassland (IPCC Section 3B3)
- Wetlands (IPCC Section 3B4)
- Settlements (IPCC Section 3B5)
- Other land (IPCC Section 3B6)

For instance, a stratification scheme determined by IPCC good practice for national reporting is:

- Level I: land-use categories;
- Level II: stratification of forest land, grassland and wetlands categories into 'managed' vs 'unmanaged land';
- Level III: stratification of all land-use categories according to the changes that have occurred in the last 20 years (i.e. land remaining in the same land use, and land converted to another land use);
- Level IV: for forest land, stratification between natural forest and forest plantations; for cropland, stratification between annual crops and perennial crops.

The Eswatini-specific classification system is shown in Table 2.

Table 2: National LULUC classification system and hierarchy.

eSwatini hierarchy			
Rank	Class	Threshold [1]	Subcategories
1	Built up	20%	• Urban area • Rural area • Peri urban • Industrial • Infrastructure
2	Cropland	20%	• Commercial • Small scale

[1] *Thresholds were established in the framework of traning course on the* <u>*Land Use and Land Use Changes assessment*</u> *conducted in cooperation with the Eswatini Ministry of Agriculture in June 2018 as part of the SECOSUD project. Activities were attended by representatives of the Ministry of Agricutlture, Eswatini National Trust Commission, University of Eswatini and the Eswatini Meteorological Services.*

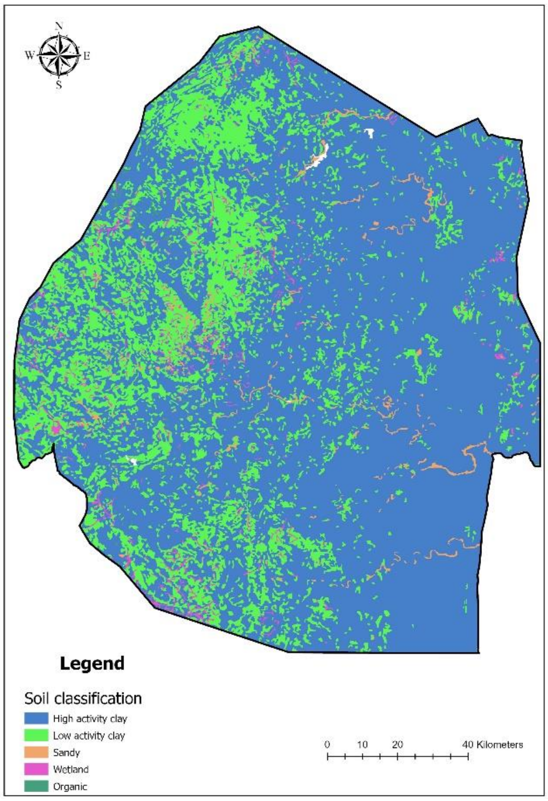
			• Tree crop
3	Wetland	20%	
4	Forestland	20%	• Indigenous 1. - Montane 2. - Riverine • Plantation
5	Woodland	20%	
6	Bushland	20%	
7	Grassland	20%	
8	Waterbody	20%	
9	Bare Area	20%	

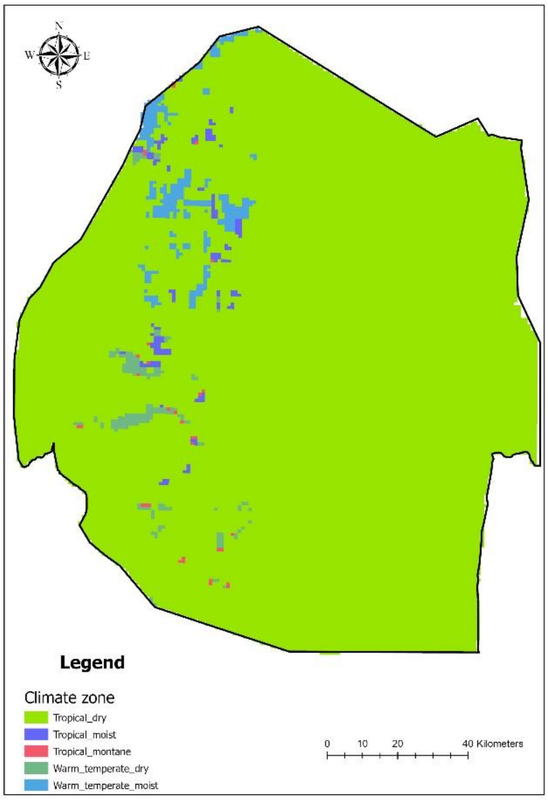
However, for consistency and cross-comparison, these classes were then collapsed to align with the categories of the recent AFOLU GHG inventory (see Table 3).

Table 3: Land use classes used for the final GHG estimates in Eswatini.

IPCC Category	Eswatini sub-categories
Forestland	Forestland – indigenous
	Forestland - plantation
Cropland	Cropland – rainfed
	Cropland – irrigated
	Tree crops (orchards)
Grassland	Grassland
Settlements	Settlements
Wetlands	Wetlands
	Waterbodies
Other Land	Other Land

All land use were further stratified according to the soil type, ecological sand climate zones. The maps were derived using the IPPC decision trees and definitions following the IPCC guidelines and best practice. The climate zones were derived using a combination of data from the Eswatini Meteorological Services, WorldClim and CHIRPS rainfall data. The soils map was derived from the only national data available which is from the work of Murdoch (1968) conducted throughout the country at a maximum of 1:10,000 and minimum of 1:25,000 scale. Vegetation data was obtained from the Loffler and Loffler which was updated in 2018. The soil types, ecological and climate zones are shown in Figure 3.





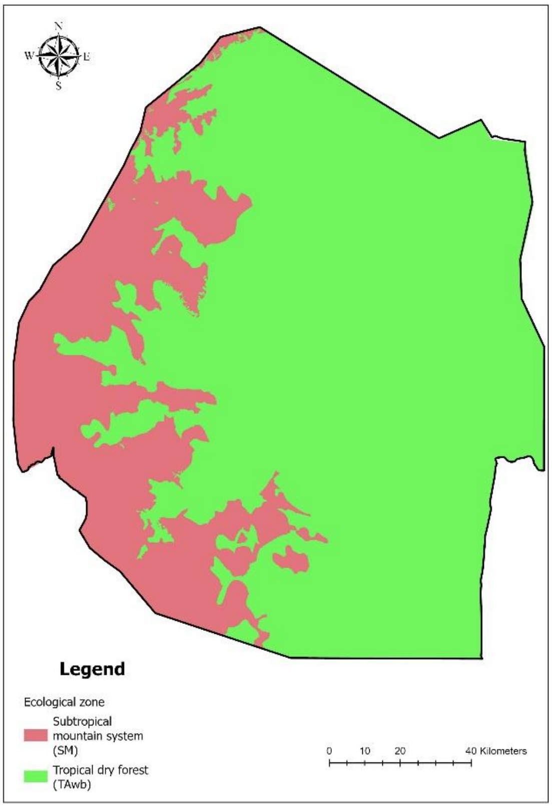


Figure 3: Maps of soil classes (left), climate zones (rights) and ecological zones derived using local data using the IPCC decision trees.

Land use change detection and analysis

The time series wall-to-wall maps form the main input for the land sector. These were created on an annual basis, particularly for the years 1990-2020, but more reliable for the period 2001-2020 considering the availability of dense time series Landsat data in the latter years compared to the earlier years. For a long time, Landsat was available at a cost, until 2008 when the United States Geological Survey (USGS) made Landsat data accessible via the internet for free. Hence, the years prior to 2002 were characterized by limited data due to limited data, the only scenes available being those collected using the random sampling approach used by the USGS back then. Owing to vigorous land change in many areas, however, the signal of that change, including disturbances, may degrade quickly and become spectrally undetectable in just a short time. As a result, some changes likely will not be captured when analyzed at sparse temporal intervals. Use of dense image acquisitions is therefore necessary in order to minimize potential omission errors in land use change analysis.

Consequently, a land-cover/land-use classification process was applied to each plot to classify it within unique land-use categories and strata, identifying a specific value or range of values for each of the land characteristics needed for estimating GHG emissions or removals. The number of land characteristics to be sampled was based on the landcover elements (i.e. type, cover density and fraction covered as well as pattern of distribution). To achieve consistent land representation, the classification process was not limited to a point in time but spanned a time series for which high resolution (Google Earth and Bing) satellite imagery and ancillary information were available. The period 2001 to 2020 was covered for developing land use matrices using Collect Earth.

Since Google Earth images were not available for the period prior to 2001, the land cover for the period from 1990 to 2020 was classified using random forest-based supervised classification methods using the same sample plots developed for the period 2001-2020 as training data. Additional training data was also derived using polygonal data drawn over high resolution imagery for the year 2020 (see Figure 4). Field (ground-truth) data was collected via both field visits to some (62) of the Collect Earth plots and actual data from the sugarcane and forestry companies. Cadastral-level information on timber and sugarcane plantations was also obtained from the institutions governing these industries, name the Eswatini Sugar Association and the individual plantation forestry companies. This were used to validate the remotely sensed data. For the plantation forests, species-specific data was sought from the relevant companies but had not been obtained at the time of compiling this report.

