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Mapping Spatiotemporal Changes of Evergreen Forest Patches that are Heritage Sites in Southern Mozambique using Google Earth Engine

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Abstract

Using forests as burial and ceremonial places is a long-standing cultural practice in Mozambique. However, this information is still not translated into land-cover and land-use maps. Thus the locations of these forests and their descriptions remain unknown. To address this gap in the knowledge, this paper presents the results of mapping 52 local heritage sites in Inhambane, and analysing land-cover changes of two locally protected forest patches. Results from spatiotemporal change analysis show that these patches experienced fewer disturbances in comparison to other areas of vegetation.

Keywords:

Landsat, remote sensing, land cover, cultural heritage

1 Introduction

"There are vast, almost impenetrable thickets, in which the ancient chiefs have been buried. The ancestors of the chiefs are buried in different sectors of the forests according to their villages. These woods are taboo. It is forbidden to gather wood here, or to allow bushfire to enter. It is forbidden to enter unless for the guardian of the forest, a priest descendant of the gods of the forest. There is a general dread to go through these forests and many frightening tales are told about them" (Junod, 1927, Vol. II, pp. 376–84).

Currently, knowledge on land cover and land use worldwide is derived from processing remote sensing data, mostly satellite images (Wondie et al., 2011; Hu & Hu, 2019). Land use evolves through the continuous or periodical activities that humans perform in a given type of land cover (Masayi et al., 2021). Land-cover changes are closely linked to past land use and cultural heritage, reflecting the ways in which people have managed the land historically (Wilson, 2022).

Agapiou (2017) used satellite images and Google Earth Engine (GEE) for the monitoring and management of cultural heritage sites. Ochungo et al. (2022) applied satellite images in GEE to map traditional wells and to describe water management systems. However, not all forms of cultural heritage are readily interpretable in satellite images or in the land-cover patterns. This is the case of forests used by local communities as burial and ceremonial sites, as found in a number of places worldwide (see e.g., Straka et al., 2022). This calls for combining satellite images with other approaches to map heritage sites in forests, or forested areas that are themselves heritage sites (hereafter referred to as 'local heritage sites'). In this context, geonarratives (Kwan & Ding, 2008; Kwan, 2008) have the ability to shed light on past landscapes and give a better understanding of the transformations reflected in satellite images. In the case of local heritage sites that have not already been documented or spatially contextualized in some way, mapping is impossible without local knowledge.

Forty percent of the land area of Mozambique is covered by some type of forest (FAO, 2020). Early descriptions of the cultural dimensions of forests were given by ethnographers such as Henri-Alexandre Junod (Junod, 1927). More recent studies (e.g., Virtanen, 2002; Izidine et al., 2008; Ekblom et al., 2017) have suggested that there are a considerable number of forest patches that still function as Junod described them almost a century ago.

Studies of land cover and land use in Mozambique (e.g., Ryan et al., 2014; Bey et al., 2020; Sedano et al., 2020) have omitted the history of forested areas, overlooking their cultural use as ceremonial and burial places. Local heritage sites therefore remain unknown, invisible in contemporary land-use and land-cover maps produced using satellite images. In concrete terms, the omission of forest heritage sites that are outside formally protected areas means that they are seen as potential logging areas awaiting concessions.

This paper sought first to identify and map the location of forest heritage sites in Inhambane province. Taking into account that the use of forests as burial places is a long-standing practice (see e.g., Junod, 1927), the second aim is to exploit time-series satellite images to analyse changes in selected heritage sites in recent decades. In Section 2, a brief description of the study area is given, followed by the methodology used. The results of mapping heritage sites and analyses of land cover are presented in Section 3. The paper ends with a reflection on the importance of mapping and monitoring heritage sites, the need to close knowledge gaps, and ways of making local heritage sites more visible by integrating them into Mozambique's land-cover and land-use maps and in the national conservation network.

2 Materials and methods

2.1 Description of the study areas

The over-arching study area is the province of Inhambane, located between latitudes 20° 57' North and 24° 51' South and longitudes 35° 34' East and 34° 41' West, within which we focused on two smaller areas in and around the villages of Luido and Chitanga (Figure 1). The coastal province covers an area of 68,615 km^2, is limited by the Save River in the north, the Indian Ocean to the east, and Gaza province in the south and west (Moçambique, 2010). Inhambane has a humid tropical climate, with a rainy season from November to April and a dry season from May to October (Moçambique, 2010).

