Deforestation and forest fragmentation in Southwestern Ethiopia from 1973 to 2019

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Master thesis

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Summary

As biodiversity and biodiversity hotspots worldwide are threatened by the effects of land use, such as habitat loss and habitat fragmentation, it is important to understand the ongoing processes and their effect on the environment. It is especially important to gain a better understanding of deforestation and forest fragmentation patterns in biodiversity hotspots, such as the Afromontane mountains in Southwestern Ethiopia, and how this might impact large mammals. This research aimed to identify deforestation and forest fragmentation in Southwestern Ethiopia from 1973-2019 and what recommendations can be given in the context of large mammal conservation. This was done creating forest cover maps and analysing those for deforestation and forest fragmentation patterns. Results showed that forest cover has been decreasing from 1973 to 2019, but during the last decade (2010-2019), the forest cover seemed to increase again. Deforestation was found mainly along the forest edges and among smaller forest patches between agricultural fields. Only the core area index showed to have a significant decreasing trend, indicating that the forest interior is decreasing. After the establishment of the Yayu Biosphere Reserve, forest cover increased and the core area remained similar. Reforestation was found at the forest edges while deforestation occurred mainly among the small forest patches. It is important to improve landscape connectivity and to halt deforestation as there is no certainty that recent reforestation efforts will have an immediate positive effect on biodiversity. This can be done by the implementation of land sharing and sparing zones in the area and the reconnection of forest patches by reforesting disconnected or nearly disconnected large forest patches. Moreover, an effort needs to be made to protect the small forest patches in the agricultural landscape as these patches are important for landscape connectivity and ecosystem services. This research identified patterns of deforestation and forest fragmentation from the 1970s to the present in the Afromontane mountains in Ethiopia, one of the world's biodiversity hotspots. Moreover, it adds to the empirical evidence to the contribution of biosphere reserves in the contribution to nature conservation. In addition, the scripts that were created in this study could be reused for similar research in the future, reducing the time needed to create forest cover maps and their analysis.

Keywords: Deforestation, forest fragmentation, landscape connectivity, Afromontane mountains, biosphere reserve

Inhoud

Introduction

During the last decades, global biodiversity and biodiversity hotspots have been increasingly under threat from anthropogenic pressures (Habel et al., 2019; IPBES, 2019). Biodiversity is crucial to humanity as it provides not fully replaceable or irreplaceable services (i.e. ecosystem services), including feed, energy, medicine, materials, and culture (IPBES, 2019). Biodiversity hotspots cover only 2.5% of the land's surface but carry about half of known terrestrial life (Myers et al., 2000; Noss et al., 2015; Stork & Habel, 2014). Most of these biodiversity hotspots are located in developing countries that face problems such as growing populations, poverty, food shortage, and unstable governments (Veech, 2003; Williams, 2011). These problems also are a big threat to biodiversity as they are drivers for land use change, which is among the main drivers of deforestation and biodiversity loss (IPBES, 2019; Habel et al., 2019). Therefore, we need a better understanding of the effects of land use change on biodiversity to be able to halt biodiversity loss, especially in important regions such as biodiversity hotspots.

Land use change is, besides overexploitation, the biggest threat to biodiversity (IPBES, 2019). The expansion of agriculture, urban areas, and infrastructure have come mostly at the expanse of wetlands, grasslands, and tropical forests. Deforestation in tropical areas is also driven by wood fuel and timber extraction, global demand for biofuel, and deforestation displacement (Busch & Ferretti-Gallon, 2017). Deforestation not only leads to a decrease in forest surface but also leads to forest fragmentation (Dixo et al., 2009). The latter is the process of large forest patches breaking up into smaller forest patches (Laurence et al., 2011), affecting the connectivity of the landscape (i.e. the extent to which the landscape is connected) (Fischer & Lindenmayer, 2007) and the degree to which species can travel through the landscape (Scolozzi & Geneletti, 2012). This is a threat to wildlife, especially large mammals, as tropical forests are able to carry a decreasing size of populations which increases the risks of extinction (Schnell et al., 2013). Differently shaped forest patches could have a different effect on different animals (Slattery & Fenner, 2021). Patches that have become more complex with longer edges and a smaller core area seem to affect dispersive species or specialist to core habitat species, while patches that are simple and create disjoined core areas affect slow sedentary animals (Slattery & Fenner, 2021). In addition, past deforestation and fragmentation can have a delayed effect on species and could increase the risk of extinction (Kuusari et al., 2009). For nature conservation, it is crucial that the patterns of deforestation and reforestation are well understood (Slattery & Fenner, 2021).

Remote sensing enables high-resolution quantification of deforestation and forest fragmentation (Taubert et al., 2018). With remote sensing, large areas can be monitored over a long period of time (Khorram et al., 2012). This is especially useful for studying areas in tropical countries as there is often a lack of data available in those countries. The ability to study land cover change in the past could provide useful insights into how deforestation and fragmentation have developed over time and how this affects wildlife in the area (Zemanova et al., 2017). In addition, remote sensing creates the ability to test the effectiveness of nature reserves considering land cover change (Liu et al., 2001). More research on deforestation, forest fragmentation, and nature reserve effectiveness using remote sensing is necessary for improving the effectiveness of nature conservation (Zemanova et al., 2017).

The effectiveness in the conservation of forest cover of the biosphere reserves in the Afromontane mountains in Ethiopia remains unknown. Ethiopia is among 25 countries with the highest biodiversity, in which the Eastern Afromontane biodiversity hotspot is one of the two hotspots found in the country (Gole et al., 2019). Additionally, the inhabitants are heavily dependent on biodiversity for their livelihood (Gole et al., 2019). Yet, deforestation in the Afromontane mountains is an ongoing process since 1973 (Hylander et al., 2013) and even before (Ango et al., 2020). Logging and agricultural

expansion are among the biggest drivers (Hylander et al., 2013), with underlying drivers including national policies, institutional instability, agricultural stagnation, poverty, and demographic pressure (Ango et al., 2020). Different deforestation rates have been found in the Goma-Gera and Bonga regions in the Afromontane mountains for different altitudes; higher altitudes (2300-2500m) have experienced more deforestation than lower altitudes (1800m) (Hylander et al., 2013). This is because coffee is growing in lower altitudes in forested areas, contributing to the conservation of forests in these areas (Hylander et al., 2013). Even in coffee growing areas, where the forests are managed, biodiversity has been decreasing as the forest structure has been altered (i.e. the removal of lianas, climbing vines, shrubs, and small trees) (Hylander et al., 2013). To protect the biodiversity in the area, biosphere reserves have been implemented, two, Yayu and Kafa, in 2010 and Sheka in 2012 (UNESCO, 2019). The effectiveness in protecting the forest cover in the reserves remains unknown as no research has been done on this matter yet. Similarly, no research has been done yet on how deforestation may lead to fragmentation in the area.

In continuation of current deforestation practices, it is expected the hotspot Afromontane Mountains, except for the protected nature areas, will have disappeared in 2050 (Habel et al., 2019). This would have a tremendous impact on biodiversity in the area (e.g. through the loss of forest or fragmentation) and global biodiversity (IPBES, 2019). More specifically, this could have a big impact on red-listed species, such as the leopard (Rodrigues et al., n.d.). When only nature reserves remain, "islands" are created (MacArthur & Wilson, 1967) and connectivity within the landscape is lost (Fischer & Lindenmayer, 2007). To prevent this, remote sensing could be used to monitor deforestation and forest fragmentation in the area (Taubert et al., 2018). This could be used to identify areas that need protection to keep forest patches connected. As of yet, no such research has been performed yet. Therefore, this research aims to *assess what conservation measures can be proposed when considering landscape connectivity for large mammals in Southwestern Ethiopia*. To do this, the following research questions need to be answered:

- How did forest cover change during 1973-2019?
- How did forest fragmentation occur in the study area during 1973-2019
- What effect did the establishment of the Yayu Biosphere Reserve have on the deforestation and forest fragmentation in the reserve?

Theory

The impact of land use change on forest cover

Land use change is the practice of converting one land use type to another, which also alters the land cover (i.e. the biophysical material of the Earth's surface including grass, croplands, and forests) (Lambin & Geist, 2010). The alteration of land cover could cause significant environmental effects at local, regional and global scales, such as biodiversity loss, soil quality loss, and alteration of local and global climate (Lambin & Geist, 2010;). Yet, some of these effects may be delayed. For example, a delayed effect in biodiversity loss may occur after habitat loss due to deforestation (Kuusaari et al., 2009). This effect is also known as extinction debt (Kuusaari et al., 2009). Some cases have been reported in which extinction debts are paid 100 (Vellend et al., 2006) to 500 years after habitat loss (Chen & Peng, 2017). It cannot be predicted whether and at what time-delayed effects will occur (Kuusaari et al., 2009), therefore, it is important to monitor the deforestation processes. Research shows that monitoring the deforestation processes in tropical forests may increase the effectiveness of species conservation (Zemanova et al., 2017) and that studying its effects may prevent large mammals from going extinct (Semper-Pascual et al., 2019).

Deforestation, which is the practice of converting forests to another land cover, is one of the biggest drivers of biodiversity loss in tropical forests (Ehrlich & Pringle, 2008; IPBES, 2019). It has been widely documented that deforestation leads to a deterioration of forest quality, forest fragmentation, and habitat loss (e.g. Dixo et al., 2009; Scolozzi & Geneletti, 2012). Interacting threats that result from deforestation, such as habitat loss, habitat degradation, habitat isolation, changes in biology, and interactions of species, may result in the decline of individual species (Fischer & Lindenmayer, 2007). The biggest driver of deforestation in Africa is agricultural expansion (commercial & subsistence) (Kissinger et al., 2012). Other drivers in Africa include fuelwood collection and charcoal production, mining, infrastructure, and urban expansion (Kissinger et al., 2012). In addition to this, forests are more likely to be cleared in locations where economic returns are high (Busch & Ferretti-Gallon, 2017). Globally, timber activity, local forest management, and demography are not consistently associated with higher or lower deforestation rates (Busch & Ferretti-Gallon, 2017). Different drivers of deforestation may also lead to different patterns of deforestation (Slattery & Fenner, 2021).

Habitat fragmentation is the process that deforestation breaks up continued patches of habitat into smaller patches (Broadbent et al., 2008). Deforestation along infrastructure and built-up is often a driver for this process (Broadbent et al., 2008). Consequences of habitat fragmentation can be understood by (1) looking at how deforestation patterns affect individual species and by (2) looking at landscape patterns and how these may affect a multitude of species (Fischer & Lindenmayer, 2007). When looking at landscape patterns, subjects to focus on include the amount and condition of native vegetation, and connectivity (Fischer & Lindenmayer, 2007). It is important to look at the amount and condition of native vegetation as many species prefer larger forest patches over smaller patches, even though smaller areas complement larger areas (Fischer & Lindenmayer, 2007). Similarly, the alteration of core area and edge length also affect species differently (Slattery & Fenner, 2018). Additionally, it is important to study the connectivity in a landscape as this shows the restrictions of animals within the landscape. Landscape connectivity is based on the human perspective on the connectedness of the landscape, thus might disregard the complexity of interactions between environmental factors (Fischer & Lindenmayer, 2007). Connectivity could be decreased when the distance between patches increases and the number of (small) patches increases, creating higher difficulty for species to move within the landscape (Fischer & Lindenmayer, 2007). To effectively measure fragmentation, a multitude of indicators are needed (Table 1)

Indicators	Measures
%forest	Amount of forest
C/A index	Condition of forest
Number of patches + average patch size	Condition of forest/connectivity
Edge density	Condition of forest

Table 1: Indicators

Opportunities for landscape connectivity

To protect landscape connectivity, different measures can be taken. One option would be to introduce conservation corridors (Hofman et al., 2018). These are long stretches of nature that connect natural core areas, aiding the dispersal of populations and contributing to the survival of a species (Hofman et al., 2018). Another option could be to apply more sustainable agriculture in the area, using the land-sharing/land-sparing model (Desquilbet et al., 2017). With land sparing, zones are implemented for biodiversity and agriculture (Desquilbet et al., 2017), as has been done in the Yayu Biosphere Reserve. On the other hand, land sharing allows for more environmentally friendly but less productive agricultural systems, such as coffee plantations (Desquilbet et al., 2017). Important to notice is that

biodiversity and agriculture can enhance each other as biodiversity provides services such as pollination and climate-resilient soils (Garibaldi et al., 2016).

Remote sensing

Remote sensing is defined as the acquisition of information on phenomena, objects, or materials by a recording device that is not physically in contact with the studied phenomena, objects, or materials (Khorram et al., 2012). In an environmental context, this often refers to technologies that record electromagnetic energy that areas and objects on the Earth's surface, oceans, or atmosphere emit (Khorram et al., 2012). This is mainly done through instruments mounted on airplanes and satellites, which allows us to study processes at places that are hard to reach for humans and study large areas of land. Satellites use different colour bands to gather information. Depending on the studied object, different coloured bands need to be used to gather data (Khorram et al., 2012). Remote sensing through satellites has a large variety of applications, such as assessing ecosystem health, atmospheric composition, seismic activity, surface vegetation, polar ice fluctuations, humanitarian violations, and the subsurface (Khorram et al., 2012). Specifically, remote sensing can be used to aid nature conservation (Liu et al., 2001; Zemanova et al., 2017), for example, through the identification of corridors (Bleyhl et al., 2017).

In addition to the ability to research remote areas and large study areas, changes in an area can be traced back to the 1970s. Since the first LANDSAT satellite has been launched in the 1970s, the LANDSAT satellites have been a continuous source of information on Earth's phenomena, objects, or materials (Khorram et al., 2012). This can help nature conservation by identifying temporal trends in land cover in a studied area. An interesting example of such research is research by Liu et al. (2001) on the ecological degradation of the Wolong Nature Reserve. They used remote sensing to assess deforestation and fragmentation of the nature reserve before and after its founding and found that deforestation rates and fragmentation increased after the founding. This provided information on the need for effective management of protected nature areas. This shows the importance of monitoring land cover change in protected nature areas. Moreover, it is important to monitor the land cover in areas that are known to be home to endangered species to aid in its conservation (Liu et al., 2001; Zemanova et al., 2017).

Biosphere Reserves

The Yayu Biosphere Reserve belongs to a worldwide network of biosphere reserves of UNESCO. The concept of the biosphere reserves is closely related to the concept of sustainability science as they both share an integrative problem-solving approach and considers everyone's knowledge (Reed, 2019). Biosphere reserves are sites for the "[conservation] of natural resources and of the genetic material they contain", while they are also sites of scientific research, monitoring, education, and training (UNESCO 1970, 1971). The reserves consist of three zones (Figure 1), the core area is a protected area in which nature should be left undisturbed, the buffer zone is an area that can be used for purposes that maintain the values of the core area (e.g. recreation and education), and the transition zone that allows for more intense human activities (Batisse, 1986). These zones allow for experimentation and understanding of the effects that human activities have on the biosphere (Reed, 2019).