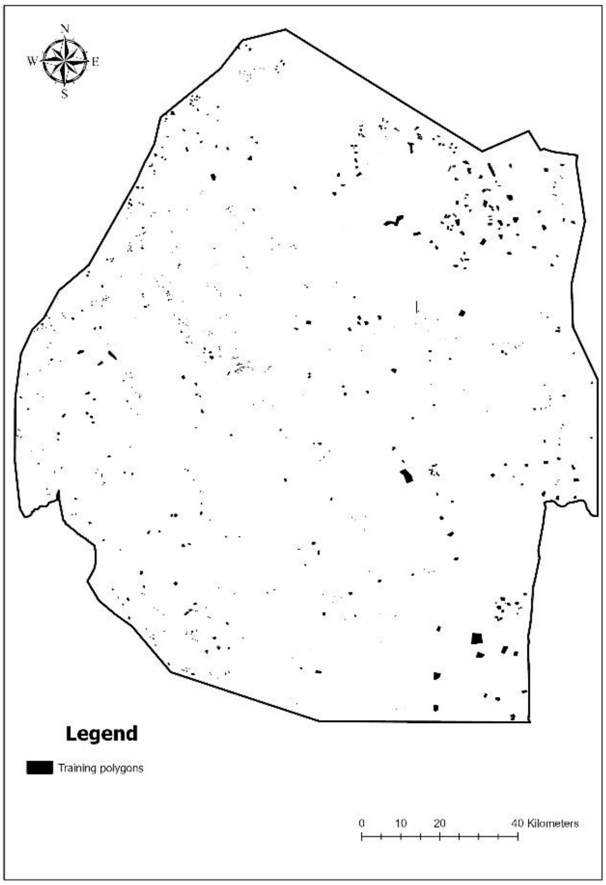


Figure 4: Map showing the additional training polygons used to generate the land use maps.

The Continuous Change Detection and Classification algorithm (Zhu & Woodcock, 2014) was used to derive land use change maps for Eswatini. The CCCD algorithm utilizes all available surface reflectance, brightness temperature, and associated quality data (together, these data are the “observations”) to create harmonic regression fits (models) for each input band to characterize the spectral response of every pixel across the entire time series. The harmonic regression fits are then used to categorize each pixel time series into temporal segments of stable periods and to estimate the dates at which the spectral time-series data diverge from past responses or patterns. Spectral time-series data divergence from past responses or patterns in a temporal segment indicates a model “break” (or “spectral break”). This is generally the result of an abrupt change (e.g., wildfire, logging, and mining), but can also result from a gradual shift (e.g., forest growth, insect infestation, disease). When a break occurs, a new temporal segment or model becomes established for the subsequent data points. Figure 5 shows an example of CCDC results for a single pixel where multiple breaks have been detected. In turn, Figure 6 illustrates the use of multiple harmonics to fit a model to a time series of observations with no breaks. All the examples presented in this paper have been obtained from running the CCDC algorithm using these Landsat shortwave infrared 1 (SWIR1) and Near Infrared (NIR) bands as inputs.

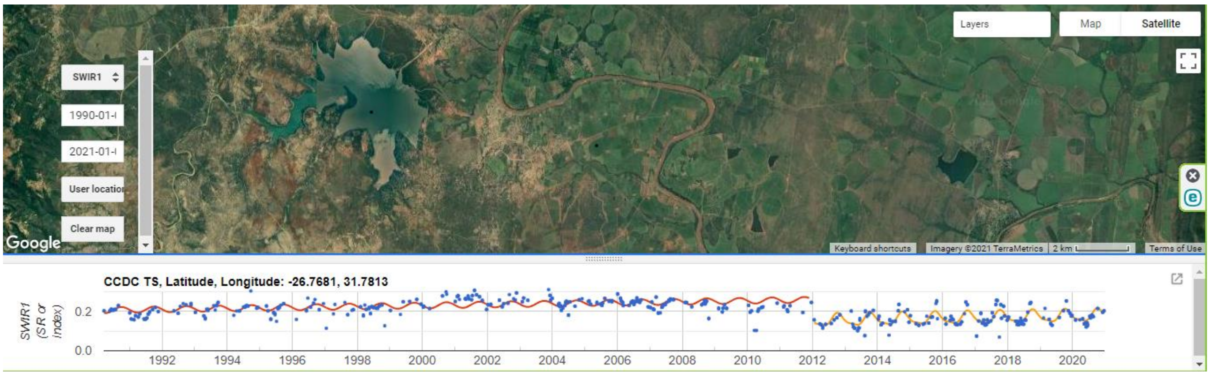


Figure 5: Landsat time series (dots) for the SWIR1 band, and the corresponding time segments detected by the CCDC algorithm, using different numbers of harmonics (The pixel depicts a stable indigenous forest converted to sugarcane circa 2011 after the construction of the Lubovane dam).

The choice of inter-annual intervals was determined by imagery availability, particularly before 2000, and coincided with years where good quality remote sensing imageries with less cloud effect were available for the entire country. This was supplemented by other ancillary spatial datasets such as high-resolution aerial imagery in our possession. This approach was expected provided estimates of greater certainty and a closer link between biomass and carbon dynamics. This included GIS-based combinations of land cover/forest types with connections to soil properties, integrating several types of monitoring and data.

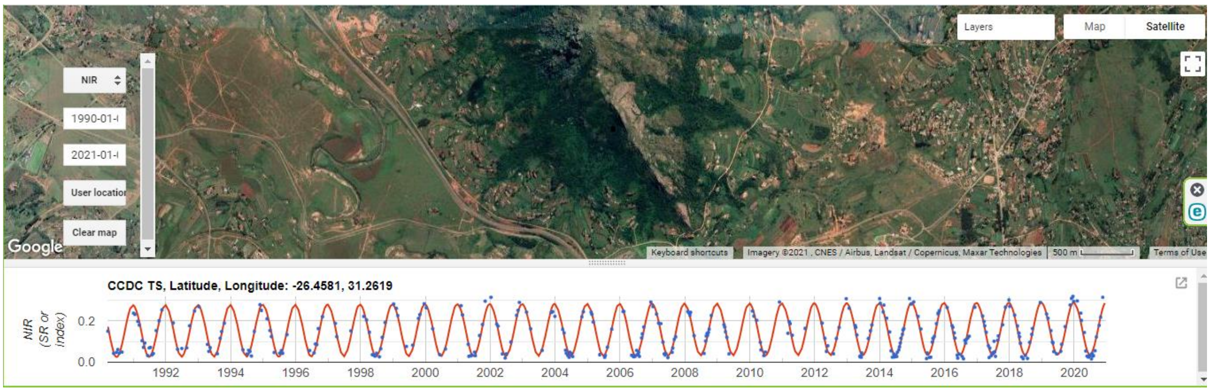


Figure 6: Landsat time series (dots) for the SWIR1 band, and the corresponding time segments detected by the CCDC algorithm, using different numbers of harmonics (The pixel depicts a stable indigenous forest on the sacred Mdzimba mountains).

To maintain, as much as possible, a consistent seasonal landscape condition from one year to the next, we constrained seasonal selection to be within the period with low cloud cover whilst also focusing on the period with high green foliage. The optimal period was therefore between April and September. This period also coincided with the period where most historical Landsat imagery was available for the country. Unfortunately, we also found that for some locations, this period coincided with the dry leaf-off season.

It is worth noting that the CCDC algorithm can detect abrupt land surface changes (Zhu and Woodcock, 2014), but not all abrupt land surface changes will lead to a thematic land use change (as defined by our classification scheme). Even though many land disturbances such as fires, logging, and grazing have ephemeral impacts on the land surface, the land use before and after the abrupt land surface change remains the same. Under certain conditions land use thematic changes may not be caused by abrupt surface events. For some transitions in time (e.g., grass/shrub transitioning to tree cover as a plantation forest clear cut regenerates to forest), no abrupt surface change occurred, but with accumulated gradual changes over a period of time (often years to decades), we observe a slower change from one land cover type to another.

The classification element of CCDC produces a land use classification for every pixel. Unlike traditional land cover approaches, which base classification on spectral measurements, CCDC classifications are based on data from the time series models (e.g. model coefficients). Inter-annual land-use changes could therefore be tracked over the period under review and linked to key drivers. This IPCC Approach 3 pixel-based approach was adopted to enable tracking of land use changes showing the exact areas of change, transition among classes and areas in accordance with IPCC guidelines. The generated change raster maps were then used to create land use change matrices which were used to identify greenhouse gas sources and sinks.

4. RESULTS

4.1. Continuous land use change analysis: 1990 – 2020

The CCDC approach is continuous and has the capability to identify the state of land cover and conditional surface change at any point in the Landsat temporal record. The Eswatini land use maps include 10 land use categories produced at an annual time step. These maps were generated for 1990-2020 for the entire Eswatini territory. The annual land use maps represent the annual status of each pixel on August 1st as a representative date of each year. They provide multiple perspectives on land characteristics and changes that have occurred throughout the country through time.

Figure 6 shows the land use map for the year 2020 whilst the rest of the years (shown in five-year intervals for the years 1990, 1995, 2000, 2005, 2010, and 2015) are shown in Annex 1. While the data sets depicted show information for those 5-year intervals, the maps produced are for every year from 1990 to 2020. The primary land uses shown represent the land use classes assigned the highest probability by the CCDC classifier.

Agreement between the land use maps produced in this analysis and that of Munyambi (2016) which was used in the recent GHG inventory was generally high for the dominant land uses, although comparisons were less satisfactory for rare classes such as wetlands which were poorly mapped by Munyambi (2016).