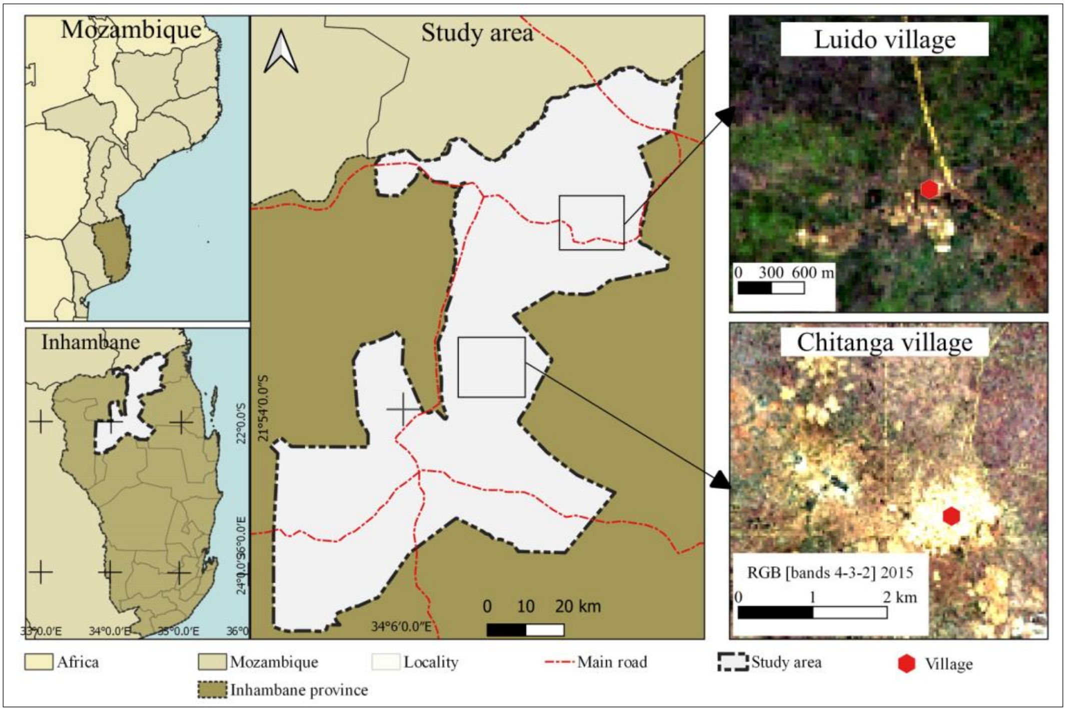

Figure 1: Geographical location of the study area and two sub-areas. Data about *country subdivisions*, administrative boundaries and national road network were derived from the National Cartography and Remote Sensing Centre in Mozambique.

The province is part of the Southern Zanzibar-Inhambane Coastal Forest Mosaic or Swahilian/Maputaland regional transition zone (Clarke, 1998) and hosts more than 50 endemic plant taxa (Darbyshire et al., 2019). The forests of Inhambane are comprised mostly of tree species that are in high demand (e.g. Androstachys johnsonii and Afzelia quanzensis), and consequently there is pressure on the forests (Mozambique, 2017). Inhambane province has fourteen districts; Chitanga in Mabote district and Luido in Govuro district were defined as sub-areas for study.

2.2 Methodological workflow

Identification and mapping of forest patches with cultural values

The process of mapping heritage sites started with the presentation of a research project to the national, provincial and district authorities dealing with cultural heritage management in Mozambique. This guaranteed smooth access to local communities for consent to conduct the project in their localities, and it was the local authorities and communities who showed us their local burial and ceremonial sites, and forests that are locally protected. Using the description given by Junod (1927) quoted at the start of this paper, communities were asked to indicate locally protected forests. This was the first phase of field work, an interactive process involving several visits to the different localities, walking with community members into the forests, documenting oral histories of the forests, and recording the narratives of the custodians of the local heritage sites. Additionally, the coordinates of all heritage sites in and around locally protected forests in Inhambane province were recorded using a Garmin64 GPS unit. A reference dataset was created from the local narratives and observations in the field to train and validate satellite images.

Classification of satellite images covering Chitanga and Luido

The classification of satellite images was performed in the GEE environment. Satellite images from Landsat were selected from the GEE Data Catalogue. The sub-areas of study are covered by path 167 and row 075 within the worldwide reference system for Landsat data. In total, three cloud-free satellite images were selected. Two images are from Landsat-5_TM, acquired in 1984 (1 June) and 2007 (20 August); the third is from Landsat-8_ OLI_TIRS (9 July 2015). All the images had a 30-metre spatial resolution with tier-1 processing level, radiometrically calibrated with systematic geometric corrections.