Nature conservation in Ethiopia has shown to be challenging (Abebe & Bekele, 2018). In countries like Ethiopia, protected areas are often referred to as "paper parks" since the pressure to exploit the areas outweighs the drive to protect the natural areas (Abebe & Bekele, 2018). Often, people have been living in the protected areas before they received such status, and as such the residents are not willing to change their way of life (Abebe & Bekele, 2018). The biosphere reserves seek a different approach;

working together with the residents as well as allowing for restricted use of the land (Reed, 2019). Research suggests that human exploitation is still a threat in the Yayu Biosphere Reserve as agricultural expansion and logging activities continue (Fekensa et al., 2016; Abera et al., 2021). However, the effectiveness of the biosphere reserve in protecting the forest cover is still unknown.
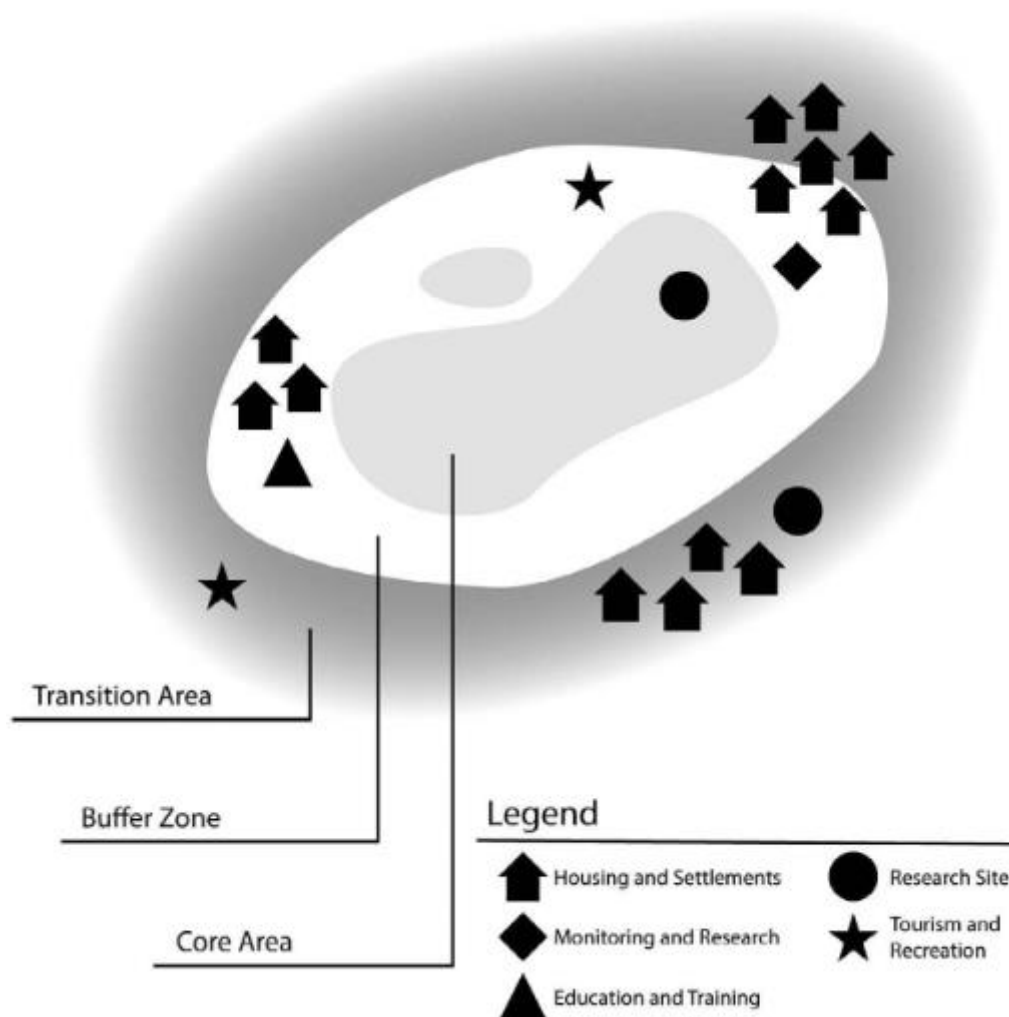

Figure 1: The layout of a biosphere reserve. Here the three different zones represent three different levels of protection. The core area in which nature is completely protected from perturbation, the transition zone that allows for some human intervention, and the buffer area that balances the values of the transition zone with the values of the core area (Batisse, 1986). Figure retrieved from Reed (2019).

Conceptual model

Figure 2 shows this research's conceptual framework. Here, land use change (e.g. agricultural expansion) leads to deforestation, which also leads to forest fragmentation. As a consequence, the length of edges increases, and the core area decreases, as well as a loss of landscape connectivity (Broadbent et al., 2017). A combination of deforestation, increasing edge to interior ratio, and loss of landscape connectivity lead to habitat loss (Kuusari et al., 2009). To protect species, conservation can aid in halting land use change in certain areas. Monitoring changes in the environment can aid in effective species conservation (Liu et al., 2001). Remote sensing can be used to monitor deforestation and forest fragmentation (Hylander et al., 2013), providing information on how a change in forest cover could impact species (Slattery & Fenner, 2021). This is why this research focuses on monitoring trends

of deforestation in Southwestern Ethiopia and the implications this could have on large mammals. With this information, recommendations can be made on conservation measures considering landscape connectivity for large mammals.
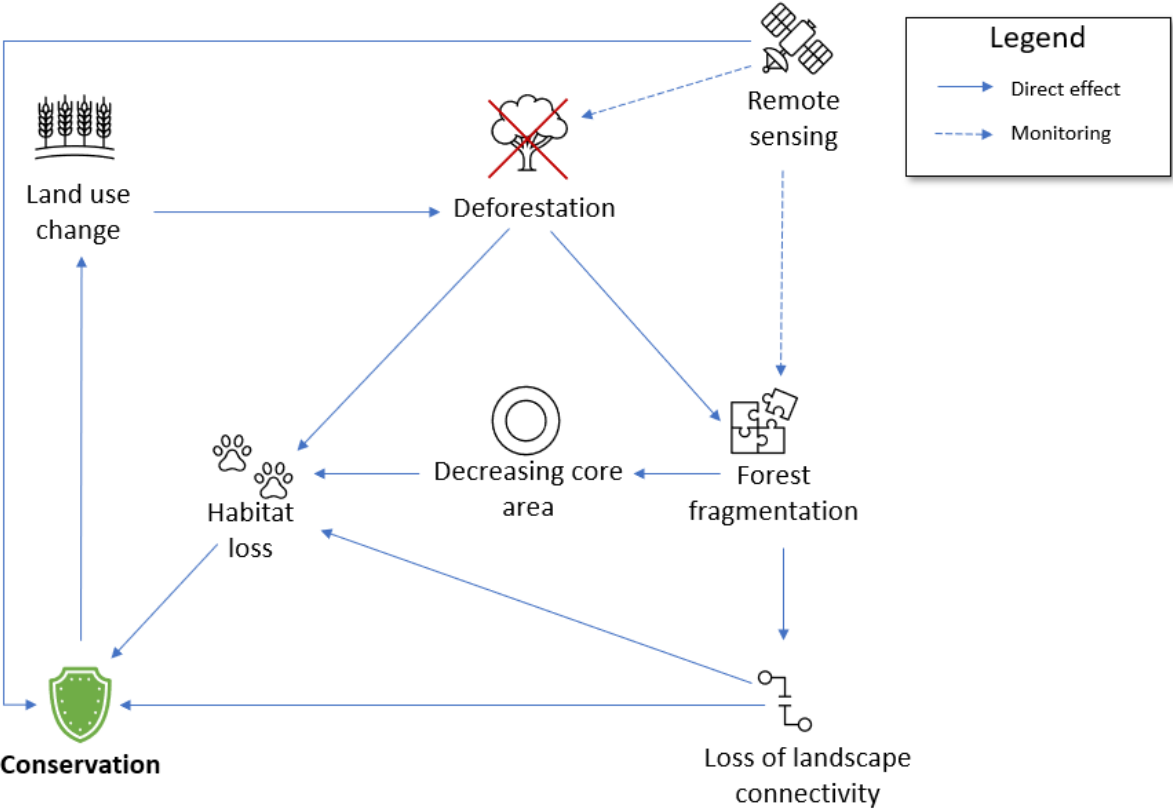

Figure 2: Conceptual model land use change, deforestation, and landscape connectivity

Research framework

This research is based on both deforestation and forest fragmentation (see Figure 3). This is done through the creation of forest cover maps using satellite images of the years 1973-2019, which is then succeeded by the calculation of deforestation and forest fragmentation indicators. To measure deforestation, the indicator percentage of forest cover in the landscape (%forest) is used. Indicators used to measure forest fragmentation are the C/A index (core area index), mean patch area, edge density, LPI (largest patch index), and the number of patches. These calculations are done for the whole study area, the Yayu Biosphere Reserve, and the area outside of Yayu. These results will then lead to conservation measures in the context of landscape connectivity for large mammals.
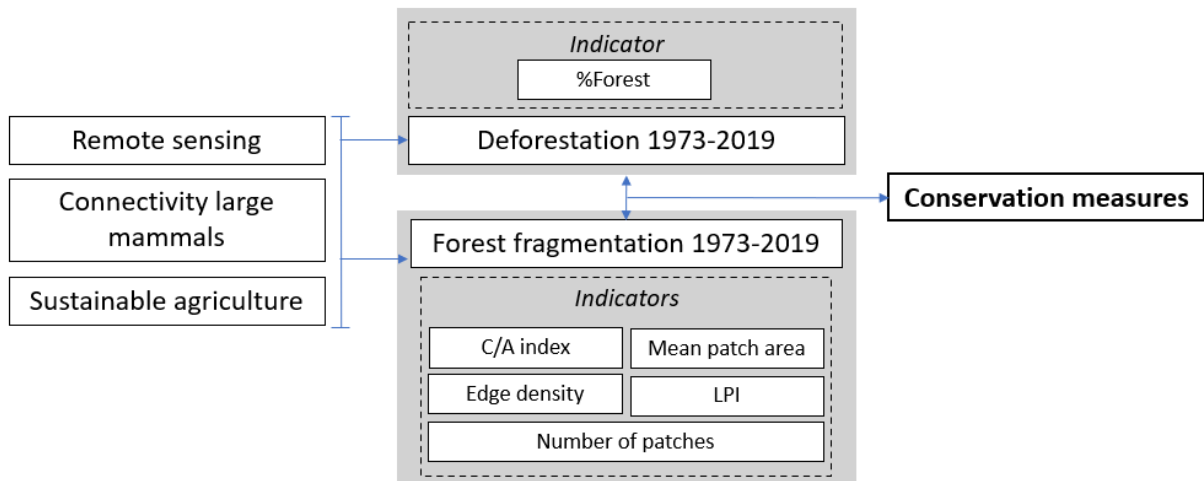
Figure 3: Research framework

Methods

Research area

The research area is located in the Afromontane Mountains in Southwestern Ethiopia and entails the Yayu Biosphere Reserve and an area that might be interesting for biosphere conservation (Ine Dorresteijn, personal communication, 07-02-2021) (see Figure 4). The study area can be found between (35.0161, 7.0458) and (37.04579, 8.7651). The Yayu biosphere reserve was founded in 2010 to preserve the biodiversity in this hotspot (UNESCO, 2019). The Yayu Biosphere Reserve is an important gene pool for several plant species and agricultural purposes (Gole et al., 2019). The biosphere also has the highest abundance of wild coffee in Ethiopia (Gole, 2003). Maintaining genetic variation is important for coffee crop development (Gole et al, 2019).
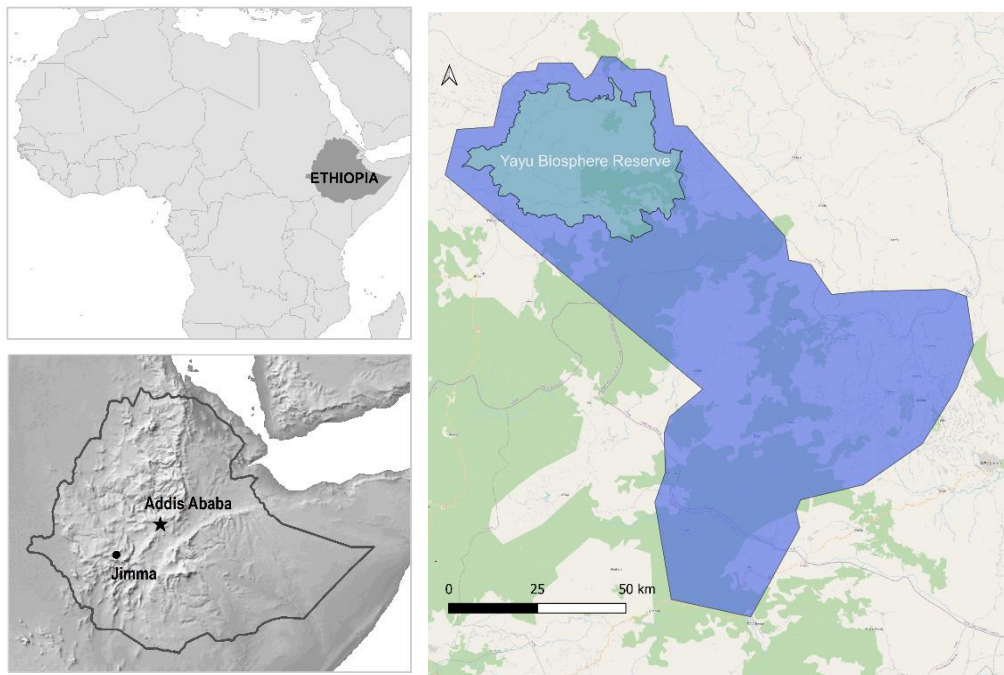

Figure 4:Map of the study area. Showing the location of Ethiopia, the location of the Afromontane forest (Jimma), the study area (dark blue polygon) and the Yayu Biosphere Reserve (in light blue). Received from Patríccia Rodrigues (personal communication, 02-03-2021) and altered.

11

The Afromontane Mountains in Southwestern Ethiopia are known as the origin of the coffee plant (Coffea arabica), which can be found in the wild. Nowadays, this area is still responsible for 45% of the country's coffee production (Kufa, 2012). Moreover, coffee is the country's main source of foreign currency, making it an important cash crop (Ango et al., 2020). As the coffee plant prefers shade, these plants are traditionally grown in forests, aiding the conservation of the forest area (Hylander et al., 2013). However, forest degradation still occurs in these areas as smaller trees, shrubs, and lianas are cut down (Hylander et al., 2013). In the Afromontane Mountains, deforestation has been an ongoing process since 1973 (Hylander et al., 2013) and even before (Ango et al., 2020). Deforestation rates are especially high above the coffee-growing heights (Hylander et al., 2013). Drivers for deforestation in Ethiopia include conversion to agriculture and wood and timber collection (Dibaba et al., 2020) with underlying drivers of national policies, institutional instability, agricultural stagnation, poverty, and demographic pressure (Ango et al., 2020).

Data preparation

Forest cover data has been collected using remote sensing. To do this, Google Earth Engine (GEE), an open-access cloud platform for earth observation analysis, has been used to retrieve satellite images and to analyse forest/non-forest cover. To analyse historic deforestation in Southwestern Ethiopia, satellite images of 1973-1984-1995-2001-2010-2019 were used. This is also in accordance with Hylander et al (2013) who researched deforestation in the Bonga and Goma-Gera areas which partly coincides with the study area. Different satellites were used to get the best images possible for the time periods researched. The satellites used in this study are also in accordance with Hylander et al. (2013). Different time periods were used because of the difference in cloud cover. January to March was the preferred time period to find satellite images as this is the dry season in Ethiopia (Hylander et al., 2013). Due to similarity in solar reflectance, it was preferred to use images that were taken in a similar time period (Khorram et al., 2012). When this was not possible, the time period searched in was extended (e.g. 2001).

Year	Satellite	Time period images were taken from
1973	LANDSAT 1	1 - 15 Feb 1973
1984	LANDSAT 5	1 Dec 1984 – 31 Mar 1985
1995	LANDSAT 5	1 Dec 1994 – 31 Mar 1995
2001	LANDSAT 7	1 Jan 2001 – 12 Dec 2001
2010	LANDSAT 5	1 Dec 2009 – 31 Mar 2010
2019	LANDSAT 8	1 Jan 2019 – 31 Mar 2019

Table 2: LANDSAT images used to identify forest cover in which year

Forest cover maps were created using GEE through unsupervised classification (Appendix 1 & 2). Several steps were undertaken to do this. First, images were selected that had less than 5% cloud cover and were within the preferred time period. Second, a composite was made of the different images for further analysis. Third, an unsupervised classification tool was used to create 10 classes (Hylander et al., 2013). These were then manually identified as "forest", "non-forest" or "both". "Forest" areas were all areas that clearly contained tall vegetation, including coffee plantations. "Non-forest" areas were all areas that contained open areas such as agriculture or built-up areas. Classes were identified as "both" when they contained categories that were considered as forest and non-forest, for example, a class that contains both agriculture and forest. This process was then repeated for the classes that were both forest and non-forest until they were all identified correctly. For most images, three repetitions were necessary until the images were deemed correct. For 1973 and 2019, however, four repetitions were needed. Then the resulting raster was saved to Google Drive to be able to further

analyse them using the programme R. The maps were also checked for their validity using maps that Hylander et al. (2013) created for part of the research area by visually comparing the borders (appendix 3). Only the forest cover map of 2019 was visually compared with the most recent satellite image provided by GEE to validate the map (appendix 3).

To prepare the land cover for further quantitative and qualitative analysis, different steps were undertaken (appendix 4). Firstly, forest and non-forest patched smaller than 1ha were converted to the other class. This was done to prevent overestimation of forest cover and to compensate for misidentified non-forest areas (Hylander et al., 2013). Secondly, a data set on water bodies in Ethiopia (ICPAC_IGAD_UNOSAT, 2017) was used to correctly classify these water bodies by classifying these areas as non-forest. This was done because GEE had difficulties with correctly identifying water bodies as non-forest areas. Thirdly, the boundaries of the study area, the Yayu Biosphere Reserve, and the area outside the reserve were used to create different maps for these areas. All data outside these areas were identified as NA.

Analysis of forest cover change

For quantitative and qualitative assessment of forest cover change, two more calculations were done using the R software. Firstly, the forest cover of the study area was calculated for all studied years (Table 2) in absolute numbers (ha) and in part of the landscape (%forest). Second, forest cover change maps were made for the combinations 1973-1984, 1984-1995, 1995-2001, 2001-2010, 2010-2019 & 1973-2019.