The land use change matrices are shown in Table 4 to Table 6. These are aimed at quantitative description of the land use state and state transition and is the most common approach used to compare maps of different sources, as it provides detailed “from-to” change class information.

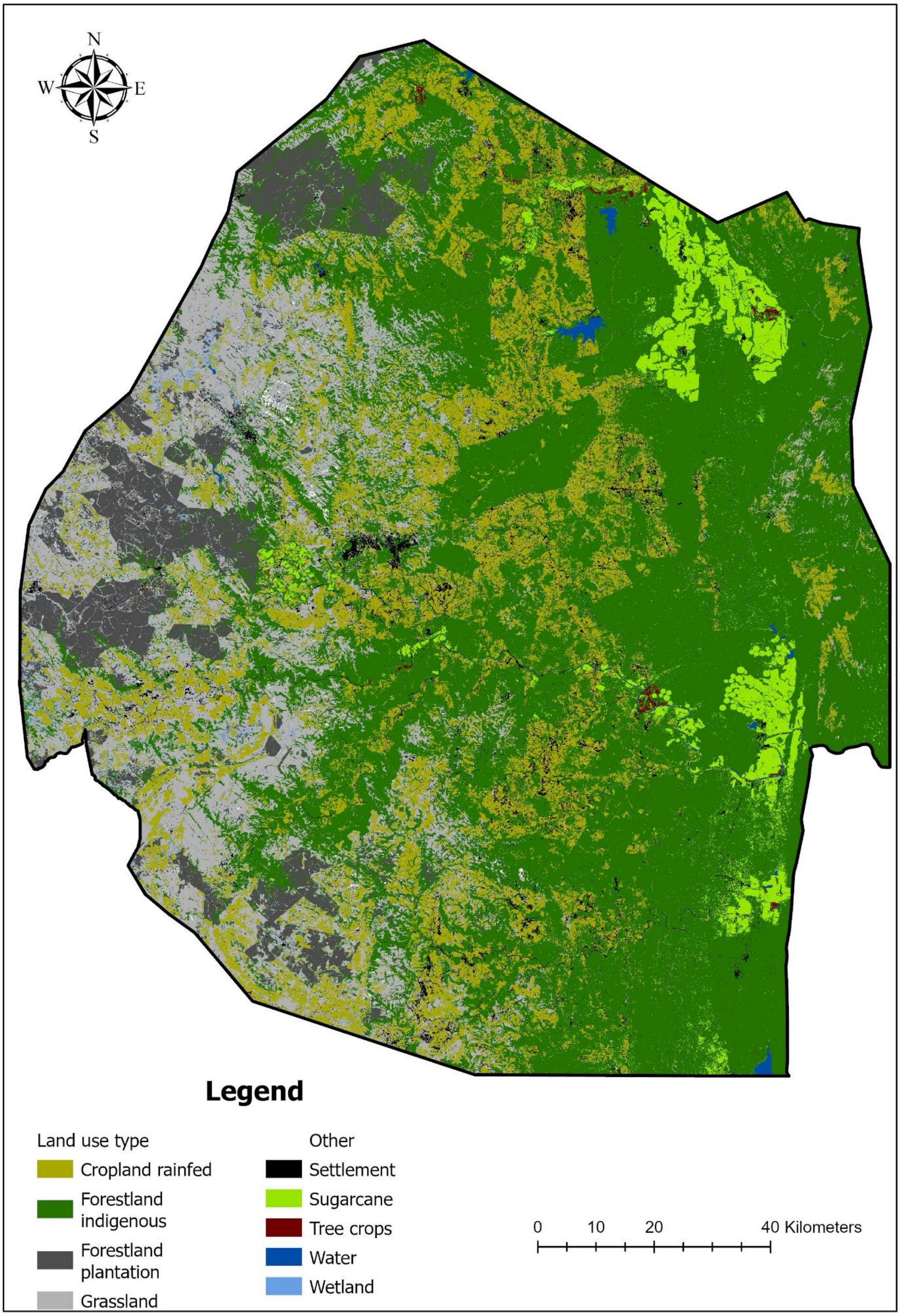


Figure 7: The classified Eswatini land use map of 1990.

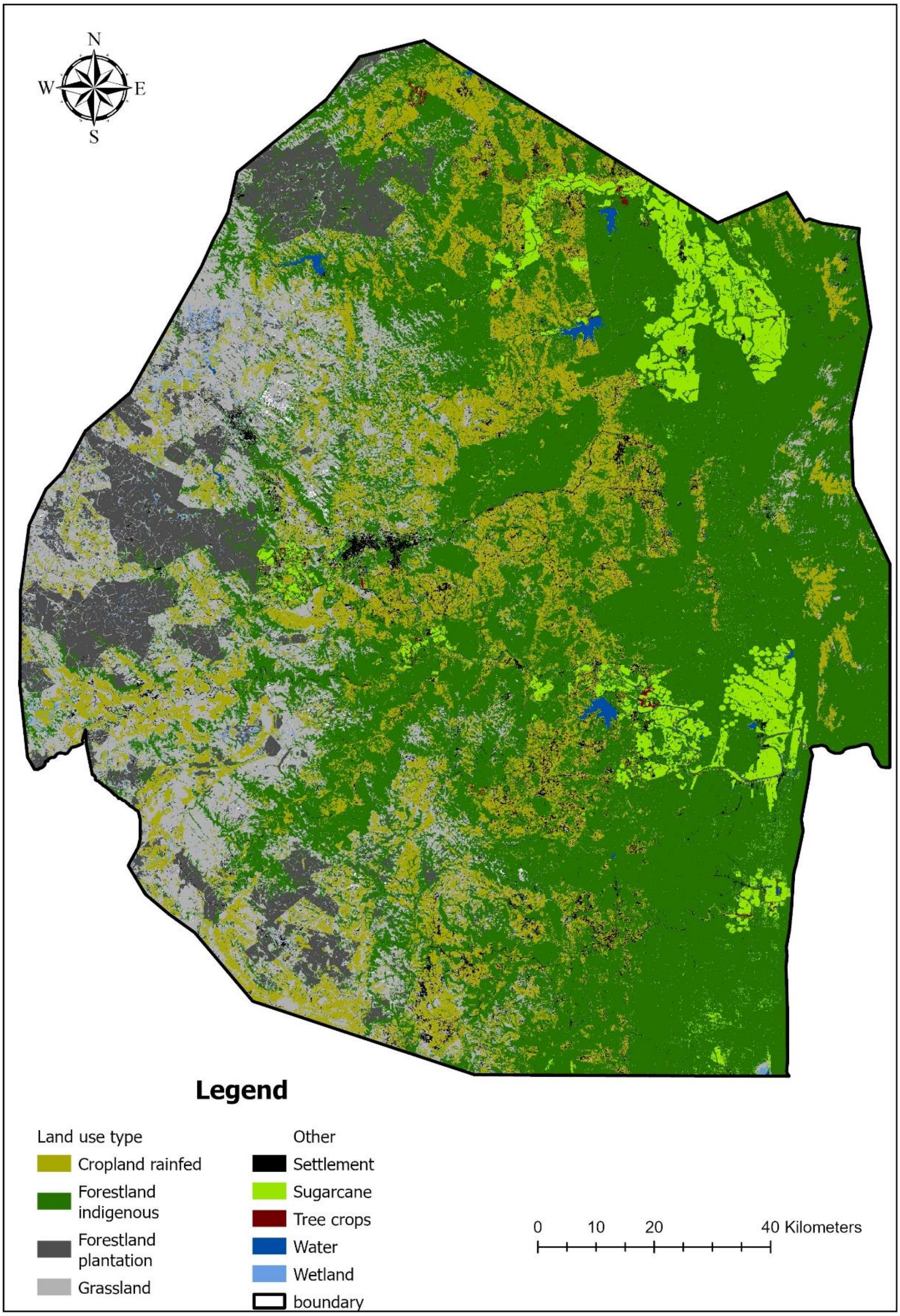


Figure 8: The classified Eswatini land use map of 2020.

Table 4: Land use transition matrix for the years 1990 to 2000 (area is expressed in hectares).

		1990									
	Land use	Cropland rainfed	Forestland indigenous	Forestland plantation	Grassland	Other	Settlement	Cropland irrigated	Tree crops	Water	Wetland
	Cropland rainfed	280507	382	184	363	4	423	501	1	1	4
	Forestland indigenous	354	908153	623	236	0	609	5215	7	20	21
	Forestland plantation	98	537	114342	338	0	19	71	1	2	93
	Grassland	528	283	1166	287304	53	540	178	0	1	27
2000	Other	2	1	49	14	3005	7	1	0	0	
	Settlement	135	198	203	80	5	36463	510	1	6	3
	Cropland irrigated	80	473	4	25		50	66821	2	5	2
	Tree crops	61	100	6	10	0	24	100	5176	1	0
	Water	0	46	0	1	0	19	154	1	5924	1
	Wetland	56	11	155	107	0	4	7	0	0	13061

Table 5: Land use transition matrix for the years 2000 to 2010 (area is expressed in hectares).

		2000									
	Land use	Cropland rainfed	Forestland indigenous	Forestland plantation	Grassland	Other	Settlement	Cropland irrigated	Tree crops	Water	Wetland
2010	Cropland rainfed	262662	22919	302	4547	4	2329	1932	424	51	307
	Forestland indigenous	5983	868327	7501	4045	16	1324	7973	678	578	249
	Forestland plantation	417	5721	95881	5447	122	621	132	10	4	725
	Grassland	5424	4909	9025	273155	113	1352	319	81	20	772
	Other	103	29	388	170	2798	99	22	0	0	2
	Settlement	4689	2505	1343	1598	24	31307	632	87	149	13
	Cropland irrigated	2390	7762	39	206	0	229	55799	721	292	17
	Tree crops	237	1266	8	98	0	105	478	3459	54	2
	Water	272	1553	1	34	0	228	153	18	4994	0
	Wetland	192	248	1010	780	0	8	23	0	3	11313

Table 6: Land use transition matrix for the years 2010 to 2020 (area is expressed in hectares).

		2010									
	Land use	Cropland rainfed	Forestland indigenous	Forestland plantation	Grassland	Other	Settlement	Cropland irrigated	Tree crops	Water	Wetland
	Cropland rainfed	264889	8916	291	7752	37	4634	975	262	66	404
	Forestland indigenous	13429	854026	3651	7938	27	1378	3099	563	390	426
	Forestland plantation	527	11509	100912	12699	439	1350	169	29	6	1178
	Grassland	5360	2816	3213	262529	195	1496	278	64	169	739
2020	Other	54	13	120	184	2833	70	6	0	0	1
	Settlement	3548	1323	471	1726	68	32028	297	61	116	30
	Cropland irrigated	6012	15786	58	487	9	908	62025	1023	642	68
	Tree crops	1367	1735	9	247	4	428	539	3696	60	7
	Water	40	338	19	9	0	44	59	7	5651	1
	Wetland	250	213	336	1599	1	10	10	1	153	10723

The intensity diagram (Figure 9) shows accelerated conversion of forestland (indigenous) to cropland (irrigated) from the year 2000 to present. However, large changes in frequency during the study period may also be driven by the number of active sensors aboard Landsat satellites which may have had an influence on the change detection record, with change detections occurring at higher rates during periods with multiple satellites in operation (e.g., between April 1999 to November 2011 while Landsats 5 and 7 were both operational) but this is subject to further investigation. This was observed by (Brown et al., 2020). Nevertheless, since the change detection element of CCDC is designed to detect abrupt changes in the land surface, land use changes associated with these abrupt changes are well represented.

The CCDC approach does not necessarily capture more gradual and incremental land cover transitions. For example, an area of grassland that undergoes gradual growth of trees (possibly to due to invasion) may not have an obvious sharp transition between grassland and forest, and the CCDC approach often defined the entire time sequence as one model segment. This was particularly true for the period between 1990 and 1999. For instance, managed forest plantations in the western part of the country typically are dominated by grass and shrub vegetation for a few years following harvest and then, as new trees are planted and grow, gradually transition back to dense tree cover over several years. Large areas of harvested trees with adequate time for regrowth may have remained classified as grassland in the evaluation results but the plantation forestland was considered as remaining forestland despite these temporary transitions (using the IPCC 20-year rule). This also applies to rainfed cropland which is temporarily abandoned primarily due to frequent dry spells and droughts, particularly in the drier parts of the country.

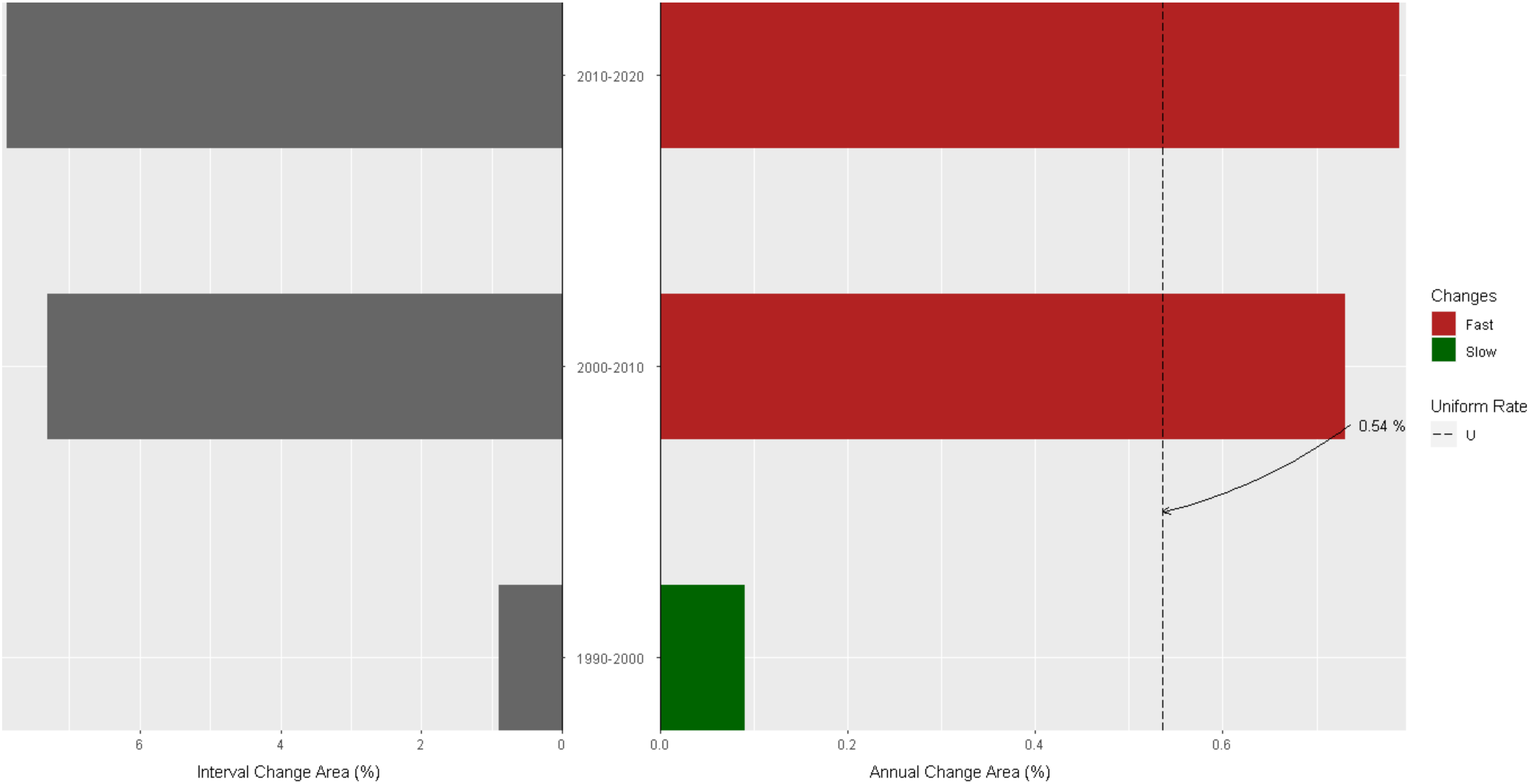


Figure 9: An intensity analysis diagram showing the rapid conversion of indigenous forestland to irrigated cropland over the three epochs. Note the acceleration from the year 2000-2010 epoch.

Overall, between the period from 1990 to 2020, the country lost approximately 25,000 ha of indigenous forest and close to 11,000 ha of grassland (Figure 8). On the contrary the land uses with the biggest gains were irrigated cropland, plantation (timber) forests and rainfed cropland. Tree crops and settlements also increased during the same period whilst water bodies and wetlands experienced very minor to no changes. These changes highlight the processes and patterns of land use change in the country.

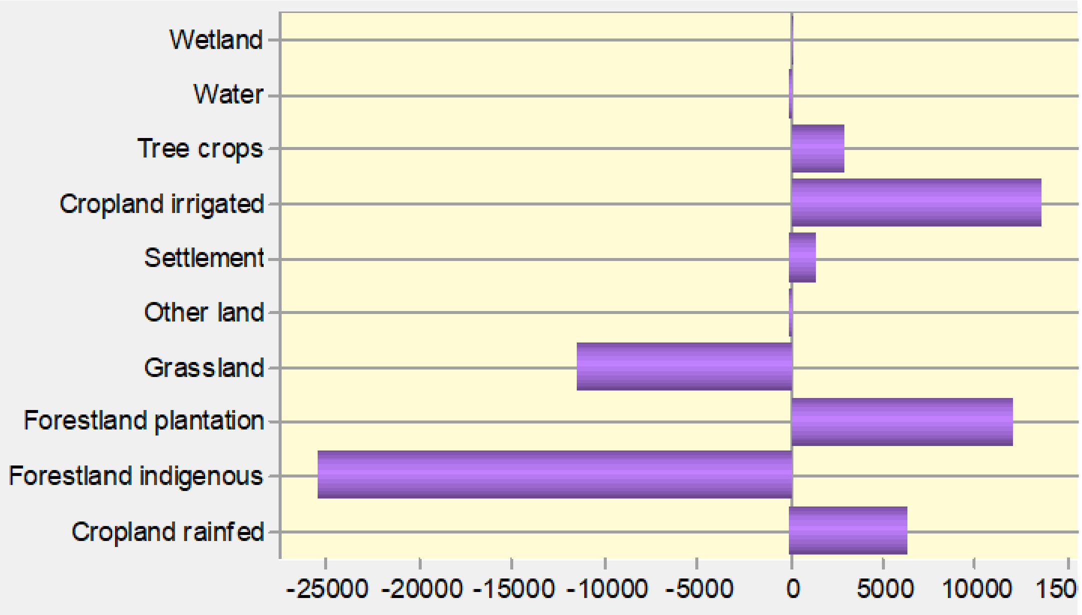


Figure 10: Net change in land use between 1990 and 2020.