The different forest cover maps were then qualitatively analysed, while the change in forest cover was quantitatively assessed. All different maps were analysed for areas of deforestation or reforestation and these areas were also numbered. In addition, the location of reforestation and deforestation was also noted (i.e. along the forest edges, in the core areas, or amongst small forest patches). For the forest cover, a regression analysis was performed using Excel. The trend was deemed significant when $\alpha < 0.05$.

Analysis of forest fragmentation

Different indicators were calculated using the R package SpatialMetrics (Hesselbarth et al., 2019). The indicators, C/A index (core area index), average patch size, edge density, and LPI (largest patch index), were chosen because they are good indicators for forest fragmentation (McGarigal, 2015). For the C/A index, the edge depth was needed for calculations. In correspondence with Rodrigues et al. (2019), a depth of 100m was chosen. After this, a regression analysis was performed using excel on the indicators.

Comparison of Yayu and area outside the reserve

The same steps were undertaken for the reserve and the area outside for the forest cover and forest fragmentation, and the results were compared to each other for the area within the reserve and outside the reserve. Deforestation and reforestation patterns were analysed for the Yayu Biosphere Reserve by numbering the areas. Then regression analyses were performed for the deforestation and forest fragmentation. The significance of the trend, the steepness of the trend, and the values of indicators were compared between the two areas. Assessment of the effectiveness of the reserve was based on qualitative analysis of forest cover change and forest fragmentation of 2010-2019. Values of the indicators were compared and the reforestation and deforestation patterns were visually analysed.

Results

Deforestation

During the studied time period, forest cover in the study area decreased (Figure 5A). Between 1973 and 2019, the forest cover decreased by 11.1% from 58.02% cover in 1973 to 51.31% in 2019 (Table 3). The largest decrease can be found between 1973-1984 (-8.27%) and 2001-2010 (-11.1%), while the biggest increase occurred between 2010 and 2019 (12%; Table 3; Figure 5A)

	1973	1984	1995	2001	2010	2019
Total study area						
Forest (ha)	575632	528018	532401	511312	454545	509024
Non-forest (ha)	416420	464034	459651	480740	537506	483028
Part forest of landscape (%)	58.02	53.22	53.66	51.53	45.81	51.31
Forest cover change since 1973		-8.27	-7.51	-11.19	-21.04	-11.57
Forest cover change since the last measurement		-8.27	0.83	-3.97	-11.10	12.01
Yayu						
Forest (ha)	110679	91855	88960	90786	86218	97367
Non-forest (ha)	56339	75162	78058	76232	80799	69650
Part forest of landscape (%)	66.27	55.00	53.26	53.26	51.62	58.29
Forest cover change since 1973		-17.01	-19.63	-17.99	-22.11	-12.04
Forest cover change since the last measurement		-17.01	-3.16	2.05	-5.02	12.92
Outside reserve						
Forest (ha)	464951	436163	443446	420524	368326	412001
Non-forest (ha)	358717	387505	380222	403144	455342	411667
Part forest of landscape (%)	56.45	52.95	53.83	51.05	44.71	49.97
Forest cover change since 1973		-6.20	-4.64	-9.57	-20.80	-11.48
Forest cover change since the last measurement		-6.20	1.66	-5.16	-12.42	11.77

Table 3: forest cover change from 1973 to 2019 for the study area, the Yayu Biosphere Reserve, and the area outside the reserve
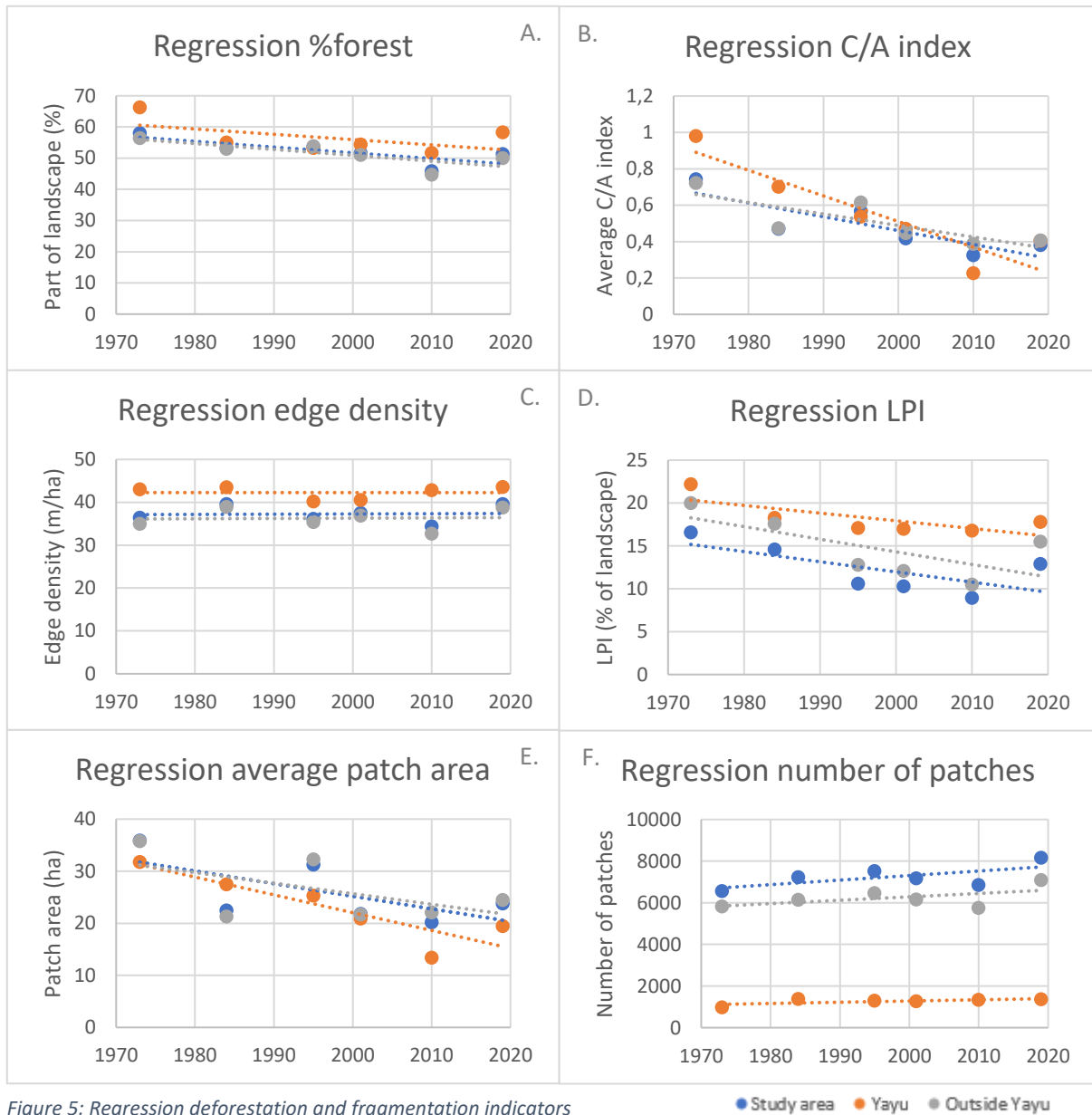
Figure 5: Regression deforestation and fragmentation indicators

	Research area			Yayu			Outside Yayu		
	Coefficient	SE	R2	Coefficient	SE	R2	Coefficient	SE	R2
%Forest	-0.184	0.074	0.608	-0.170	0.132	0.293	-0.188	0.074	0.619
C/A index	-0.007*	0.002	0.718	-0.014*	0.003	0.828	-0.006	0.002	0.647
Edge density	0.006	0.061	0.02	-0.0002	0.045	6*10-6	0.007	0.071	0.023
LPI	-0.119	0.063	0.471	-0.089	0.041	0.547	-0.147	0.078	0.471
Average patch size	-0.242	0.140	0.428	-0.342*	0.090	0.782	-0.203	0.154	0.302
Number of patches	21.78	12.36	0.471	5.836	3.211	0.312	16.31	12.10	0.452

Table 4: Coefficient, R2, and SE for the regression of the fragmentation indicators. *P<0.05 **P<0.01.
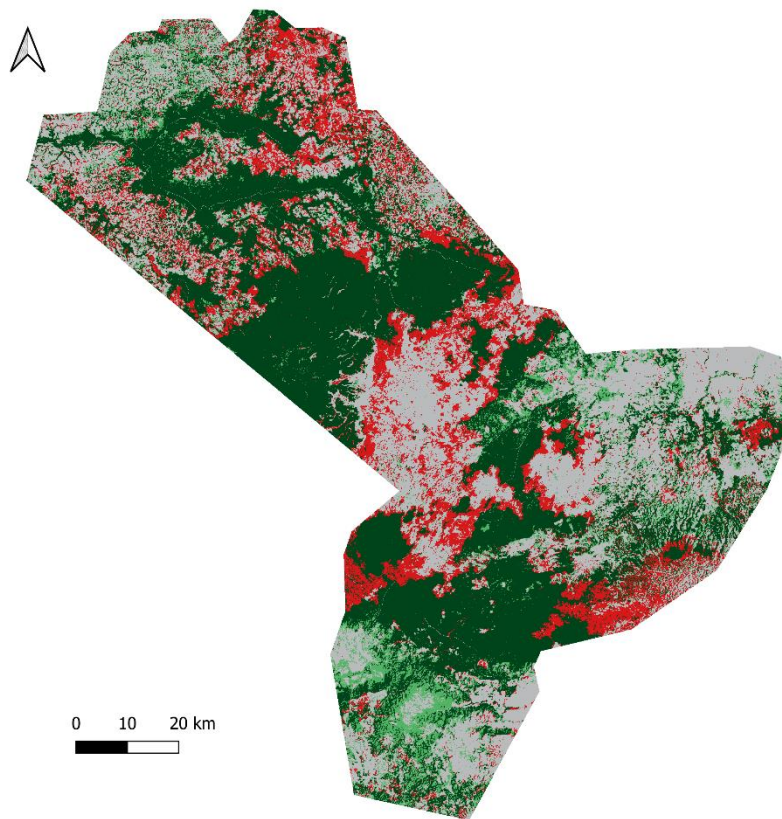
Figure 6). Deforestation mainly took place along the forest edge and in smaller forest patches. The Yayu area (Figure 6, area 1) shows high forest loss in the smaller patches outside the continuous forest. Some reforestation can be found at the edges of the continuous forest. It is also visible that the core areas within large forest patches remain largely intact (Figure 6, area 2). In the Sidamo/Sentama area (Figure 6, area 3) large-scale deforestation can be identified. Here, small patches have been removed from the landscape and the deforestation expands to the edges of the large continuous forest patches next to the area. This results in forest patches being cut off around Sidamo (Figure 6, area 4) and Boto (Figure 6, area 5). In the Agaro area (Figure 6, area 6), reforestation can be seen among small patches, resulting in a mosaic of patches. In the Sentama area (Figure 6, area 7), similar patterns can be found as in Sidamo (Figure 6, area 3) deforestation can be found around the edges of the forest and in the smaller forest patches. Lastly, the Seka Chekorsa area (Figure 6, area 8) is an area that shows clear reforestation around the forest edges.
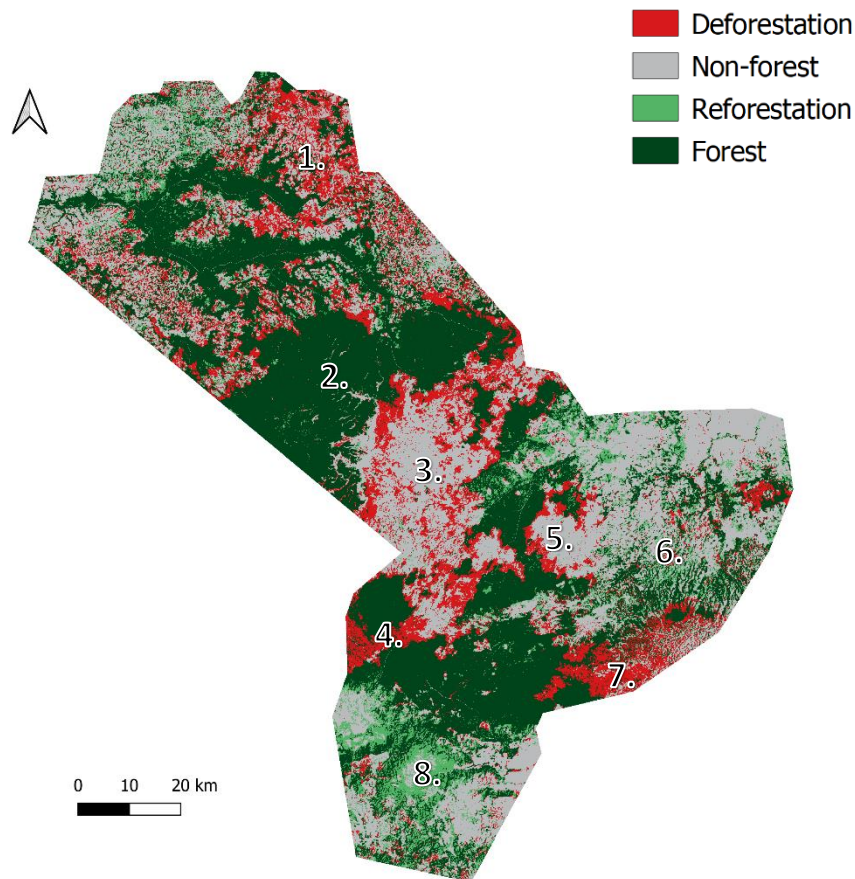
Figure 6: Forest cover change study area 1973-2020. The numbers in the map represent areas that are interesting to consider for deforestation/reforestation purposes. Areas 1,3,4,5, & 7 are areas of high deforestation, while areas 6 & 8 show noticeable reforestation. Area 2 shows how well preserved the core areas in the study area are, even though they are still shrinking in size due to deforestation along the edges.

When observing the changes in deforestation and deforestation through the decades, it can be noted that patterns have developed differently throughout the study area (Figure 7). The periods of 1973-1984 and 2001-2010 were periods that know high deforestation in the whole study area (Table 1). From 1973 to 1984, areas 1,3 & 7 (Figure 7A) were the deforestation hotspots (i.e. areas with high deforestation). Especially the smaller forest patches in Yayu (Figure 7A, area 1) disappeared, during this period. In areas 3 and 7 (Figure 7A), deforestation focused on both the smaller forest patches and the edges of continuous forest. Area 8 shows reforestation around the forest edges between 1973-1984 (Figure 7A). From 2001 to 2010, deforestation hotspots spread throughout the study area (Figure 7D). In areas 1, 3, and 7 of Figure 7D, deforestation still occurs among the small forest patches in the landscape. Especially in area 7 of Figure 7D, deforestation has also spread to the edges. Also, other deforestation hotspots can be identified. Area 4, 6 &8 (Figure 7D) have now also become deforestation hotspots (Figure 7D). In area 4, a large forest patch is cut off from a larger continuous forest patch (Figure 7D). The period of 2010-2019 seems to be a period of reforestation (Figure 7E). Deforestation still occurs in 1,5 and 7 of Figure 7E, but in other areas reforestation can be identified (areas 6 & 8 in Figure 7E), especially at the edges of the forest.