A primary challenge for consistent change detection over the entire Landsat record is the variability of observation frequency across space and time. Three major sources of variability in the frequency of observations are: (1) Landsat orbital characteristics, (2) changes in data availability over time, and (3) variations in seasonal data availability due to geographical differences in cloud cover. Seasonal variation in available observations and the differences across parts of the country is largely driven by the presence of clouds.

The most obvious changes over time are driven by the inclusion of ETM+ data following the launch of Landsat 7 in 1999, the absence of TM data following the loss of Landsat 5 in 2012, and the addition of OLI data from Landsat 8 in 2013. Smaller changes can be attributed to a variety of technical, programmatic, and orbital changes over time. This variability throughout the Landsat archive has been documented previously (Loveland and Dwyer, 2012; Roy and Yan, 2018). The main goal of this analysis and a subsequent operational land monitoring system for Eswatini is that change detection and classification algorithms operate consistently across the country regardless of input observation quality and irregularity.

The data from the Collect Earth analysis reveals the disturbance factors within the different land use types between 2001 and 2021 (Table 7). It is apparent that human activity is the primary disturbance factor (7). In total, about 4 120 ha of land were affected by disturbances. The main disturbance factor are paths which are characteristic of human presence in the landscape. These are followed by shifting cultivation and/or cropland abandonment and logging.

Table 7: Disturbance factors within different land use types in Eswatini between 2001 and 2021.

Disturbance type		Area (ha)	Percentage %
Logging		2 060.1	25.0
Fire		294.3	3.6
Grazing		588.6	7.1
Shifting Cultivation		2354.4	28.6
Constructions		294.3	3.6
Path		2 648.7	32.1
Total		8 240.4	100.0

Disturbances within forestland are primarily due to logging mainly in the plantation (exotic) forests. Shifting cultivation and paths are also prominent particularly in indigenous forests.

Table 8: Disturbance factors in forest areas in Eswatini between 2001 and 2021.

Disturbance type		Area (ha)	Fr (%)
Logging		2 060.1	50.0
Shifting Cultivation		1 177.2	28.6
Constructions		294.3	7.1
Path		588.6	14.3
Total		4 120.20	100.0

Figure 11 shows the spatial distribution of disturbances over the period under review. Most disturbances occur under plantation forests to the west of the country, primarily due to logging. The regrowth map also depicts sugarcane expansion on the eastern part of the country.

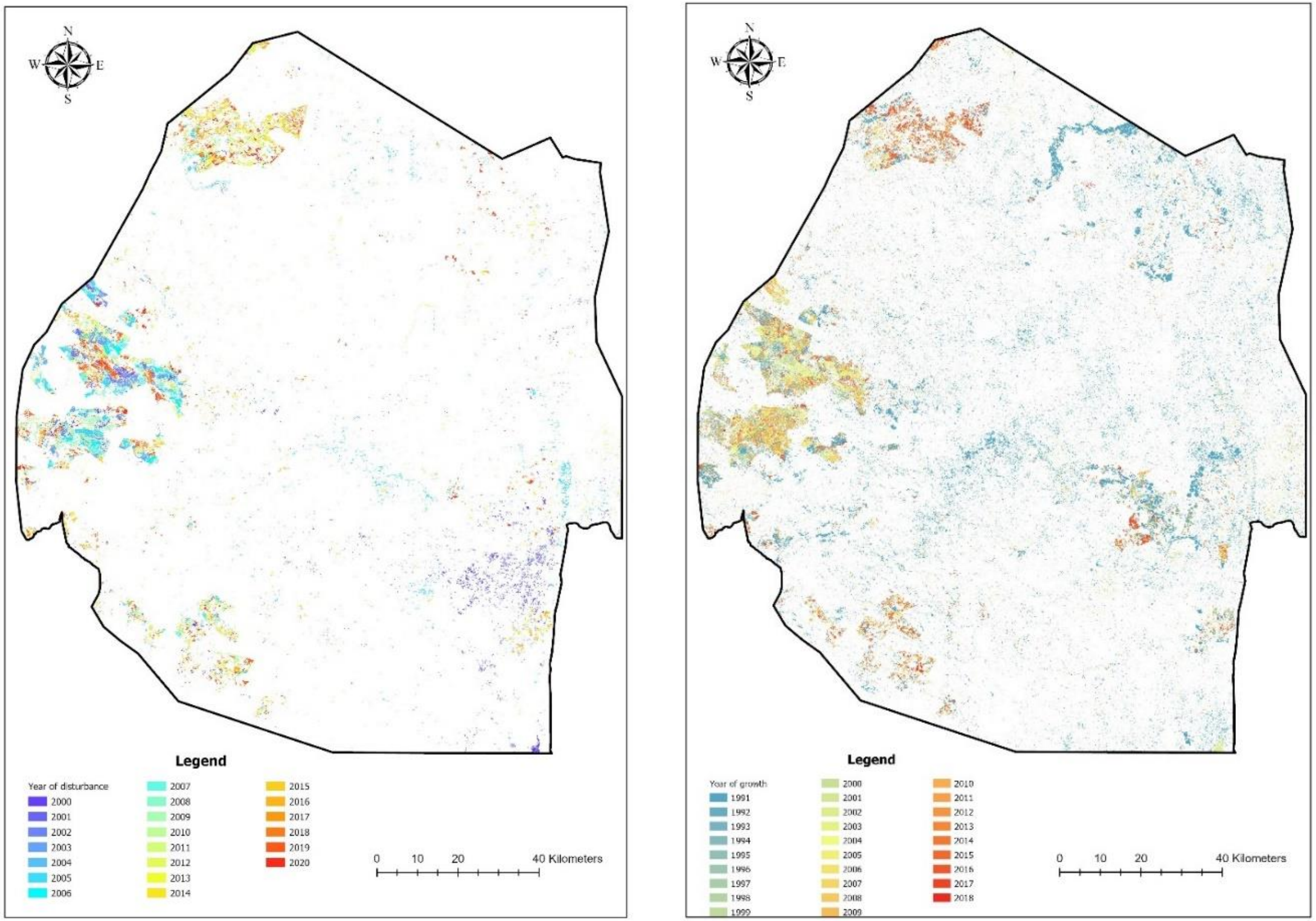


Figure 11: Land disturbance and vegetation regrowth maps for the period 1990-2020.

The change detection results were generally observed to be consistent with known processes that drive change. Forest clearing, fire, agricultural expansion, and infrastructure development, as well as changes in water level and coverage for reservoirs, were usually readily discernible in the land use maps. However, subtle changes that may not result in a land use (thematic) change such as selective harvesting or fuelwood harvesting could be better detected using a different approach for trend analysis. This could be easily detected if the indigenous forestland is subdivided into classes based on tree and bush density wherein a reduction in tree density would indicate degradation due to firewood extraction and/or logging.

Change detection was observed to be especially reliable when the time series data were relatively well-behaved and predictable (e.g., plantation forests), while areas with frequent sharp changes (e.g., sugarcane estates) or high inter-annual variability (e.g., grasslands) were less consistent. In the drier parts of the country, the CCDC produced frequent detection of spectral changes, particularly in cropland and grass/shrub land cover which, in many cases, could be attributed to changing weather patterns that can cause ephemeral land surface change in herbaceous vegetation and associated reflectance properties over relatively short periods of time. Similarly, the rapid expansion of invasive alien plants, the most invasive of which are predominantly shrubs and/or short trees, is evident in most parts of the country.

4.2Drivers of land use change in Eswatini

The derived land use change patterns can be related to a wide variety of factors, including different socioeconomic conditions, climatological factors, and land use history, and can help to tell a more complete temporal story of land use change. On the one hand, drivers of tree cover loss in Eswatini include deforestation, agricultural expansion, large-scale forestry operations, wildfire, and human settlement expansion (including urbanization) (Dlamini, 2016). On the other hand, land use change is caused by both human and climate drivers. Decisions on land use are often based on short-term economic factors and are influenced by globalization, technological innovation, and policies at different levels (i.e. local, regional or national). For forest lands, the risk of conversion to other land uses is correlated with environmental, political, social, cultural, and economic factors.

Key drivers of this conversion include changes in demographic variables, human settlement expansion, distance to the nearest road, and deforestation for commodity production. A study by Dlamini (2016) indicated that deforestation patterns in Eswatini are determined by an interaction of proximate and underlying factors (see Figure 12) primarily fuelwood use, human population and settlements, sugarcane expansion, protection and land ownership status. Other important drivers include small-scale agriculture and wildfires. The former also includes the rapid expansion of illegal cannabis cultivation in many of the country’s riverine and mountain ecosystems. The illegal nature of cannabis pushes the growers to remote and secluded forest ecosystems thereby resulting in deforestation during the process of land preparation. Underlying this problem is also the widespread poverty and unemployment which forces the predominantly young population to this trade. Poverty and unemployment also result in the reduced affordability to use electricity for energy-intensive applications such as cooking and heating. As such, a majority of Emaswati use firewood sourced from the country’s forests for cooking and heating. This can be seen along major roads where heaps of firewood are sold, albeit illegally, to passers-by. Therefore, understanding the trends and long-term demographic context for population change could aid decision makers and other stakeholders in mitigating the effects of human settlement development and socio-economic conditions and anticipate future demographic and economic changes.

Overall, the study of land use change is critical in land carbon (C) dynamics and better land use planning is needed to secure ecosystem services provided by forests. Even though some C stocks may be increasing due to forest regrowth, bush encroachment or alien plant invasion, it is critical that Eswatini addresses the issue of forest conversion due to its significant contribution on the C budget.

An analysis of the drivers of land use change in Eswatini assists in developing scenarios for future land use changes up to 2050. This will be primarily based on the trends and land use change matrices from the past 30 years. The results point to both proximate and underlying causes taking into account key policy drivers for each of the land use categories (Figure 12).

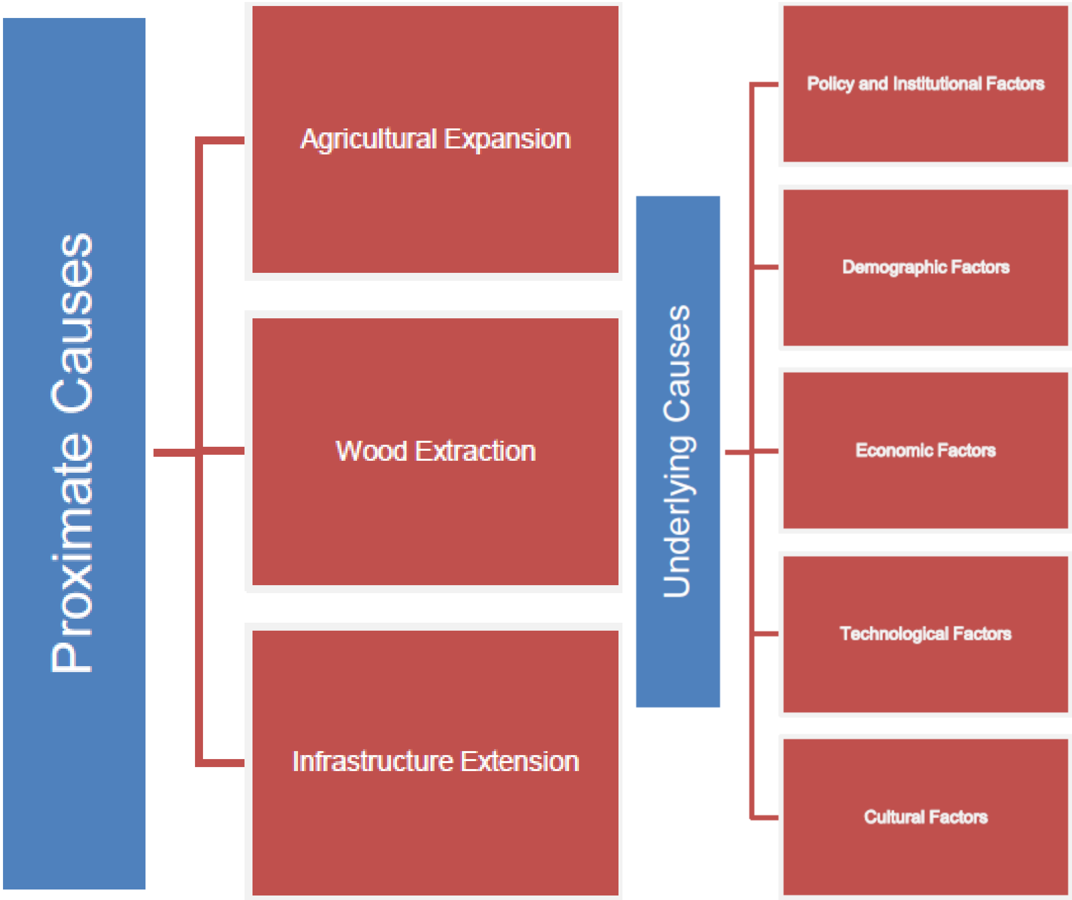


Figure 12: Examples of proximate and underlying drivers of land use change in Eswatini.

The effect of cropland expansion can be seen in Figure 13 and Figure 14. Cultivated agriculture is by far the largest contributor to the agriculture sector GDP and by extension to the country's economic growth. The major crops grown in the country include sugar cane, maize, pineapples, citrus fruits, bananas, conventional and baby vegetables and other fruits (Ministry of Agriculture, 2017). Sugarcane production and its downstream processing is the major export crop and has a significant contribution to agriculture GDP which stands at 80-85% of the total output. However, the liberalization of the European Union (EU) sugar market and unstable global sugar prices negatively affect the Eswatini sugar industry. Despite this, the sugarcane industry continues to expand geographically driven by the efforts of the Eswatini Water and Agriculture Development Agency (ESWADE). This has resulted in the rapid expansion of small-holder sugarcane estates in several parts of the Lowveld where the soils and climate are particularly suitable. The Ministry of Agriculture has led programmes aimed at increasing area under sugar cane production and to date over 10,000 ha under smallholder producers have been put under sugarcane production while another 4.000 has recently been developed in the LUSIP phase 2 project. These investments have been made possible through initial investments in water harvesting projects under the Komati River basin (Maguga dam) and the Usuthu river basin (Lubovane dam) which in themselves resulted in the loss of carbon stocks from indigenous forest. Associated investment in road infrastructure and downstream irrigation further accelerate these land use changes. Modest improvement in the land use rights have also unlocked more investments extend by the private sector.

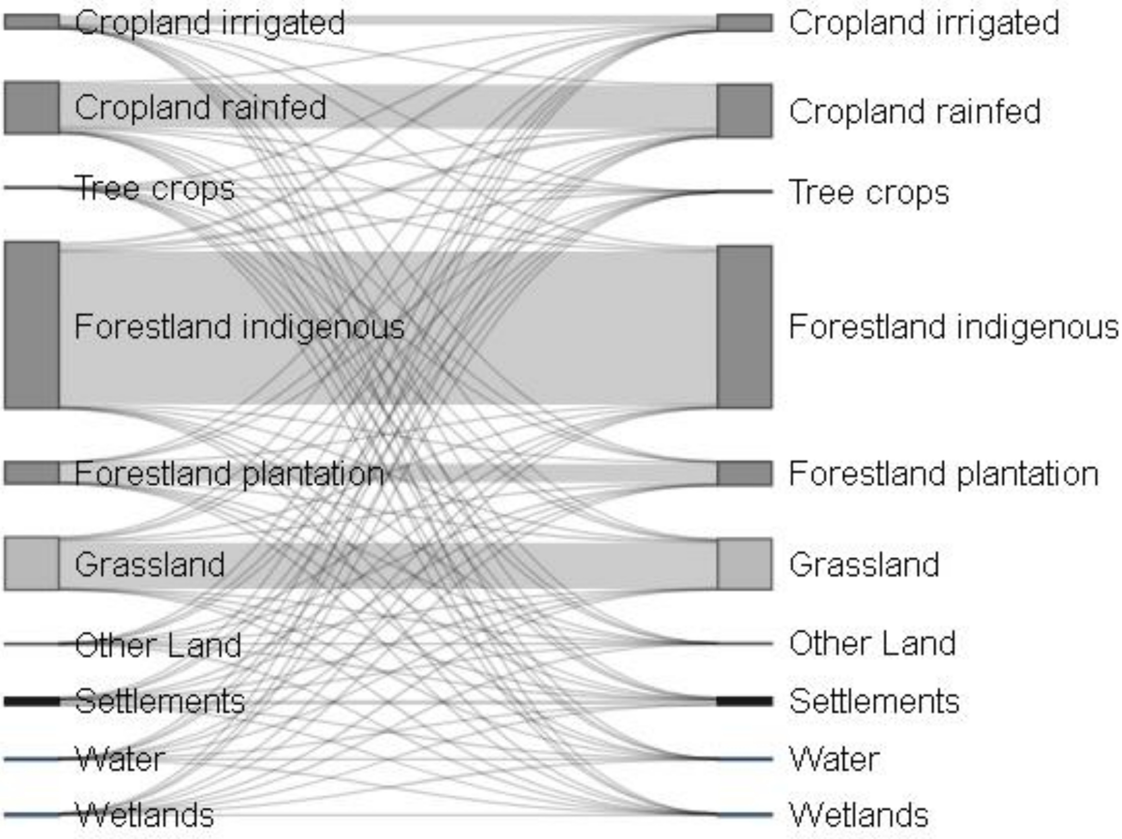


Figure 13: Sankey diagram of land use change from 1990 to 2020.