Not only is the forest cover decreasing in the area, but fragmentation indicators also suggest that fragmentation is occurring in the study area (Figure 5; Table 4). The C/A index shows a significant decreasing trend (Figure 5B; Table 4), which indicates that the cores areas are decreasing in size. Other indicators show trends that are not statistically significant (Figure 5C-F; Table 4). Edge density remained similar throughout the studied period (Figure 5C; Table 4). The LPI (Figure 5D; Table 4) and

the average patch (Figure 5E; Table 4) seem to be decreasing during the time period while the number of patches (Figure 5F; Table 4) is increasing.
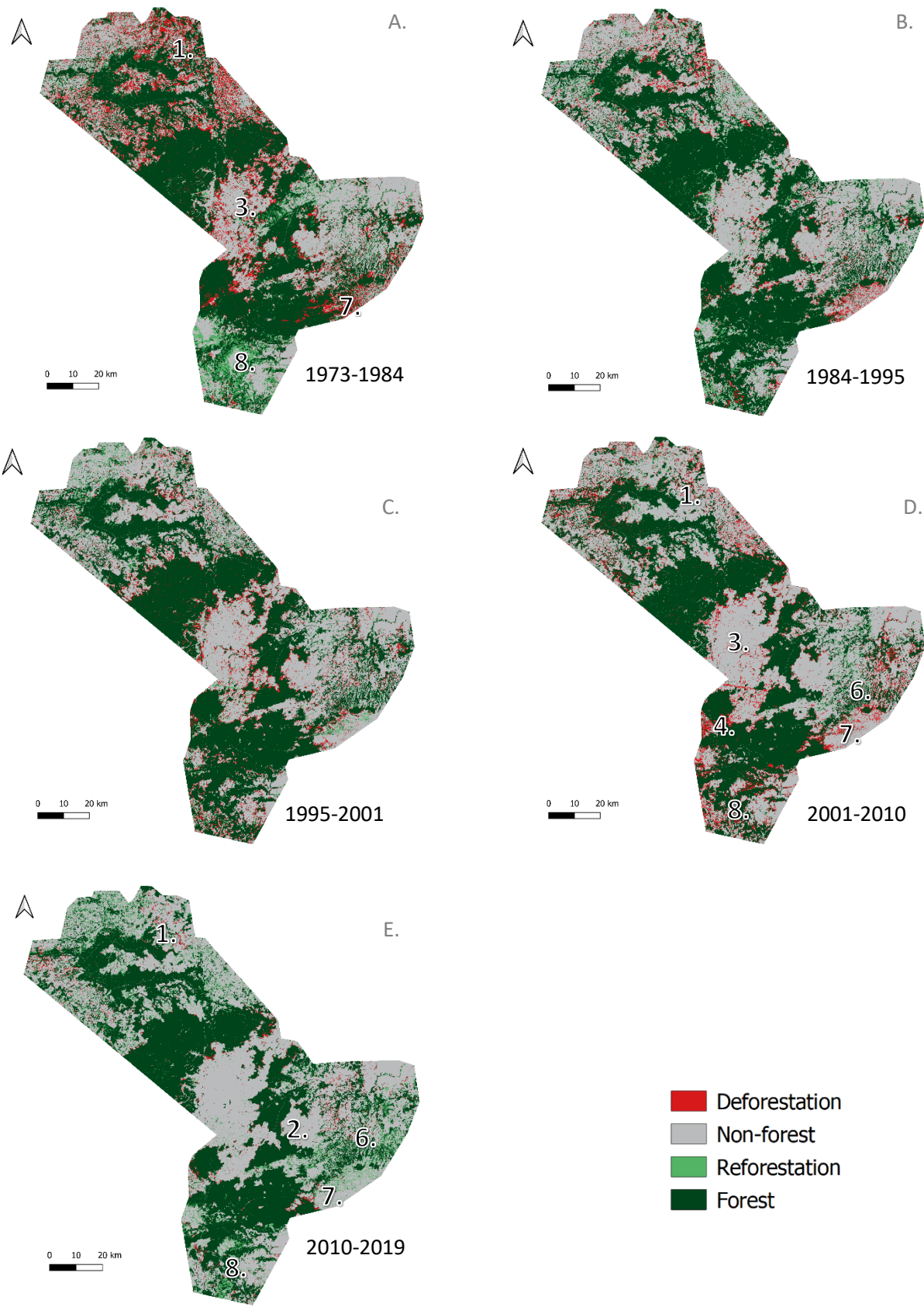
Figure 7: Change in forest cover through the different decadess

Differences between the Yayu Biosphere Reserve and the area outside the reserve

Both within the biosphere reserve as in the area outside, forest cover decreased between 1973-2019 (Figure 5; Table 4). In 1973, the forest within the Yayu Biosphere Reserve covered 66.27% of the landscape while this reduced to 58.29% in 2020 (Table 3). The forest decreased from 56.45% of the total landscape in 1973 to 49.97% in 2019 for the area outside the reserve (Table 3). The biggest loss in forest cover was between 1973 and 1984 when the forest cover decreased by -17.01% (Table 3). For the area outside of the reserve, the biggest forest cover loss occurred between 2001-2010 with -12.42% (Table 3). Between 2010 and 2020, the forest cover greatly increased from 51.62% of the landscape to 58.29% (+12.9%; Table 3). During this period the forest cover outside of the reserve also increased by 11.77% (Table 3). The Yayu Biosphere Reserve still shows to have a higher relative forest cover than the area outside in 2019.

Most of the deforestation in the Yayu area occurred before the establishment of the Biosphere Reserve in 2010. During this period, most deforestation occurred around the forest edges and among the smaller forest patches (Figure 8). Since the establishment of the reserve, it can be seen that much reforestation has taken place around the forest edges (e.g. are A in Figure 8). Even though deforestation can still be found in the area, along the forest patches and among smaller patches (Figure 8, area C), the continuous forest remains intact (Figure 8, area B).
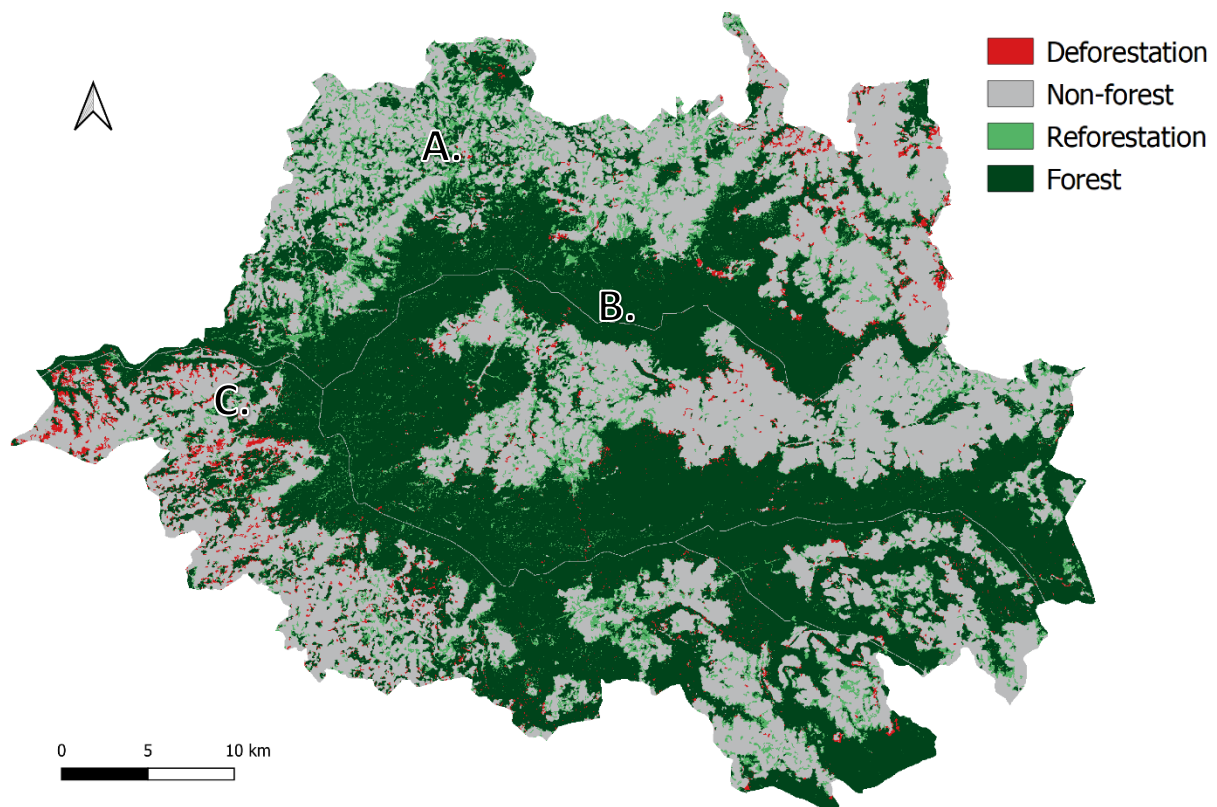

Figure 8: Forest cover change Yayu Biosphere Reserve 2010-2020. Area A shows reforestation along the edge. Area B shows that the core area within the reserve stays intact. Area C shows an area that remains high in deforestation after the establishment of the reserve.

The C/A index and the average size of patches suggest that the Yayu biosphere reserve has become more fragmented between 1973 and 2019 (Figure 5; Table 4). These indicators suggest that the patches have decreased in size. The average size of patches only shows to be significantly decreasing in the Yayu Biosphere Reserve, as the area outside the reserve does not show any significant trends The C/A index shows a steeper decreasing slope in the Yayu area (-0.014 %patch/yr) than in the area

outside (-0.006 %patch/yr; Table 4). Similar to the area outside the reserve, a positive trend can be observed for the number of patches in the Yayu Biosphere Reserve, while edge density remains similar and the average patch size and the LPI show to be decreasing.

After the establishment of the Yayu Biosphere Reserve, the fragmentation seems reduced. The C/A index, the LPI, and the average patch size increased. This indicates that forest patches have increased in size. In addition, the edge density and the number of patches also increased, however, this coincides with an increase in forest area.

Discussion

As biodiversity and biodiversity hotspots worldwide are threatened by the effects of land use, such as habitat loss and habitat fragmentation, it is important to understand the ongoing processes and their effect on the environment (Dixo et al., 2019; IBPES, 2019; Schnell et al., 2013; Zemanova et al., 2017). It is especially important to gain a better understanding of deforestation and forest fragmentation patterns in biodiversity hotspots, such as the Afromontane mountains in Southwestern Ethiopia, and how this might impact wildlife (Desquilbet et al., 2021; Zemanova et al., 2017). This research aimed to identify deforestation and forest fragmentation in Southwestern Ethiopia from 1973-2019 and what recommendations can be given in the context of large mammal conservation. In addition, this research aimed to assess the effects of the establishment of the Yayu Biosphere Reserve in Southwestern Ethiopia. This was done creating forest cover maps and analysing those for deforestation and forest fragmentation patterns. It was found that forest cover decreased between 1973 and 2019 for the whole study area, but the forest cover showed recovery in the last decade. The Yayu Biosphere Reserve aided in the protection of the core area but small patches were still lost after establishment, possibly affecting the connectivity of the landscape for large mammals.

Decreasing forest cover

Deforestation in the study area did not show a constant rate. Between 1973-2019, forest cover showed a decline, with the biggest declines in the periods 1973-1984 and 2001-2010. This is also in line with the findings of Ango et al. (2020) for the Gera region. Research has shown that deforestation in Southwestern Ethiopia is mainly driven by intensification and expansion of agricultural activities, as well as logging activities (Tadesse, 2003; Gole et al., 2019). Reforestation occurred between 2010 and 2019 (**Fout! Verwijzingsbron niet gevonden.**). Hylander et al. (2013) suggested that forest cover change in Southwestern Ethiopia is often heavily influenced by coffee; from planting coffee shade trees outside of the forest patches to the conversion of grazing or agricultural lands to semi-forest coffee plantations. This might also be the reason why reforestation can be found in area 6 of Figure 6, which is an area known for its coffee plantations. Coffee plantations enhance forest retention, as coffee requires shade, but above coffee-growing altitude deforestation is widespread (Hylander et al., 2013).

Even though reforestation has been widely occurring in the study area during the last 10 years, it is important to take into consideration what kind of vegetation has been planted. In the study area, Eucalyptus trees and coffee trees are commodities that are known to impact the biodiversity in the area (Cordero-Rivera et al., 2017; Hylander et al., 2013). Yet it is hard to distinguish the difference between forests and plantations using remote sensing (Hylander et al., 2013). Therefore, ground research must be done on what kind of trees are used for reforestation in the study area. Moreover, as the forest has only recovered during the last decade, the effects this might have on large mammals may not be visible yet. Future research could focus on researching the effects of deforestation in Southwestern Ethiopia on large mammal abundance.

Forest fragmentation in Southwestern Ethiopia

Forest fragmentation has occurred throughout the study region between 1973 and 2019, however, only the core areas showed a significant decreasing trend. This could have a big impact on specialised core species as their habitat is decreasing in size (Desquilbet et al., 2021). The reason why no other regression showed to be significant, could be because only 6 data points were used for analysis. This could be because only 6 data points were used for the analysis, making the results of the statistical tests a bit weaker. However, the forest cover map of the study area (Figure 6) shows that forest patches have been cut off in the region, suggesting that forest fragmentation is taking place. Important to notice is that small forest patches are disappearing throughout the study area. From the satellite images, it could be observed that this mainly occurred on a large scale in the agricultural area. Here, they seem to remove forest patches between the agricultural fields for expansion of agricultural activities (Ango et al., 2014). This, however, harms the connectivity of the landscape for large mammals as they may use those patches as stepping stones to move around in the area (Fischer et al., 2010). Core areas remained largely intact but decreased in size, possibly because few main roads are going through continuous forests (Abebe et al., 2018). This is a large driver of forest fragmentation in Brazil; large-scale deforestation occurs directly next to the road; expansion of the infrastructure leads to forest fragmentation (Taubert et al., 2018). For Ethiopia, it is recommendable to prevent the expansion of roads into remote forests (Abebe et al., 2021).

Yayu

The establishment of the Yayu Biosphere Reserve seems to have halted deforestation and forest fragmentation within the area. Overall, the forest cover, patch size, and core area were higher in 2019 compared to 2010, suggesting that forest unification is occurring in the area. Even though deforestation has been observed in the area, widespread reforestation efforts have contributed to a netto increase in forest cover in the area. A similar trend, however, has been observed outside the study area as well, which is why this process cannot be attributed to the establishment of the reserve only.

Deforestation was found to be very low in the core area of the Yayu Biosphere Reserve, while deforestation still occurred among small forest patches and along the forest edges. Similar patterns were found by Beyene (2014). Yet, they did not observe reforestation during the period of their research (2000-2013). This could suggest that reforestation efforts in the Biosphere Reserve only started after 2013. However, a more detailed annual study of deforestation in the Yayu Biosphere Reserve from the establishment to the present is needed to understand reforestation efforts within the reserve.

Not only the Yayu Biosphere Reserve showed successes in the conservation of forests, but also the Monarch Butterfly Biosphere Reserve in Mexico showed that forests in the core area were well protected and even gained forest cover (Manzo-Delgado et al., 2014). Similarly, Sasanifar et al. (2019) found that nitrogen, potassium, and organic carbon content was higher in the protected areas of Arasbaran Biosphere Reserve in Northwest Iran, suggesting that biosphere reserves are successful in nature conservation. However, challenges remain for biosphere reserves worldwide (Reed & Price, 2019). First, there seems to be a lack of understanding between different levels of the government considering the objectives of biosphere reserves (Moreira-Muñoz et al., 2019). Second, there is limited participation by local inhabitants (Gole et al., 2019). The latter also showed to be an issue in biosphere reserves in Ethiopia (Gole et al., 2019). Better participation of locals in the protection of the biosphere is among the key components for biosphere reserves (Reed, 2019) and should prove useful in the effectiveness of the conservation of nature (Abebe & Bekele, 2018).

Recommendations

Based upon the discussion above, I provide several recommendations for the study area:

1. Adopt an approach that includes both land sharing and land sparing in the study area
2. Conserve small forest patches between agricultural areas to conserve connectivity of the landscape for large mammals
3. Reconnect important core areas through corridors

For the protection of biodiversity in the study area, it is important to consider the implementation of land sharing and land sparing agriculture in the area (Desquilbet et al., 2021). Both biodiversity and agricultural activities are crucial for the livelihood in the study area, for example, 90% of the residents in the Yayu Biosphere Reserve are reliant on agriculture (Fakensa et al., 2018) and the natural resources in the area (Gole et al., 2019). It's crucial that these are united. Moreover, as different species prefer edges while others prefer core areas, the edge-core ratio must stay in balance (Desquilbet et al., 2021). The land-sparing land-sharing principle could help balance the edge-core ratio. Area A in Figure 9 would be an interesting area for land sparing. In this area, a large agricultural area can be found, which is surrounded by continuous forest. The continuous forests must not get fragmented any further, as the core areas are crucial for biodiversity (Desquilbet et al., 2021). Agricultural land also needs to be protected from unsustainable use by its users (Fekensa et al., 2018). Areas B and C in Figure 9 would be interesting for land sharing as these areas have a mosaic of forest patches. Firstly, this would benefit the connectivity of the landscape for large mammals (Fischer et al., 2010). Secondly, the forest patches between the fields provide many ecosystem services to the resident and should be protected (Shumi et al., 2019). Residents have already shown a preference for land sharing agriculture (Jiren et al., 2020), thus such measures are likely to be supported.
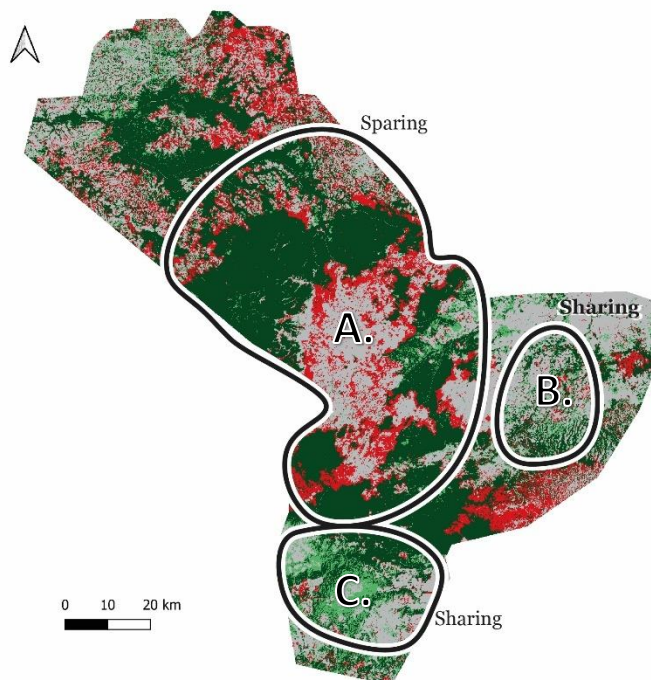

Figure 9: Land sparing (A) and land sharing (B&C) areas in the study area based on forest cover change 1973-2019

Small forest patches between agricultural patches have shown to be essential for landscape connectivity (Fischer et al., 2010) and the livelihood of residents (Shumi et al., 2019). Therefore, it is recommended that these are largely forest patches are protected. Literature suggests that residents are often unaware of the overexploitation of woody species in the area (Shumi et al., 2019), thus raising awareness among residents could help to protect the smaller forest patches.

Landscape corridors have shown to be a useful tool in increasing the connectivity of a landscape (Hofman et al., 2018). Five areas have been identified as areas that where reforestation efforts with native vegetation could help connect forest large forest patches (Figure 10). These are areas where forest patches are nearly cut off or already cut off but can be still be reconnected.
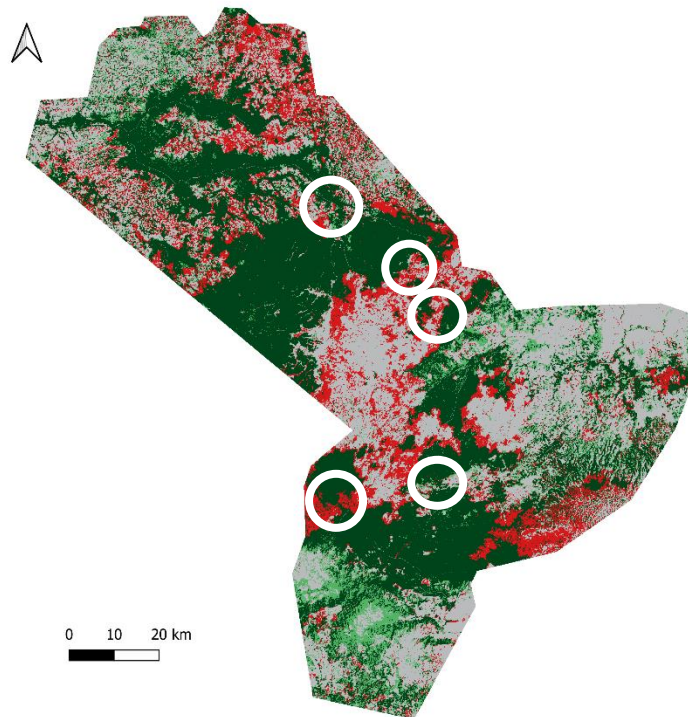

Figure 10: Areas in the study area to consider for corridors (white circles)

Limitations

As this research is heavily reliant on the maps created, the quality of the maps is essential for the results of this research. To do this, good-quality satellite images are of great importance (Khorram et al., 2012). Especially for the earlier images (i.e. 1973), this was a challenge as the quality of LANDSAT1 was much lower than the newer LANDSATs. This might have caused a differently mapped forest cover than it was in reality. The validation of past forest cover might also be a challenge as there were no forest points or old photographs available. Validation was done using maps provided by Hylander (personal communication, [date]), however, this could only be done for region B in Figure 9 as the maps only covered that part of the study region, possibly leading to the overestimation or underestimation of forest cover. Lastly, the method used for classification can greatly influence the accuracy of the maps (Khorram et al., 2012). For example, one programme could be more user-friendly than the other or the decision of whether to use supervised or unsupervised classification could result in a different bias.

Another limitation of this research was the limited amount of data points that could be used for linear regression. Perhaps a different study with more data points, such as annual data points or bi-annual data points. Another suggestion could be to test for non-linear regressions as well

Results of this research could aid in further research concerning forest cover in the area, such as research concerning quantitative research on landscape connectivity of large mammals. The maps created during this research could also be used as validation for research on forest cover on a grander scale than this research has done. Larger maps of the area are necessary when one wants to research the connectivity of the landscape. There is also a need to research what kind of vegetation can be found in reforested areas, as the kind of vegetation can greatly influence the quality of the environment (Hylander et al., 2013). The scripts created in this research can also be reused for other research, making it faster to do a similar kind of research.

Conclusion

This research aimed to *assess what conservation measures can be proposed when considering landscape connectivity for large mammals in Southwestern Ethiopia*. This was done by identifying deforestation fragmentation patterns in Southwestern Ethiopia from 1973 to 2019 and by assessing the effects of the establishment of the Yayu Biosphere Reserve on deforestation and forest fragmentation. Based on the quantitative and qualitative assessment of forest cover in the study area, it can be concluded that reforestation efforts can turn the tides of a negative trend of forest loss and forest fragmentation. Results indicate that forest cover in Southwestern Ethiopia increased between 2010 and 2019 after decades of decline. Because of this late increase in forest cover, only the core area showed a significant decreasing trend, while the other indicators showed no significant trend. A qualitative assessment of the forest cover in Yayu suggests that the establishment of the reserve has a positive effect on forest cover in the area, but a quantitative analysis of annual forest cover is needed to support this.

Despite the absence of significant trends in deforestation and fragmentation indicators, practitioners should still consider efforts to increase the connectivity and to halt deforestation of the landscape as there is no certainty that recent reforestation efforts will have an immediate positive effect on biodiversity. This can be done by the implementation of land sharing and sparing zones in the area and the reconnection of forest patches by reforesting disconnected or nearly disconnected large forest patches. Moreover, an effort needs to be made to protect the small forest patches in the agricultural landscape.

This research identified deforestation and forest fragmentation from the 1970s to the present in the Afromontane mountains in Ethiopia, one of the world's biodiversity hotspots. Moreover, it identified patterns of deforestation and forest fragmentation and adds empirical evidence to the contribution of biosphere reserves in the contribution to nature conservation. In addition, the scripts that were created in this study could be reused for similar research in the future, reducing the time needed to create forest cover maps and their analysis.

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Appendix 1: Code unsupervised classification using GEE (1984-2019)

```
// Advice! Use /* and */ to comment text, especially useful for the reclassification part as you do not
know how often you need to iterate to create a correct map.

//// Data Preparation ////

// Import study area
var StudyArea = ee.FeatureCollection("users/soostdi/New_srudy_area");

// Import collection
var collection = ee.ImageCollection('LANDSAT/LC08/C01/T1')
            .filterDate('2020-01-01','2020-12-31')
            .filterBounds(StudyArea);
//print(collection);

//Create composite
var composite = ee.Algorithms.Landsat.simpleComposite({
  collection:collection,
  cloudScoreRange:5,
  percentile:75,
  asFloat:true
  });
//print(composite);

// Use these bands for prediction.
var bands = ['B2', 'B3', 'B4', 'B5', 'B6', 'B7', 'B10', 'B11'];

// Add layer to map
Map.setCenter(36.14224165757499,8.139329789820918, 9);
Map.addLayer(composite, {bands:['B4', 'B3', 'B2'], max:0.3,gamma:1.1},'Satellite image');


//// Unsupervised classification ////

// Make the training dataset.
var training = composite.sample({
  region: StudyArea,
  scale: 30,
  numPixels: 5000
});

// Instantiate the clusterer and train it.
var clusterer = ee.Clusterer.wekaKMeans(10).train(training);

// Cluster the input using the trained clusterer.
var result = composite.cluster(clusterer);
var result_clip = result.clip(StudyArea);
```

```javascript
// Display classification.
Map.addLayer(result_clip, {min:0, max:9, palette: [
    'YellowGreen', //0
    'Gold', //1
    'ForestGreen', //2
    'Aquamarine', //3
    'DodgerBlue', //4
    'DarkOrange', //5
    'FireBrick', //6
    'Fuchsia', //7
    'LemonChiffon', //8
    'DarkSlateBlue', //9
    ]},
'clusters');


//// Reclass clusters ////

// Define from to values
var fromForest = [5,7,8]; //original values
var toForest = [1,1,1];//new values

var fromBoth = [2,3];
var toBoth = [1,1];

// Remap the pixel values and rename
var Forest =  result_clip.remap(fromForest, toForest, 0, 'cluster').rename('Forest');
var Both = result_clip.remap(fromBoth, toBoth, 0, 'cluster').rename('Both');

// Create image
var image = ee.Image.cat([Forest]);
Map.addLayer(image.clip(StudyArea),{palette: ['grey','green']},"merged clusters");


//// Iterate for doubtful areas ////

//Create input of doubtful areas
var mask = composite;
var masked_composite = mask.mask(Both.eq(1));

// Make the training dataset.
var training2 = masked_composite.sample({
  region: StudyArea,
  scale: 30,
  numPixels: 5000
});

// Instantiate the clusterer and train it.
var clusterer2 = ee.Clusterer.wekaKMeans(10).train(training2);
```

```javascript
// Cluster the input using the trained clusterer.
var result2 = composite.cluster(clusterer2);
var result2_clip = result2.clip(StudyArea);
var masked_result2 = result2_clip.mask(Both.eq(1));

// Display the clusters with random colors.
Map.addLayer(masked_result2, {min:0, max:9, palette: [
    'YellowGreen', //0
    'Gold', //1
    'ForestGreen', //2
    'Aquamarine', //3
    'DodgerBlue', //4
    'DarkOrange', //5
    'FireBrick', //6
    'Fuchsia', //7
    'LemonChiffon', //8
    'DarkSlateBlue', //9
    ]},
'new clusters');

//Convert to forest
var fromForest2 = [0,1,6,7,8,9];
var toForest2 = [1,1,1,1,1,1];

var fromBoth2 = [3,4,5];
var toBoth2 = [1,1,1];

var Forest2 =  masked_result2.remap(fromForest2, toForest2, 0, 'cluster').rename('Forest');
var Both2 = masked_result2.remap(fromBoth2, toBoth2, 0, 'cluster').rename('Both');


////Iterate again for doubtful areas////

//Create input of doubtful areas
var masked2_composite = mask.mask(Both2.eq(1));

// Make the training dataset.
var training3 = masked2_composite.sample({
  region: StudyArea,
  scale: 30,
  numPixels: 5000
});

// Instantiate the clusterer and train it.
var clusterer3 = ee.Clusterer.wekaKMeans(10).train(training3);

// Cluster the input using the trained clusterer.
var result3 = composite.cluster(clusterer3);
var result3_clip = result3.clip(StudyArea);
```

```javascript
var masked_result3 = result3_clip.mask(Both2.eq(1));

// Display the clusters with random colors.
Map.addLayer(masked_result3, {min:0, max:9, palette: [
    'YellowGreen', //0
    'Gold', //1
    'ForestGreen', //2
    'Aquamarine', //3
    'DodgerBlue', //4
    'DarkOrange', //5
    'FireBrick', //6
    'Fuchsia', //7
    'LemonChiffon', //8
    'DarkSlateBlue', //9
    ]},
'newest clusters');

//Convert to forest
var fromForest3 = [0,1,2,3,8];
var toForest3 = [1,1,1,1,1];

var Forest3 = masked_result3.remap(fromForest3, toForest3, 0, 'cluster').rename('Forest');

// Add forest, forest2 and forest3 together
var combinedForest = ee.ImageCollection([Forest,Forest2,Forest3]);
var Forested = combinedForest.reduce(ee.Reducer.max());

Map.addLayer(Forested.clip(StudyArea),{palette: ['grey','green']},"Forest cover");

//// Exporting images ////

// Export image to drive
Export.image.toDrive({
  image: Forested,
  description: 'forest_2020_New',
  scale: 30,
  region: StudyArea,
  fileFormat: 'GeoTIFF',
  skipEmptyTiles:true,
  formatOptions: {cloudOptimized: true}
});

// Export image to asset
/*Export.image.toAsset({
  image: Forested,
  description: 'Unsupervised_class_2020',
  assetId: 'Unsupervised_class_2020',
  scale:30,
  region: StudyArea,
```

});*/

Appendix 2: Code unsupervised classification (1973)

////Prepare data////

```
// Define a region in which to generate a sample of the input.
var StudyArea = ee.Geometry.Polygon(
    [[[35.01614302480194, 8.765073235177475],
     [35.01614302480194, 7.045797077749566],
     [37.02664107167694, 7.045797077749566],
     [37.02664107167694, 8.765073235177475]]]);

//Import best images 1973
var img1 = ee.Image('LANDSAT/LM01/C01/T2/LM01_182054_19730201');
var img2 = ee.Image('LANDSAT/LM01/C01/T2/LM01_182055_19730201');
var img3 = ee.Image('LANDSAT/LM01/C01/T2/LM01_183054_19730202');
var img4 = ee.Image('LANDSAT/LM01/C01/T2/LM01_183055_19730202');

//get information on projection
var repr1 = img1.reproject({
 crs:img1.projection(),
 scale:30
 });
var repr2 = img2.reproject({
 crs:img2.projection(),
 scale:30
 });
var repr3 = img3.reproject({
 crs:img3.projection(),
 scale:30
 });
var repr4 = img4.reproject({
 crs:img4.projection(),
 scale:30
 });

//Create composite
var collection = ee.ImageCollection([repr1,repr2,repr3,repr4]);
var composite = collection.reduce(ee.Reducer.median());
//print(composite);

//Add LANDSAT image to map
Map.setCenter(36.0213920482, 7.905435505, 8);
Map.addLayer(composite, {bands:['B4_median', 'B5_median', 'B6_median']},'Satellite image');


//// Unsupervised classification ////

// Make the training dataset.
var training = composite.sample({
 region: StudyArea,
 scale: 30,
 numPixels: 5000
```

```
});

// Instantiate the clusterer and train it.
var clusterer = ee.Clusterer.wekaKMeans(12).train(training);

// Cluster the input using the trained clusterer.
var result = composite.cluster(clusterer);
var result_clip = result.clip(StudyArea);

// Display the clusters with random colors.
Map.addLayer(result_clip, {min:0, max:11, palette: [
   'YellowGreen', //0
   'Gold', //1
   'ForestGreen', //2
   'Aquamarine', //3
   'DodgerBlue', //4
   'DarkOrange', //5
   'FireBrick', //6
   'Fuchsia', //7
   'LemonChiffon', //8
   'DarkSlateBlue', //9
   'HotPink', //10
   'DarkGray', //11
   ]},
'clusters');

////Reclass clusters////
var fromForest = [0,4,5,7]; //original values
var toForest = [1,1,1,1]; //new values

//Identify doubtful classes
var fromBoth = [2,6,9,10];
var toBoth = [1,1,1,1];

//Remap the pixel values and rename
var Forest =  result_clip.remap(fromForest, toForest, 0, 'cluster').rename('Forest');
var Both = result_clip.remap(fromBoth, toBoth, 0, 'cluster').rename('Both');

//Create image
var image = Forest;
//print(image);

//// Iterate for doubtful areas ////
//Create input of doubtful areas
var mask = composite;
var masked_composite = mask.mask(Both.eq(1));

// Make the training dataset.
var training2 = masked_composite.sample({
 region: StudyArea,
 scale: 30,
 numPixels: 5000
```

```
});

// Instantiate the clusterer and train it.
var clusterer2 = ee.Clusterer.wekaKMeans(12).train(training2);

// Cluster the input using the trained clusterer.
var result2 = composite.cluster(clusterer2);
var result2_clip = result2.clip(StudyArea);
var masked_result2= result2_clip.mask(Both.eq(1));

// Display the clusters with random colors.
Map.addLayer(masked_result2, {min:0, max:11, palette: [
   'YellowGreen', //0
   'Gold', //1
   'ForestGreen', //2
   'Aquamarine', //3
   'DodgerBlue', //4
   'DarkOrange', //5
   'FireBrick', //6
   'Fuchsia', //7
   'LemonChiffon', //8
   'DarkSlateBlue', //9
   'HotPink', //10
   'DarkGray', //11
   ]},
'new clusters');


//Convert to forest
var fromForest2 = [8];
var toForest2 = [1];

var Forest2 =  masked_result2.remap(fromForest2, toForest2, 0, 'cluster').rename('Forest');
/*
//add forest and forest2 together
var combinedForest = ee.ImageCollection([Forest,Forest2]);
var Forested = combinedForest.reduce(ee.Reducer.max());

Map.addLayer(Forested.clip(StudyArea),{palette: ['grey','green']},"Forest cover");

*/

//// Iterate AGAIN for doubtful areas ////
var fromBoth2= [3,4,5,9];
var toBoth2 = [1,1,1,1];

var Both2= masked_result2.remap(fromBoth2, toBoth2, 0, 'cluster').rename('Both');

//Create input of doubtful areas
var masked2_composite = mask.mask(Both2.eq(1));

// Make the training dataset.
```

```
var training3 = masked2_composite.sample({
  region: StudyArea,
  scale: 30,
  numPixels: 5000
});

// Instantiate the clusterer and train it.
var clusterer3 = ee.Clusterer.wekaKMeans(12).train(training3);

// Cluster the input using the trained clusterer.
var result3 = composite.cluster(clusterer3);
var result3_clip = result3.clip(StudyArea);
var masked_result3= result3_clip.mask(Both2.eq(1));

// Display the clusters with random colors.
Map.addLayer(masked_result3, {min:0, max:11, palette: [
    'YellowGreen', //0
    'Gold', //1
    'ForestGreen', //2
    'Aquamarine', //3
    'DodgerBlue', //4
    'DarkOrange', //5
    'FireBrick', //6
    'Fuchsia', //7
    'LemonChiffon', //8
    'DarkSlateBlue', //9
    'HotPink', //10
    'DarkGray', //11
    ]},
'newest clusters');


//Convert to forest
var fromForest3 = [3,4,5,6,8,11];
var toForest3 = [1,1,1,1,1,1];

var Forest3 =  masked_result3.remap(fromForest3, toForest3, 0, 'cluster').rename('Forest');
/*
//add forest, forest2 and forest3 together
var combinedForest = ee.ImageCollection([Forest,Forest2,Forest3]);
var Forested = combinedForest.reduce(ee.Reducer.max());

Map.addLayer(Forested.clip(StudyArea),{palette: ['grey','green']},"Forest cover");

*/


//// Iterate AGAIN AGAIN for doubtful areas ////
var fromBoth3= [7,10];
var toBoth3 = [1,1];

var Both3= masked_result3.remap(fromBoth3, toBoth3, 0, 'cluster').rename('Both');
```

```
//Create input of doubtful areas
var masked3_composite = mask.mask(Both3.eq(1));

// Make the training dataset.
var training4 = masked3_composite.sample({
  region: StudyArea,
  scale: 30,
  numPixels: 5000
});

// Instantiate the clusterer and train it.
var clusterer4 = ee.Clusterer.wekaKMeans(5).train(training4);

// Cluster the input using the trained clusterer.
var result4 = composite.cluster(clusterer4);
var result4_clip = result4.clip(StudyArea);
var masked_result4= result4_clip.mask(Both3.eq(1));

// Display the clusters with random colors.
Map.addLayer(masked_result4, {min:0, max:4, palette: [
    'YellowGreen', //0
    'Gold', //1
    'ForestGreen', //2
    'Aquamarine', //3
    'DodgerBlue', //4
    ]},
'newer newest clusters');

//Convert to forest
var fromForest4 = [1,2,3,4];
var toForest4 = [1,1,1,1];

var Forest4 =  masked_result4.remap(fromForest4, toForest4, 0, 'cluster').rename('Forest');

//add forest, forest2, forest3 & forest 4 together
var combinedForest = ee.ImageCollection([Forest,Forest2,Forest3,Forest4]);
var Forested = combinedForest.reduce(ee.Reducer.max());
var Forested_clip = Forested.clip(StudyArea);

Map.addLayer(Forested_clip,{palette: ['grey','green']},"Forest cover");

//Raster to vector conversion

/*Select forested area
var forest = image.select("Reclassification").eq(1).selfMask();
print(forest);

//Projection
var prj = composite.projection();
var scale = prj.nominalScale();
print (scale);
```

```
//// Exporting ////
/*
//Export image to drive
Export.image.toDrive({
  image: Forested_clip,
  description: 'forest_2020_2',
  scale: 30,
  region: StudyArea,
  fileFormat:'GeoTIFF',
  skipEmptyTiles:true,
  formatOptions: {cloudOptimized: true}
});

//Export image to asset
/*Export.image.toAsset({
  image: Forested_clip,
  description: 'Unsupervised_class_2020',
  assetId: 'Unsupervised_class_2020',
  scale:30,
  region: StudyArea,
  });*/
```