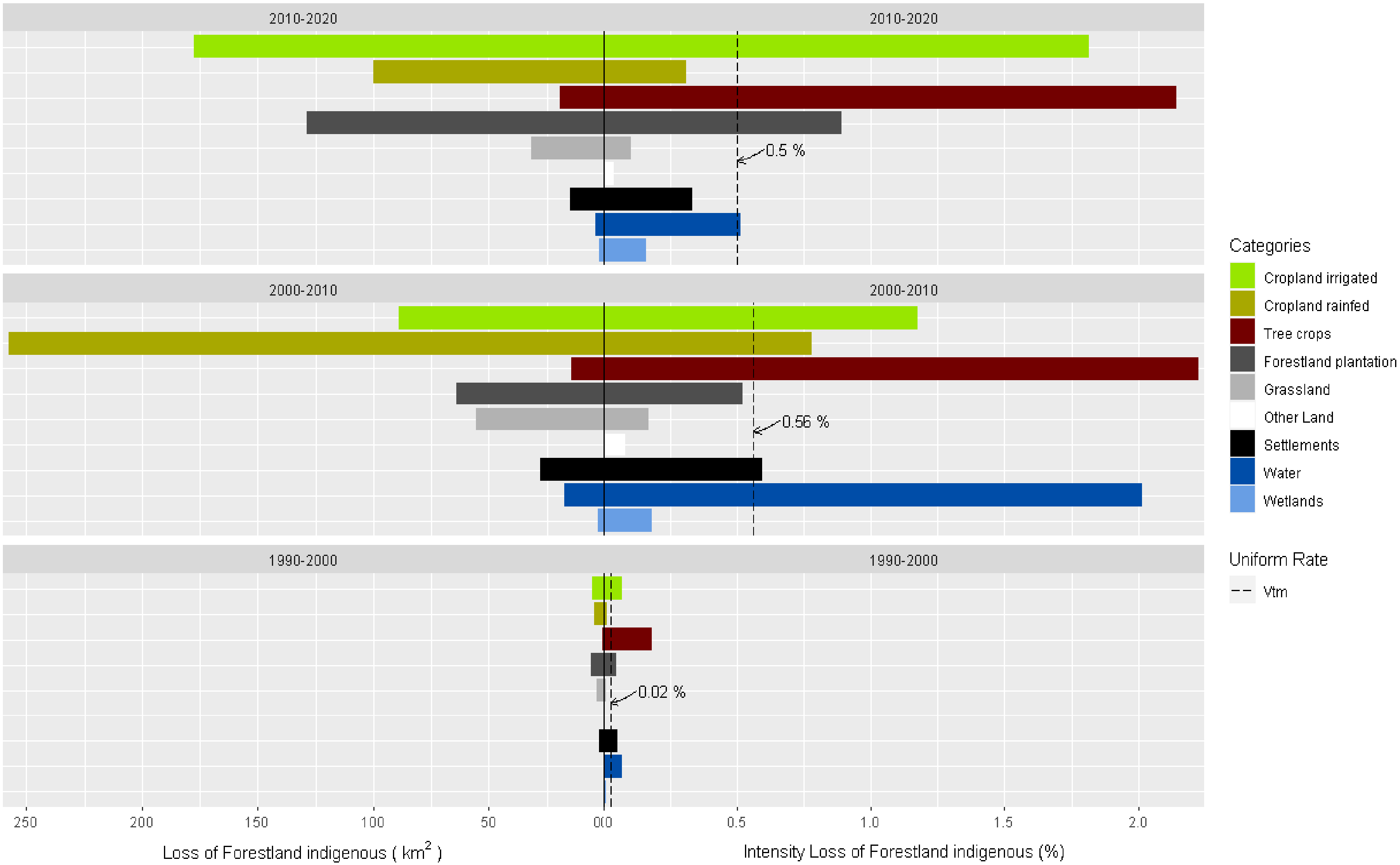


Figure 14: A graph showing the key driver of forestland (indigenous) loss in Eswatini. The effect of cropland expansion (both rainfed and irrigated) is evident.

The expansion of the rainfed cropland is naturally follows the demographic trends wherein an increasing rural population requires more land to grow crops predominantly for domestic consumption. With a population that is largely rural (~75%)(Central Statistical Office, 2018), forestland on Swazi Nation Land is predominantly converted for settlements and accompanying cropland. This is also closely linked to the general lack of a national land policy resulting in uncontrolled clearing of land even in ecosystems that have sensitive and valuable carbon sinks.

Ending hunger (SDG 2) is also one of the prioritized goals that Eswatini has considered in the medium term and is based on the premise of expanded agricultural activity. This is enshrined in all national development strategies, such as the National Development Strategy (NDS), the Strategy for Sustainable Development & Inclusive Growth (SSDIG), the National Development Plan 2019/2023, the Kingdom of Eswatini Strategic Roadmap 2019/2022 and other sectoral policies and programmes including the National Food Security Policy and Eswatini National Agricultural Investment Plan (ENAIP). The National Comprehensive Agriculture Policy, for instance, explicitly calls for the diversification and intensification of rainfed crop production on smallholder SNL. Potential trade-offs between providing sufficient food for a growing human population in the future and sustaining ecosystems and their services are driven by various biophysical and socio-economic parameters at different scales.

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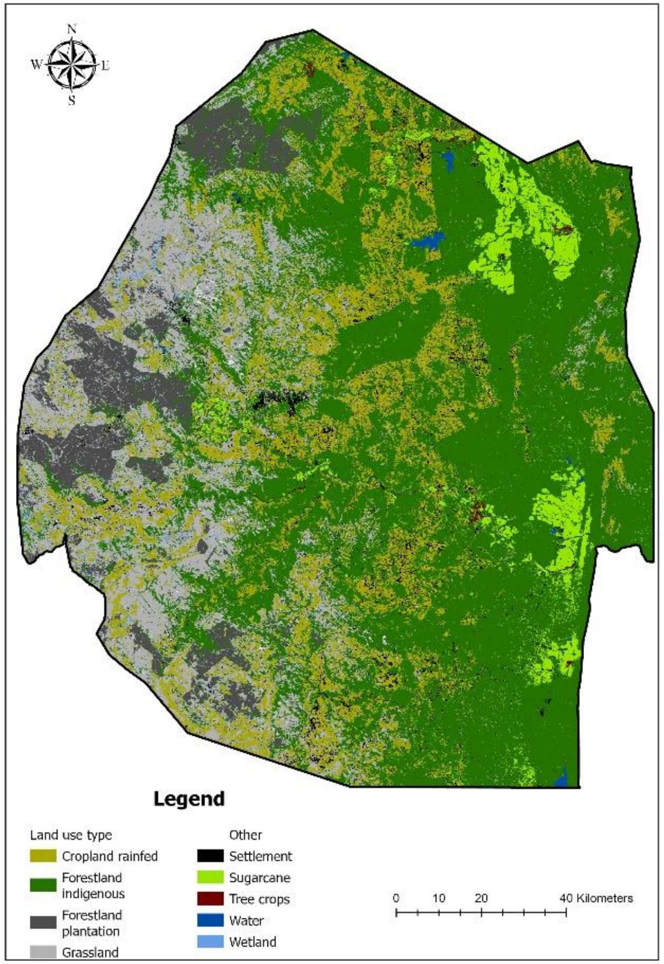
Annex 1: Eswatini land use maps between 1990-2015.



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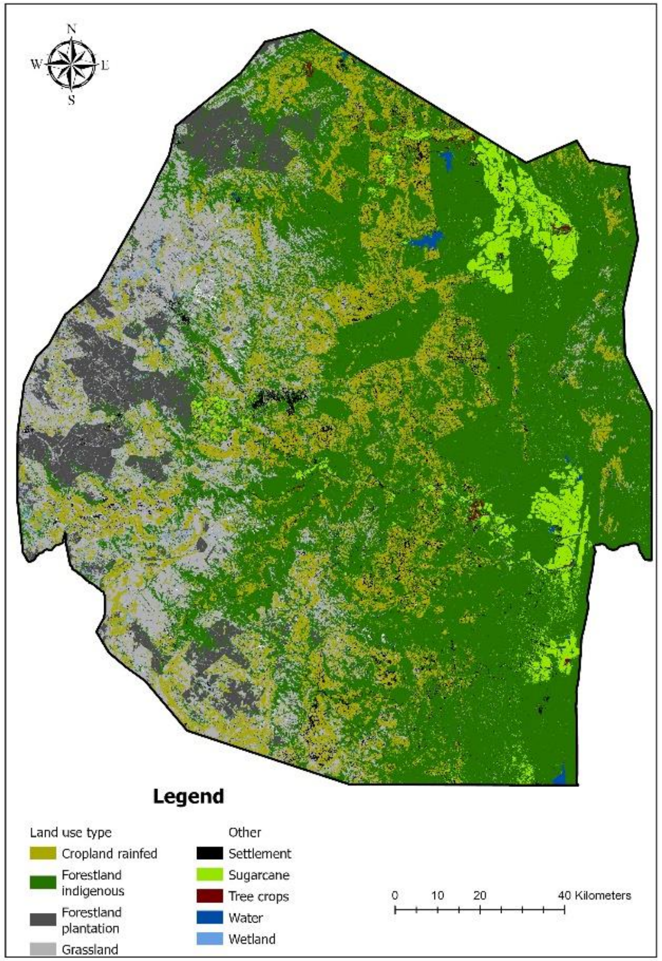