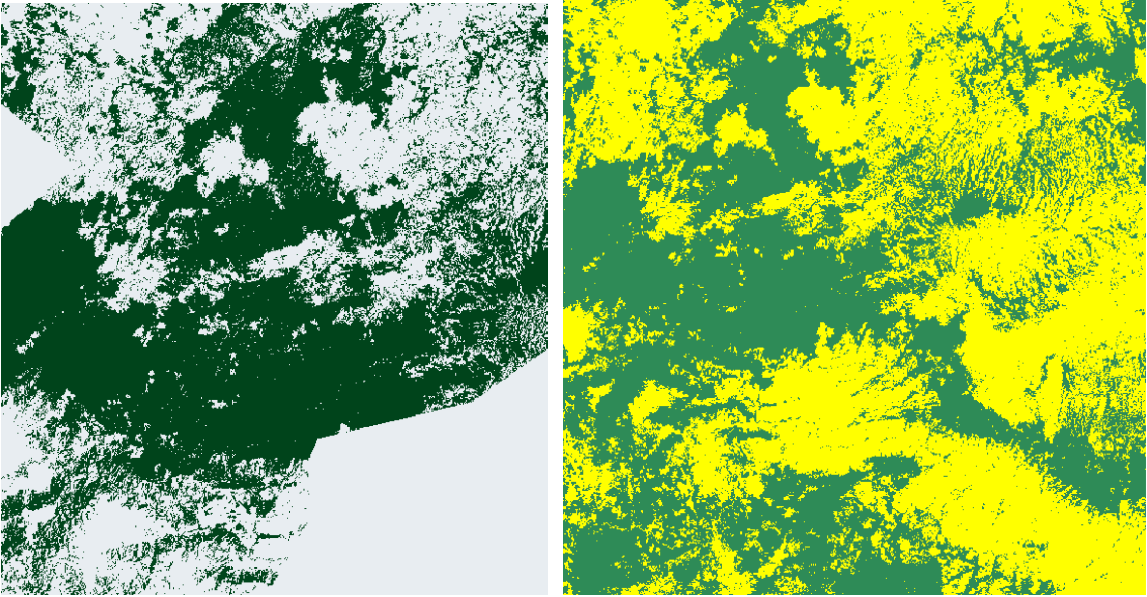# Appendix 3: Validation forest cover maps

Figure 11: Validation 1973. Left part of the map created during this study. On the right Hylander's map (Hylander et al., 2013)
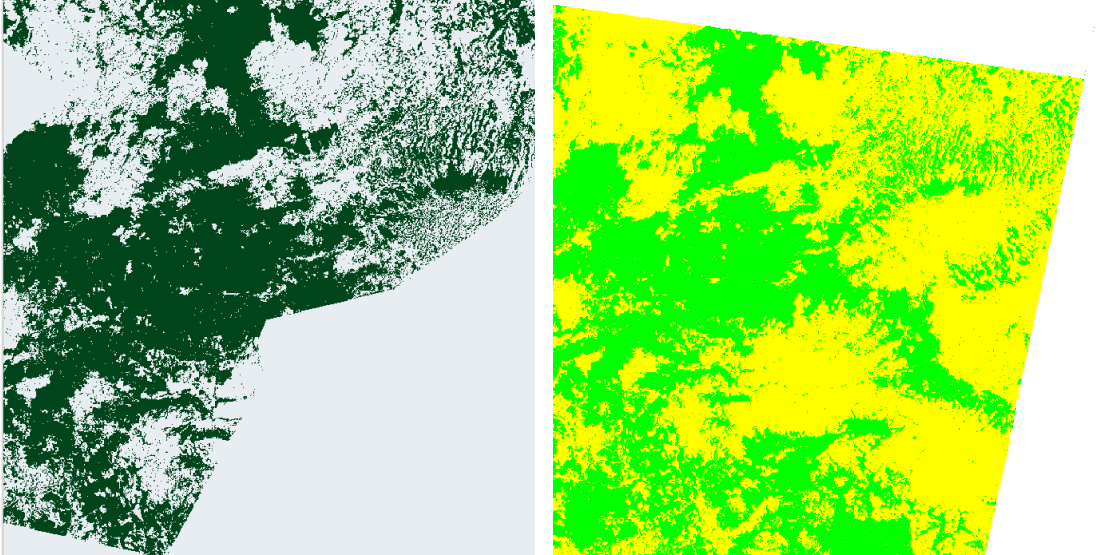

Figure 12: Visual validation of 1984. Left map created during this study. On the right the map created by Hylander et al (2013)
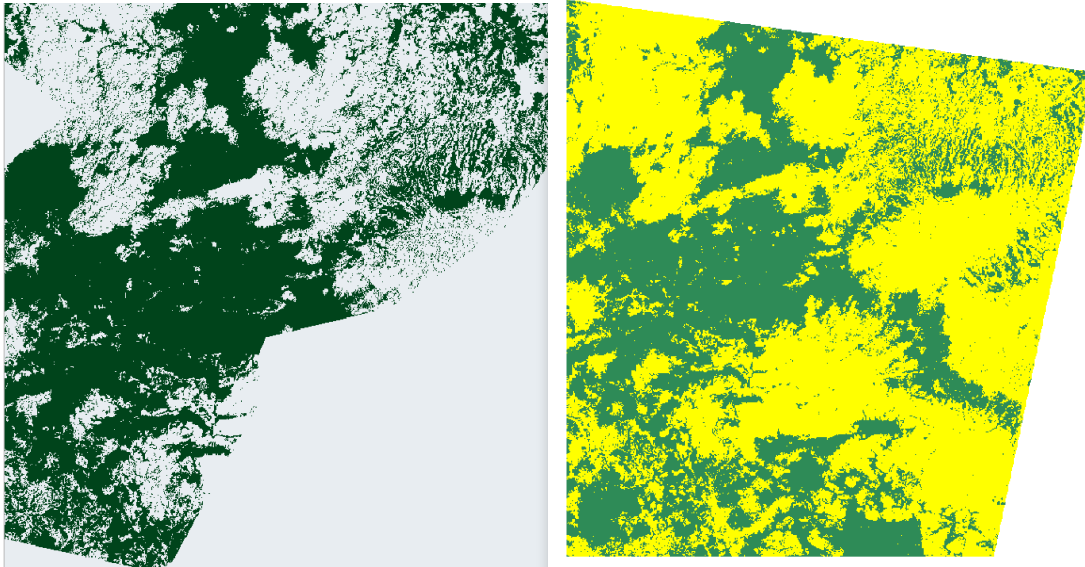
Figure 14: Visual validation of forest cover map 1995. Left the map created in this study. Right the map created by Hylander et al. (2013)
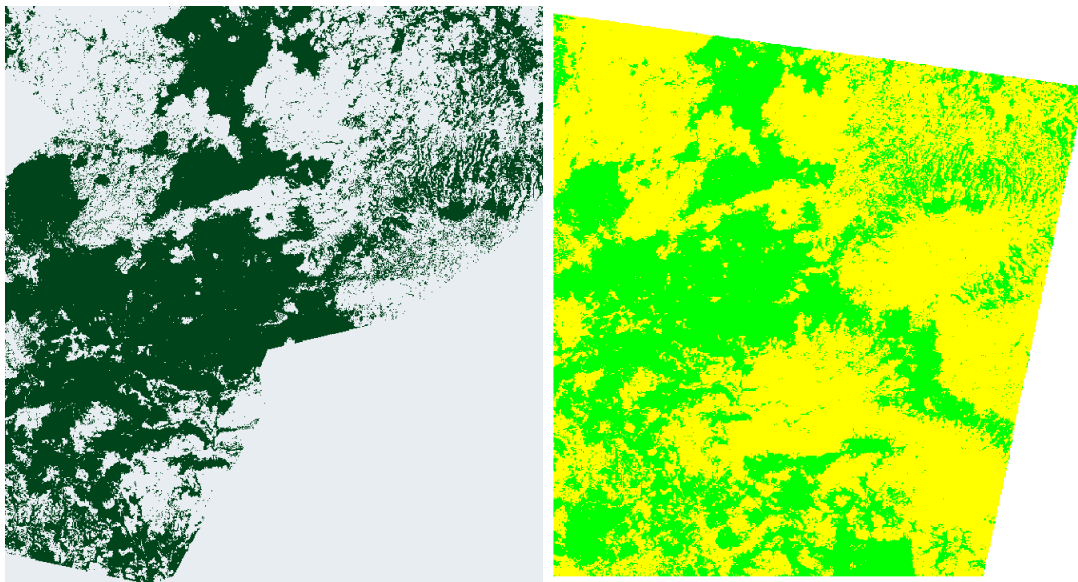

Figure 13:Visual validation of forest cover map 2001. Left the map created during this study and on the right the forest cover map created by Hylander et al. (2013)
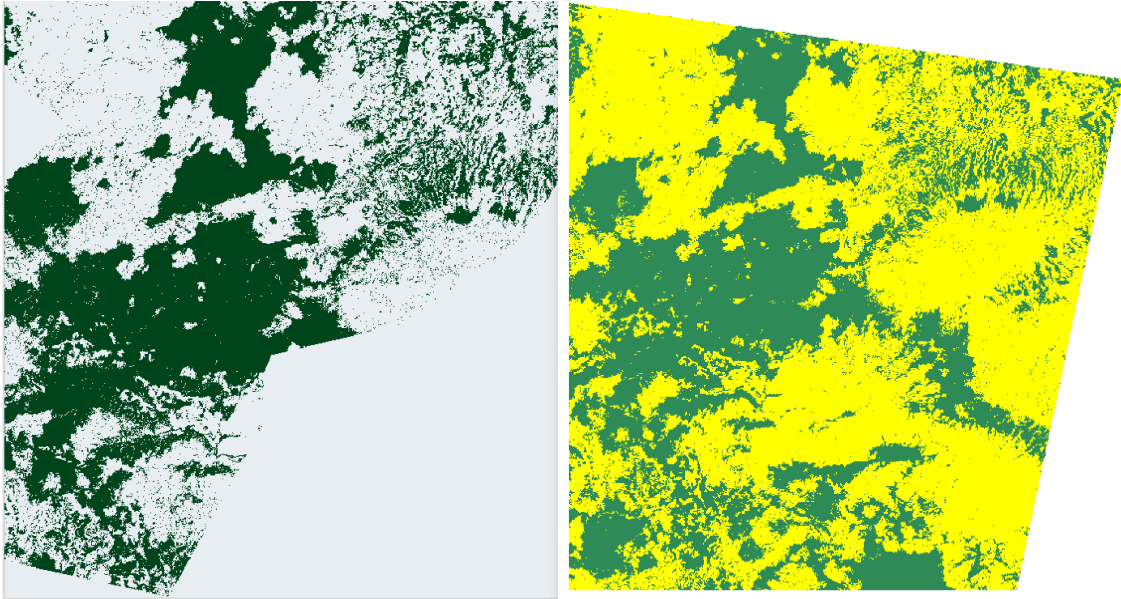
Figure 16: Visual validation of forest cover map 2010. On the left the ma created in this study and on the right the forest cover map created by Hylander et al. (2013)
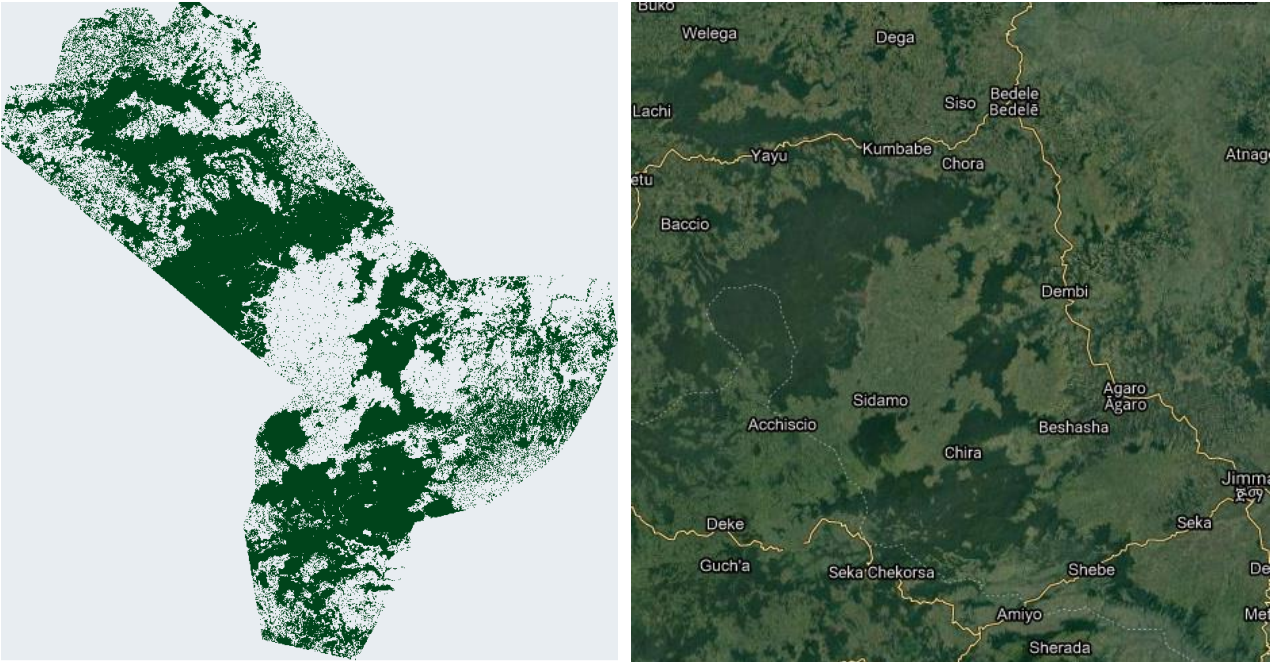