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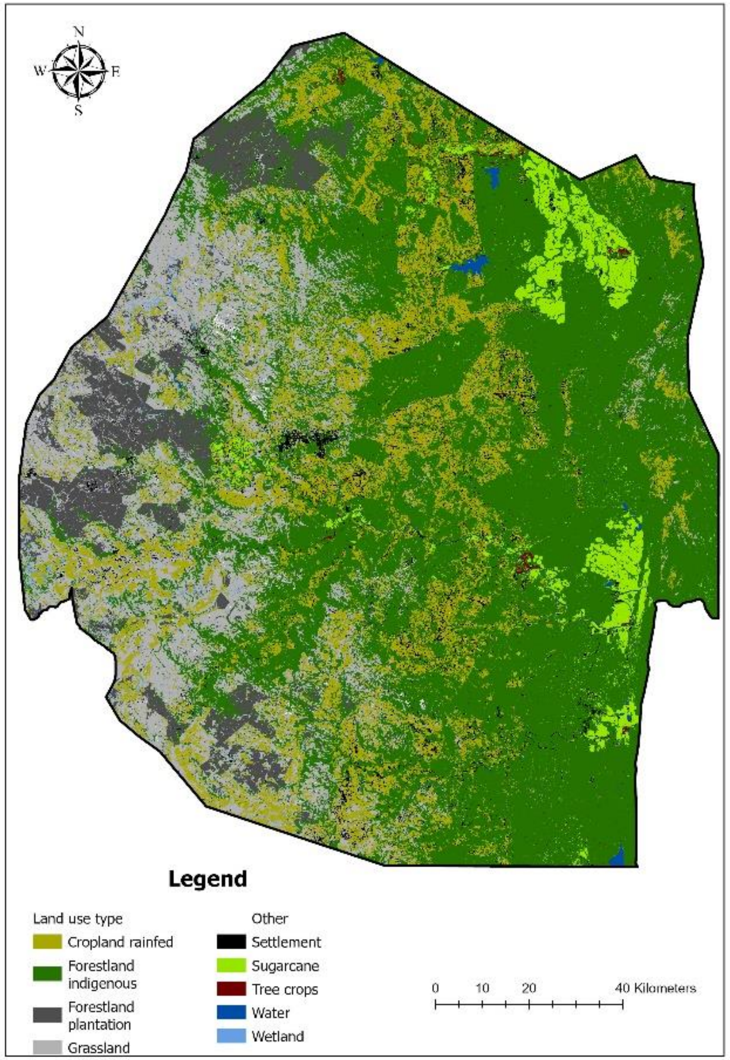
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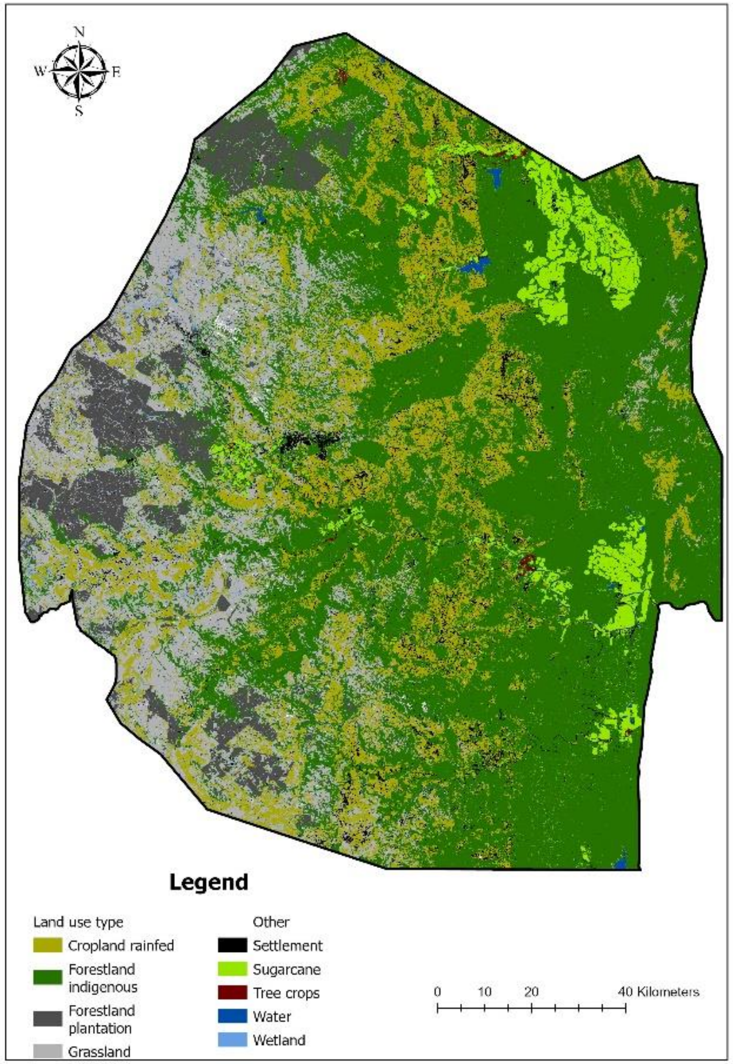
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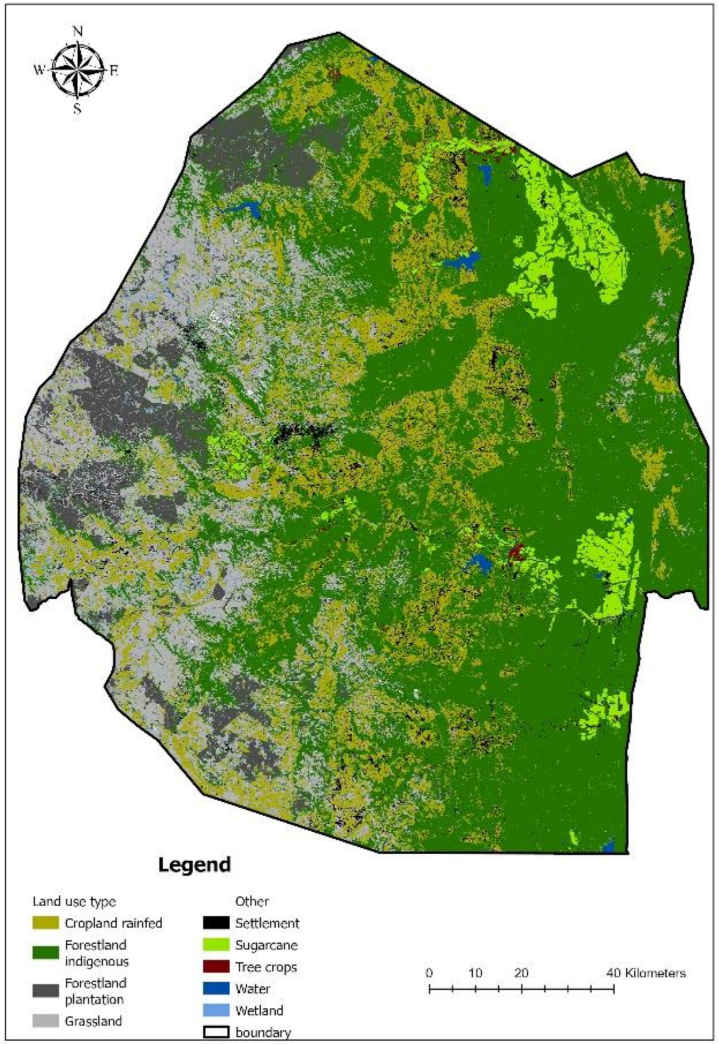
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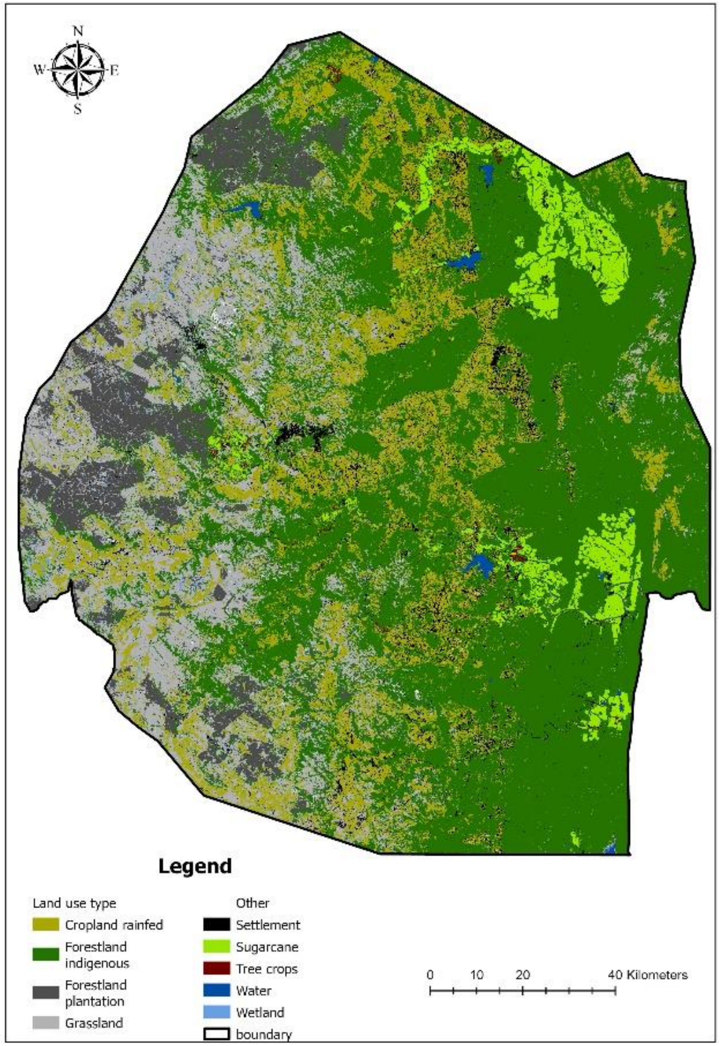
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