Figure 15: Visual validation of forest cover map 2020. On the left the map of the sdtusy area created during this research. On the right a recent satellite image provided by GEE

Appendix 4: R script

```r
## Install libraries
install.packages('raster')
install.packages('rgdal')
install.packages('devtools')
library(devtools)
install_github('dutri001/bfastSpatial') #Rtools is needed
install.packages('igraph')
install.packages('fieldRS')
install.packages("spatialEco")
install.packages('landscapemetrics')
install.packages('rasterVis')
install.packages('RColorBrewer')
install.packages('ggplot2')

## Call libraries
library(raster)
library(rgdal)
library(bfastSpatial)
library(igraph)
library(sp)
library(fieldRS)
library(spatialEco)
library(landscapemetrics)
library(sf)
library(rasterVis)
library(RColorBrewer)

## Set working directory
setwd("~/SUSD/Master thesis")
## Load data
load("R/Truedata3.RData")
## Load rasters forest cover (geotif)
fc_1973 <- raster("GIS/New_supervised/1973.tif")
fc_1984 <- raster("GIS/New_supervised/1984.tif")
fc_1995 <- raster("GIS/New_supervised/1995.tif")
fc_2001 <- raster("GIS/New_supervised/2001.tif")
fc_2010 <- raster("GIS/New_supervised/2010_2.tif")
fc_2019 <- raster("GIS/New_supervised/2019.tif")
r<-raster(fc_1973)

## Load water bodies (vector)
water <- readOGR("GIS/eth_water_lines_dcw/eth_water_lines_dcw.shp")
# Create raster
water_r<-rasterize(water,r,field= c(1:4070), fun=min, background=NA)
water_r <- extend (water_r,(c(1,1)))
water_r[water_r>0]<-1

## Load study area
aoi <- readOGR("GIS/Files Patricia/New Study Area/studyarea.shp")
yayu <- readOGR("GISFiles Patricia/yayu_zone.shp")
```

```r
outside <- readOGR("GIS/Files Patricia/Outside_Study_Area.shp")

## Rasterize aoi
# change crs
aoi_rprj <- spTransform(aoi,crs(fc_1973))
# Get extent
aoi_ext <- extent (aoi_rprj)
# Create raster
r <- raster(aoi_ext)
res(r) <- res(fc_1973)
aoi_r <- rasterize(aoi_rprj,r,field = 1, fun=min, background=0)
aoi_r <- extend(aoi_r, (c(1,1)))
aoi_r[is.na(aoi_r)]<-0

## Rasterize yayu
# change crs
yayu_rprj<- spTransform(yayu,crs(fc_1973))
# Get extent
yayu_ext <- extent (yayu_rprj)
# Create raster
r <- raster(yayu_ext)
res(r) <- res(fc_1973)
yayu_r <- rasterize(yayu_rprj,r,field = 1, fun=min, background=0)

## Rasterize outside reserve
# change crs
crs(outside)<- crs(fc_1973)
# Get extent
outside_ext <- extent (outside)
# Create raster
r <- raster(outside_ext)
res(r) <- res(fc_1973)
outside_r <- rasterize(outside,r,field = 1, fun=min, background=0)

## Create function for data preparation
sieve <- function(fc){

  ## Remove all NAs from data
  fc[is.na(fc)]<-0

  ## Create logical (True/FALSE) raster
  fc <- as.logical(fc)

  ## Extend rasters to isolate clumps at the edges
  r2 <- extend (fc, (c(1,1)))
  rc <- clump (r2, directions = 4)

  ## Create frequency of unigue IDS of clumps
  f <- freq (rc)
  f <- as.data.frame(f)

  ## Check all clumps that are smaller than 11 pixels (about 1 ha)
```
46

```
str(which(f$count < 11))
str(f$value[which(f$count < 11)])
excludeID <- f$value[which(f$count < 11)]

## Reverse values (0 to 1 and vice versa) for clusters smaller than 11 pixels
fc_sieve <- r2
fc_sieve[rc %in% excludeID] <- !fc_sieve[rc %in% excludeID]
fc_sieve[is.na(fc_sieve)] <- 0

## Remove water
fc_sieve[water_r==1]<-0

## Make all 0s outside study area NA
fc_sieve[aoi_r==0]<-NA

return(fc_sieve)
}

## Perform data preparation
sieve_1973 <- sieve(fc_1973)
sieve_1984 <- sieve(fc_1984)
sieve_1995 <- sieve(fc_1995)
sieve_2001 <- sieve(fc_2001)
sieve_2010 <- sieve(fc_2010)
sieve_2019 <- sieve(fc_2019)

## Crop map to create raster for yayu reserve
get_area <- function (map, intended_area){
  cropped <- crop(map,extent(intended_area))
  cropped [intended_area==0]<-NA
  return(cropped)
}

yayu_1973 <- get_area(sieve_1973,yayu_r)
yayu_1984 <- get_area(sieve_1984,yayu_r)
yayu_1995 <- get_area(sieve_1995,yayu_r)
yayu_2001 <- get_area(sieve_2001,yayu_r)
yayu_2010 <- get_area(sieve_2010,yayu_r)
yayu_2019 <- get_area(sieve_2019,yayu_r)

outs_1973 <- get_area(sieve_1973,outside_r)
outs_1984 <- get_area(sieve_1984,outside_r)
outs_1995 <- get_area(sieve_1995,outside_r)
outs_2001 <- get_area(sieve_2001,outside_r)
outs_2010 <- get_area(sieve_2010,outside_r)
outs_2019 <- get_area(sieve_2019,outside_r)

#### Start analysing fragmentation ####

## Calcute reforestation and deforestation
## Create functions
funn <- function (map_old, map_new){
```

```
  return(map_old+map_new)
}

ref_def <- function (map_old, map_new){
  diff <- overlay(map_old,map_new,
         fun = funn)
  diff[map_old>map_new]<--1
  diff[map_old<map_new]<-1
  return(diff)
}

## Create maps of reforestation/deforestation
d73_84 <- ref_def(sieve_1973, sieve_1984) # 1973-1984
d84_95 <- ref_def(sieve_1984, sieve_1995) # 1984-1995
d95_01 <- ref_def(sieve_1995, sieve_2001) # 1995-2001
d01_10 <- ref_def(sieve_2001, sieve_2010) # 2001-2010
d10_19 <- ref_def(sieve_2010, sieve_2019) # 2010-2019
d73_19 <- ref_def(sieve_1973, sieve_2019) # 1973-2019

yayu_d73_84 <- ref_def(yayu_1973, yayu_1984) # yayu 1973-1984
yayu_d84_95 <- ref_def(yayu_1984, yayu_1995) # yayu 1984-1995
yayu_d95_01 <- ref_def(yayu_1995, yayu_2001) # yayu 1995-2001
yayu_d01_10 <- ref_def(yayu_2001, yayu_2010) # yayu 2001-2010
yayu_d10_19 <- ref_def(yayu_2010, yayu_2019) # yayu 2010-2019
yayu_d73_19 <- ref_def(yayu_1973, yayu_2019) # yayu 1973-2019

## Calculate %forest
per_forest <- function (map){
  freq0 <- freq(map, value=0)
  freq1 <- freq(map, value=1)
  total <- freq0+freq1
  for_lan <- freq1/total*100
  return(for_lan)
}

for_1973 <- per_forest(sieve_1973)
for_1984 <- per_forest(sieve_1984)
for_1995 <- per_forest(sieve_1995)
for_2001 <- per_forest(sieve_2001)
for_2010 <- per_forest(sieve_2010)
for_2019 <- per_forest(sieve_2019)

yayu_for_1973 <- per_forest(yayu_1973)
yayu_for_1984 <- per_forest(yayu_1984)
yayu_for_1995 <- per_forest(yayu_1995)
yayu_for_2001 <- per_forest(yayu_2001)
yayu_for_2010 <- per_forest(yayu_2010)
yayu_for_2019 <- per_forest(yayu_2019)

outs_for_1973 <- per_forest(outs_1973)
outs_for_1984 <- per_forest(outs_1984)
outs_for_1995 <- per_forest(outs_1995)
```

```r
outs_for_2001 <- per_forest(outs_2001)
outs_for_2010 <- per_forest(outs_2010)
outs_for_2019 <- per_forest(outs_2019)


#### Landscape metrics ####
## Change CRS to meters
ncrs<- CRS("+proj=utm +zone=37 +datum=WGS84 +units=m")
#projection<-"+proj=longlat +datum=WGS84 +units=m +no_defs"
sieve_1973_rprj <- projectRaster(sieve_1973, crs= ncrs, method="ngb") # Adjust using the nearest
     neighbour method
sieve_1984_rprj <- projectRaster(sieve_1984, crs=ncrs, method="ngb")
sieve_1995_rprj <- projectRaster(sieve_1995, crs=ncrs, method="ngb")
sieve_2001_rprj <- projectRaster(sieve_2001, crs=ncrs, method="ngb")
sieve_2010_rprj <- projectRaster(sieve_2010, crs=ncrs, method="ngb")
sieve_2019_rprj <- projectRaster(sieve_2019, crs=ncrs, method="ngb")

yayu_1973_rprj <- projectRaster(yayu_1973, crs=ncrs, method="ngb")
yayu_1984_rprj <- projectRaster(yayu_1984, crs=ncrs, method="ngb")
yayu_1995_rprj <- projectRaster(yayu_1995, crs=ncrs, method="ngb")
yayu_2001_rprj <- projectRaster(yayu_2001, crs=ncrs, method="ngb")
yayu_2010_rprj <- projectRaster(yayu_2010, crs=ncrs, method="ngb")
yayu_2019_rprj <- projectRaster(yayu_2019, crs=ncrs, method="ngb")

outs_1973_rprj <- projectRaster(outs_1973, crs=ncrs, method="ngb")
outs_1984_rprj <- projectRaster(outs_1984, crs=ncrs, method="ngb")
outs_1995_rprj <- projectRaster(outs_1995, crs=ncrs, method="ngb")
outs_2001_rprj <- projectRaster(outs_2001, crs=ncrs, method="ngb")
outs_2010_rprj <- projectRaster(outs_2010, crs=ncrs, method="ngb")
outs_2019_rprj <- projectRaster(outs_2019, crs=ncrs, method="ngb")

## Distance between patches
patches_1973 <- get_patches(sieve_1973_rprj,class=1,return_raster = TRUE)
patches_1984 <- get_patches(sieve_1984_rprj,class=1,return_raster = TRUE)
patches_1995 <- get_patches(sieve_1995_rprj,class=1,return_raster = TRUE)
patches_2001 <- get_patches(sieve_2001_rprj,class=1,return_raster = TRUE)
patches_2010 <- get_patches(sieve_2010_rprj,class=1,return_raster = TRUE)
patches_2019 <- get_patches(sieve_2019_rprj,class=1,return_raster = TRUE)

yayu_patches_1973 <- get_patches(yayu_1973_rprj,class=1,return_raster = TRUE)
yayu_patches_1984 <- get_patches(yayu_1984_rprj,class=1,return_raster = TRUE)
yayu_patches_1995 <- get_patches(yayu_1995_rprj,class=1,return_raster = TRUE)
yayu_patches_2001 <- get_patches(yayu_2001_rprj,class=1,return_raster = TRUE)
yayu_patches_2010 <- get_patches(yayu_2010_rprj,class=1,return_raster = TRUE)
yayu_patches_2019 <- get_patches(yayu_2019_rprj,class=1,return_raster = TRUE)

outs_patches_1973 <- get_patches(outs_1973_rprj,class=1,return_raster = TRUE)
outs_patches_1984 <- get_patches(outs_1984_rprj,class=1,return_raster = TRUE)
outs_patches_1995 <- get_patches(outs_1995_rprj,class=1,return_raster = TRUE)
outs_patches_2001 <- get_patches(outs_2001_rprj,class=1,return_raster = TRUE)
outs_patches_2010 <- get_patches(outs_2010_rprj,class=1,return_raster = TRUE)
outs_patches_2019 <- get_patches(outs_2019_rprj,class=1,return_raster = TRUE)
```

```
dton_1973 <- get_nearestneighbour(patches_1973)
dton_1984 <- get_nearestneighbour(patches_1984)
dton_1995 <- get_nearestneighbour(patches_1995)
dton_2001 <- get_nearestneighbour(patches_2001)
dton_2010 <- get_nearestneighbour(patches_2010)
dton_2019 <- get_nearestneighbour(patches_2019)

yayu_dton_1973 <- get_nearestneighbour(yayu_patches_1973)
yayu_dton_1984 <- get_nearestneighbour(yayu_patches_1984)
yayu_dton_1995 <- get_nearestneighbour(yayu_patches_1995)
yayu_dton_2001 <- get_nearestneighbour(yayu_patches_2001)
yayu_dton_2010 <- get_nearestneighbour(yayu_patches_2010)
yayu_dton_2019 <- get_nearestneighbour(yayu_patches_2019)

outs_dton_1973 <- get_nearestneighbour(outs_patches_1973)
outs_dton_1984 <- get_nearestneighbour(outs_patches_1984)
outs_dton_1995 <- get_nearestneighbour(outs_patches_1995)
outs_dton_2001 <- get_nearestneighbour(outs_patches_2001)
outs_dton_2010 <- get_nearestneighbour(outs_patches_2010)
outs_dton_2019 <- get_nearestneighbour(outs_patches_2019)

## Coefficient of variation nearest neighbour distance
cnn_1973 <- lsm_l_enn_cv(sieve_1973_rprj,directions = 4)
cnn_1984 <- lsm_l_enn_cv(sieve_1984_rprj,directions = 4)
cnn_1995 <- lsm_l_enn_cv(sieve_1995_rprj,directions = 4)
cnn_2001 <- lsm_l_enn_cv(sieve_2001_rprj,directions = 4)
cnn_2010 <- lsm_l_enn_cv(sieve_2010_rprj,directions = 4)
cnn_2019 <- lsm_l_enn_cv(sieve_2019_rprj,directions = 4)

yayu_cnn_1973 <- lsm_l_enn_cv(yayu_1973_rprj,directions = 4)
yayu_cnn_1984 <- lsm_l_enn_cv(yayu_1984_rprj,directions = 4)
yayu_cnn_1995 <- lsm_l_enn_cv(yayu_1995_rprj,directions = 4)
yayu_cnn_2001 <- lsm_l_enn_cv(yayu_2001_rprj,directions = 4)
yayu_cnn_2010 <- lsm_l_enn_cv(yayu_2010_rprj,directions = 4)
yayu_cnn_2019 <- lsm_l_enn_cv(yayu_2019_rprj,directions = 4)

outs_cnn_1973 <- lsm_l_enn_cv(outs_1973_rprj,directions = 4)
outs_cnn_1984 <- lsm_l_enn_cv(outs_1984_rprj,directions = 4)
outs_cnn_1995 <- lsm_l_enn_cv(outs_1995_rprj,directions = 4)
outs_cnn_2001 <- lsm_l_enn_cv(outs_2001_rprj,directions = 4)
outs_cnn_2010 <- lsm_l_enn_cv(outs_2010_rprj,directions = 4)
outs_cnn_2019 <- lsm_l_enn_cv(outs_2019_rprj,directions = 4)

## Edge to interior ratio(E/I)/core area index (CAI)
caisd_1973 <- lsm_l_cai_sd(sieve_1973_rprj, edge_depth = 4)
caisd_1984 <- lsm_l_cai_sd(sieve_1984_rprj, edge_depth = 4)
caisd_1995 <- lsm_l_cai_sd(sieve_1995_rprj, edge_depth = 4)
caisd_2001 <- lsm_l_cai_sd(sieve_2001_rprj, edge_depth = 4)
caisd_2010 <- lsm_l_cai_sd(sieve_2010_rprj, edge_depth = 4)
caisd_2019 <- lsm_l_cai_sd(sieve_2019_rprj, edge_depth = 4)

yayu_caisd_1973 <- lsm_l_cai_sd(yayu_1973_rprj, edge_depth = 4)
```

```
yayu_caisd_1984 <- lsm_l_cai_sd(yayu_1984_rprj, edge_depth = 4)
yayu_caisd_1995 <- lsm_l_cai_sd(yayu_1995_rprj, edge_depth = 4)
yayu_caisd_2001 <- lsm_l_cai_sd(yayu_2001_rprj, edge_depth = 4)
yayu_caisd_2010 <- lsm_l_cai_sd(yayu_2010_rprj, edge_depth = 4)
yayu_caisd_2019 <- lsm_l_cai_sd(yayu_2019_rprj, edge_depth = 4)

outs_caisd_1973 <- lsm_l_cai_sd(outs_1973_rprj, edge_depth = 4)
outs_caisd_1984 <- lsm_l_cai_sd(outs_1984_rprj, edge_depth = 4)
outs_caisd_1995 <- lsm_l_cai_sd(outs_1995_rprj, edge_depth = 4)
outs_caisd_2001 <- lsm_l_cai_sd(outs_2001_rprj, edge_depth = 4)
outs_caisd_2010 <- lsm_l_cai_sd(outs_2010_rprj, edge_depth = 4)
outs_caisd_2019 <- lsm_l_cai_sd(outs_2019_rprj, edge_depth = 4)

caimn_1973 <- lsm_l_cai_mn(sieve_1973_rprj, edge_depth = 4)
caimn_1984 <- lsm_l_cai_mn(sieve_1984_rprj, edge_depth = 4)
caimn_1995 <- lsm_l_cai_mn(sieve_1995_rprj, edge_depth = 4)
caimn_2001 <- lsm_l_cai_mn(sieve_2001_rprj, edge_depth = 4)
caimn_2010 <- lsm_l_cai_mn(sieve_2010_rprj, edge_depth = 4)
caimn_2019 <- lsm_l_cai_mn(sieve_2019_rprj, edge_depth = 4)

yayu_caimn_1973 <- lsm_l_cai_mn(yayu_1973_rprj, edge_depth = 4)
yayu_caimn_1984 <- lsm_l_cai_mn(yayu_1984_rprj, edge_depth = 4)
yayu_caimn_1995 <- lsm_l_cai_mn(yayu_1995_rprj, edge_depth = 4)
yayu_caimn_2001 <- lsm_l_cai_mn(yayu_2001_rprj, edge_depth = 4)
yayu_caimn_2010 <- lsm_l_cai_mn(yayu_2010_rprj, edge_depth = 4)
yayu_caimn_2019 <- lsm_l_cai_mn(yayu_2019_rprj, edge_depth = 4)

outs_caimn_1973 <- lsm_l_cai_mn(outs_1973_rprj, edge_depth = 4)
outs_caimn_1984 <- lsm_l_cai_mn(outs_1984_rprj, edge_depth = 4)
outs_caimn_1995 <- lsm_l_cai_mn(outs_1995_rprj, edge_depth = 4)
outs_caimn_2001 <- lsm_l_cai_mn(outs_2001_rprj, edge_depth = 4)
outs_caimn_2010 <- lsm_l_cai_mn(outs_2010_rprj, edge_depth = 4)
outs_caimn_2019 <- lsm_l_cai_mn(outs_2019_rprj, edge_depth = 4)

## Edge density
ed_1973 <- lsm_l_ed(sieve_1973_rprj,directions=4)
ed_1984 <- lsm_l_ed(sieve_1984_rprj,directions=4)
ed_1995 <- lsm_l_ed(sieve_1995_rprj,directions=4)
ed_2001 <- lsm_l_ed(sieve_2001_rprj,directions=4)
ed_2010 <- lsm_l_ed(sieve_2010_rprj,directions=4)
ed_2019 <- lsm_l_ed(sieve_2019_rprj,directions=4)

yayu_ed_1973 <- lsm_l_ed(yayu_1973_rprj,directions=4)
yayu_ed_1984 <- lsm_l_ed(yayu_1984_rprj,directions=4)
yayu_ed_1995 <- lsm_l_ed(yayu_1995_rprj,directions=4)
yayu_ed_2001 <- lsm_l_ed(yayu_2001_rprj,directions=4)
yayu_ed_2010 <- lsm_l_ed(yayu_2010_rprj,directions=4)
yayu_ed_2019 <- lsm_l_ed(yayu_2019_rprj,directions=4)

outs_ed_1973 <- lsm_l_ed(outs_1973_rprj,directions=4)
outs_ed_1984 <- lsm_l_ed(outs_1984_rprj,directions=4)
outs_ed_1995 <- lsm_l_ed(outs_1995_rprj,directions=4)
```

```
outs_ed_2001 <- lsm_l_ed(outs_2001_rprj,directions=4)
outs_ed_2010 <- lsm_l_ed(outs_2010_rprj,directions=4)
outs_ed_2019 <- lsm_l_ed(outs_2019_rprj,directions=4)

## Size biggest patch
lpi_1973 <- lsm_c_lpi(sieve_1973_rprj,directions = 4)
lpi_1984 <- lsm_c_lpi(sieve_1984_rprj,directions = 4)
lpi_1995 <- lsm_c_lpi(sieve_1995_rprj,directions = 4)
lpi_2001 <- lsm_c_lpi(sieve_2001_rprj,directions = 4)
lpi_2010 <- lsm_c_lpi(sieve_2010_rprj,directions = 4)
lpi_2019 <- lsm_c_lpi(sieve_2019_rprj,directions = 4)

yayu_lpi_1973 <- lsm_c_lpi(yayu_1973_rprj,directions = 4)
yayu_lpi_1984 <- lsm_c_lpi(yayu_1984_rprj,directions = 4)
yayu_lpi_1995 <- lsm_c_lpi(yayu_1995_rprj,directions = 4)
yayu_lpi_2001 <- lsm_c_lpi(yayu_2001_rprj,directions = 4)
yayu_lpi_2010 <- lsm_c_lpi(yayu_2010_rprj,directions = 4)
yayu_lpi_2019 <- lsm_c_lpi(yayu_2019_rprj,directions = 4)

outs_lpi_1973 <- lsm_c_lpi(outs_1973_rprj,directions = 4)
outs_lpi_1984 <- lsm_c_lpi(outs_1984_rprj,directions = 4)
outs_lpi_1995 <- lsm_c_lpi(outs_1995_rprj,directions = 4)
outs_lpi_2001 <- lsm_c_lpi(outs_2001_rprj,directions = 4)
outs_lpi_2010 <- lsm_c_lpi(outs_2010_rprj,directions = 4)
outs_lpi_2019 <- lsm_c_lpi(outs_2019_rprj,directions = 4)

## Average size patch
mn_1973 <- lsm_l_area_mn(sieve_1973_rprj, directions = 4)
mn_1984 <- lsm_l_area_mn(sieve_1984_rprj, directions = 4)
mn_1995 <- lsm_l_area_mn(sieve_1995_rprj, directions = 4)
mn_2001 <- lsm_l_area_mn(sieve_2001_rprj, directions = 4)
mn_2010 <- lsm_l_area_mn(sieve_2010_rprj, directions = 4)
mn_2019 <- lsm_l_area_mn(sieve_2019_rprj, directions = 4)

yayu_mn_1973 <- lsm_l_area_mn(yayu_1973_rprj, directions = 4)
yayu_mn_1984 <- lsm_l_area_mn(yayu_1984_rprj, directions = 4)
yayu_mn_1995 <- lsm_l_area_mn(yayu_1995_rprj, directions = 4)
yayu_mn_2001 <- lsm_l_area_mn(yayu_2001_rprj, directions = 4)
yayu_mn_2010 <- lsm_l_area_mn(yayu_2010_rprj, directions = 4)
yayu_mn_2019 <- lsm_l_area_mn(yayu_2019_rprj, directions = 4)

outs_mn_1973 <- lsm_l_area_mn(outs_1973_rprj, directions = 4)
outs_mn_1984 <- lsm_l_area_mn(outs_1984_rprj, directions = 4)
outs_mn_1995 <- lsm_l_area_mn(outs_1995_rprj, directions = 4)
outs_mn_2001 <- lsm_l_area_mn(outs_2001_rprj, directions = 4)
outs_mn_2010 <- lsm_l_area_mn(outs_2010_rprj, directions = 4)
outs_mn_2019 <- lsm_l_area_mn(outs_2019_rprj, directions = 4)

## Total patch area\
ca_1973 <- lsm_c_ca(sieve_1973_rprj, directions = 4)
ca_1984 <- lsm_c_ca(sieve_1984_rprj, directions = 4)
ca_1995 <- lsm_c_ca(sieve_1995_rprj, directions = 4)
```

```
ca_2001 <- lsm_c_ca(sieve_2001_rprj, directions = 4)
ca_2010 <- lsm_c_ca(sieve_2010_rprj, directions = 4)
ca_2019 <- lsm_c_ca(sieve_2019_rprj, directions = 4)

yayu_ca_1973 <- lsm_c_ca(yayu_1973_rprj, directions = 4)
yayu_ca_1984 <- lsm_c_ca(yayu_1984_rprj, directions = 4)
yayu_ca_1995 <- lsm_c_ca(yayu_1995_rprj, directions = 4)
yayu_ca_2001 <- lsm_c_ca(yayu_2001_rprj, directions = 4)
yayu_ca_2010 <- lsm_c_ca(yayu_2010_rprj, directions = 4)
yayu_ca_2019 <- lsm_c_ca(yayu_2019_rprj, directions = 4)

outs_ca_1973 <- lsm_c_ca(outs_1973_rprj, directions = 4)
outs_ca_1984 <- lsm_c_ca(outs_1984_rprj, directions = 4)
outs_ca_1995 <- lsm_c_ca(outs_1995_rprj, directions = 4)
outs_ca_2001 <- lsm_c_ca(outs_2001_rprj, directions = 4)
outs_ca_2010 <- lsm_c_ca(outs_2010_rprj, directions = 4)
outs_ca_2019 <- lsm_c_ca(outs_2019_rprj, directions = 4)

## Patch variability (patch size standard deciation)
sd_1973 <- lsm_c_area_sd(sieve_1973_rprj, directions = 4)
sd_1984 <- lsm_c_area_sd(sieve_1984_rprj, directions = 4)
sd_1995 <- lsm_c_area_sd(sieve_1995_rprj, directions = 4)
sd_2001 <- lsm_c_area_sd(sieve_2001_rprj, directions = 4)
sd_2010 <- lsm_c_area_sd(sieve_2010_rprj, directions = 4)
sd_2019 <- lsm_c_area_sd(sieve_2019_rprj, directions = 4)

yayu_sd_1973 <- lsm_c_area_sd(yayu_1973_rprj, directions = 4)
yayu_sd_1984 <- lsm_c_area_sd(yayu_1984_rprj, directions = 4)
yayu_sd_1995 <- lsm_c_area_sd(yayu_1995_rprj, directions = 4)
yayu_sd_2001 <- lsm_c_area_sd(yayu_2001_rprj, directions = 4)
yayu_sd_2010 <- lsm_c_area_sd(yayu_2010_rprj, directions = 4)
yayu_sd_2019 <- lsm_c_area_sd(yayu_2019_rprj, directions = 4)

outs_sd_1973 <- lsm_c_area_sd(outs_1973_rprj, directions = 4)
outs_sd_1984 <- lsm_c_area_sd(outs_1984_rprj, directions = 4)
outs_sd_1995 <- lsm_c_area_sd(outs_1995_rprj, directions = 4)
outs_sd_2001 <- lsm_c_area_sd(outs_2001_rprj, directions = 4)
outs_sd_2010 <- lsm_c_area_sd(outs_2010_rprj, directions = 4)
outs_sd_2019 <- lsm_c_area_sd(outs_2019_rprj, directions = 4)

## Number of patches/core areas
id_1973 <- get_unique_values(patches_1973,simplify = TRUE)
id_1984 <- get_unique_values(patches_1984,simplify = TRUE)
id_1995 <- get_unique_values(patches_1995,simplify = TRUE)
id_2001 <- get_unique_values(patches_2001,simplify = TRUE)
id_2010 <- get_unique_values(patches_2010,simplify = TRUE)
id_2019 <- get_unique_values(patches_2019,simplify = TRUE)

yayu_id_1973 <- get_unique_values(yayu_patches_1973,simplify = TRUE)
yayu_id_1984 <- get_unique_values(yayu_patches_1984,simplify = TRUE)
yayu_id_1995 <- get_unique_values(yayu_patches_1995,simplify = TRUE)
yayu_id_2001 <- get_unique_values(yayu_patches_2001,simplify = TRUE)
```

```r
yayu_id_2010 <- get_unique_values(yayu_patches_2010,simplify = TRUE)
yayu_id_2019 <- get_unique_values(yayu_patches_2019,simplify = TRUE)

outs_id_1973 <- get_unique_values(outs_patches_1973,simplify = TRUE)
outs_id_1984 <- get_unique_values(outs_patches_1984,simplify = TRUE)
outs_id_1995 <- get_unique_values(outs_patches_1995,simplify = TRUE)
outs_id_2001 <- get_unique_values(outs_patches_2001,simplify = TRUE)
outs_id_2010 <- get_unique_values(outs_patches_2010,simplify = TRUE)
outs_id_2019 <- get_unique_values(outs_patches_2019,simplify = TRUE)

np_1973 <- which.max(id_1973)
np_1984 <- which.max(id_1984)
np_1995 <- which.max(id_1995)
np_2001 <- which.max(id_2001)
np_2010 <- which.max(id_2010)
np_2019 <- which.max(id_2019)

yayu_np_1973 <- which.max(yayu_id_1973)
yayu_np_1984 <- which.max(yayu_id_1984)
yayu_np_1995 <- which.max(yayu_id_1995)
yayu_np_2001 <- which.max(yayu_id_2001)
yayu_np_2010 <- which.max(yayu_id_2010)
yayu_np_2019 <- which.max(yayu_id_2019)

outs_np_1973 <- which.max(outs_id_1973)
outs_np_1984 <- which.max(outs_id_1984)
outs_np_1995 <- which.max(outs_id_1995)
outs_np_2001 <- which.max(outs_id_2001)
outs_np_2010 <- which.max(outs_id_2010)
outs_np_2019 <- which.max(outs_id_2019)

##Note down all data

##Export dton to csv
write.csv2(dton_1973,
      "R/dton_1973.csv",
      row.names=FALSE)
write.csv2(dton_1984,
      "R/dton_1984.csv",
      row.names=FALSE)
write.csv2(dton_1995,
      "R/dton_1995.csv",
      row.names=FALSE)
write.csv2(dton_2001,
      "R/dton_2001.csv",
      row.names=FALSE)
write.csv2(dton_2010,
      "R/dton_2010.csv",
      row.names=FALSE)
write.csv2(dton_2019,
      "R/dton_2019.csv",
      row.names=FALSE)
```

```
write.csv2(yayu_dton_1973,
      "R/yayu_dton_1973.csv",
      row.names=FALSE)
write.csv2(yayu_dton_1984,
      "R/yayu_dton_1984.csv",
      row.names=FALSE)
write.csv2(yayu_dton_1995,
       "R/yayu_dton_1995.csv",
       row.names=FALSE)
write.csv2(yayu_dton_2001,
       "R/yayu_dton_2001.csv",
       row.names=FALSE)
write.csv2(yayu_dton_2010,
       "R/yayu_dton_2010.csv",
       row.names=FALSE)
write.csv2(yayu_dton_2019,
       "R/yayu_dton_2019.csv",
       row.names=FALSE)

write.csv2(outs_dton_1973,
      "R/outs_dton_1973.csv",
      row.names=FALSE)
write.csv2(outs_dton_1984,
      "R/outs_dton_1984.csv",
      row.names=FALSE)
write.csv2(outs_dton_1995,
       "R/outs_dton_1995.csv",
       row.names=FALSE)
write.csv2(outs_dton_2001,
       "R/outs_dton_2001.csv",
       row.names=FALSE)
write.csv2(outs_dton_2010,
       "R/outs_dton_2010.csv",
       row.names=FALSE)
write.csv2(outs_dton_2019,
       "R/outs_dton_2019.csv",
       row.names=FALSE)

##Save rasters for visualisation in QGIS
writeRaster(d73_84, "Rasters difference/d73_84.tif")
writeRaster(d84_95, "Rasters difference/d84_95.tif")
writeRaster(d95_01, "Rasters difference/d95_01.tif")
writeRaster(d01_10, "Rasters difference/d01_10.tif")
writeRaster(d10_19, "Rasters difference/d10_19.tif")
writeRaster(d73_19, "Rasters difference/d73_19.tif")

writeRaster(yayu_d73_84, "Rasters difference/Yayu d73-84.tif")
writeRaster(yayu_d84_95, "Rasters difference/Yayu d84-95.tif")
writeRaster(yayu_d95_01, "Rasters difference/Yayu d95-01.tif")
writeRaster(yayu_d01_10, "Rasters difference/Yayu d01_10.tif")
```

```
writeRaster(yayu_d10_19, "Rasters difference/Yayu d10-19.tif")
writeRaster(yayu_d73_19, "Rasters difference/Yayu d73-19.tif")
```