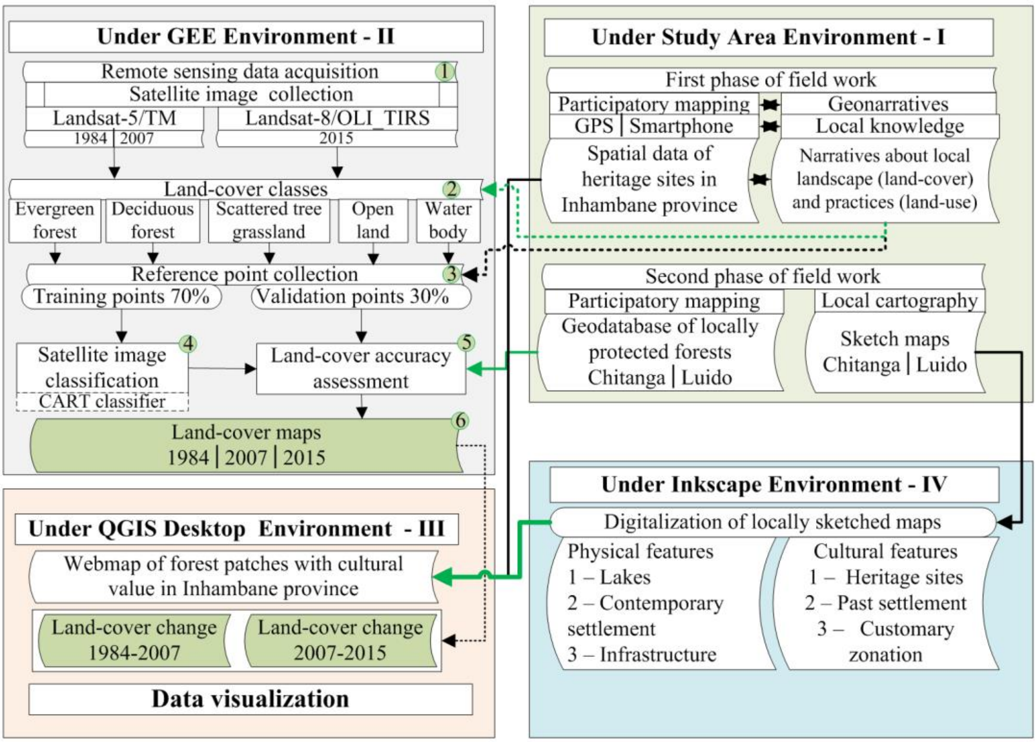

Figure 2: Methodological workflow

Five land-cover classes were specified to classify satellite images, namely: (1) evergreen forests, defined as areas with a large quantity of *Androstachys johnsonii*, *Carpodiptera Africana* and *Brachystegia speciformis* trees; (2) deciduous forests, with a high occurrence of trees such as *Strychnos spinosa*, *Strychno spungens* and *Afzelia quanzensis*; (3) Scattered tree grasslands were defined as areas dominated by grasses but with *Acacia nigrescens*, *Cordyla africana* and *Combretum imberbe* trees; (4) open land comprised villages, rocky areas and sparse habitation, including areas that during the rainy season have seasonal lakes; (5) water bodies.

Very high resolution satellite imagery which is built in in GEE and historical imagery from Google Earth Pro were used alongside the reference dataset collected in the first phase of field work. This allowed the identification of more reference data points, mostly in the areas that were inaccessible during field work due to taller vegetation. For the collection of training samples, research suggests that for areas covering a maximum of 4,046.9 km^2 and 12 land-cover classes, a minimum of 50 samples should be taken for each land-cover class (Deribew & Dalacho, 2019; Basheer et al., 2022). Taking into account the size of the sub-area (6,603.82 km^2), each land-cover class had a minimum of 150 training points. 70% of the total points in the dataset were employed to classify the satellite images (Ochungo et al., 2022). The Classification and Regression Trees (CART) algorithm was applied alongside the training points to produce land-cover maps for 1984, 2007 and 2015.

The most frequently used method to assess the classification performance of satellite images is a confusion matrix containing producer accuracy, consumer accuracy, overall accuracy and kappa coefficient (Yang et al., 2021; Basheer et al., 2022). The remaining 30% of the points (validation points) were applied to compute a confusion matrix comparing all three land-cover maps to their reference points (Basheer et al., 2022; Ochungo et al., 2022). Producer accuracy, consumer accuracy, overall accuracy and kappa coefficient were also computed for each land-cover class for all three maps.

Two techniques were applied to detect and analyse land-cover changes: visual inspection of the images, and image differencing (Abdo & Prakash, 2020). Visual inspection was done by indentifying areas that had changed between the land-cover maps of 1984 and 2007, and then between 2007 and the map of 2015. Next, image differencing was performed by subtracting the land cover shown in the 2007 map from the land cover shown in the 1984 map. The same procedure was then used for the 2015 and 2007 maps. These techniques provided information about the changes in all land-cover classes in the sub-areas between 1984 and 2015.

In the second phase of fieldwork, the information derived from the three maps was taken into the field. This allowed for a better understanding of the changes indentified in the maps, and for local communities to give their narratives and perceptions about past use of the landscape. The community was asked about extreme events. For instance, in the land cover of 1984 the surface of Banamana Lake, a great saline lake, is represented as dried out, but in the maps of 2007 and 2015 it has water. Elders were also asked about natural remarkable events (extreme floods, droughts and fires) which took place in the 1980s (during the civil war) and the 2000s. They were also asked about settlements and agricultural areas before and after the civil war. Together with members of their communities, the elders made sketch maps of their territories, pointing out places where their ancestors are buried. Data from the sketch maps was incorporated in the webmap of forest patches in Inhambane that have cultural value.

The GEE was heavily used to host the whole process of classifying satellite images. It was also used to calculate the area of different land-cover classes in the satellite images and to compute statistics for land-cover changes. Other data sources (geonarratives, spatial data of heritage sites, sketch maps) were integrated directly or indirectly in the GEE environment. The interactive webmap was produced using the qgis2web plugin.

3 Results and discussion

3.1 Forest patches with cultural value and other heritage sites in Inhambane province

The results of the identification and mapping of heritage sites in Inhambane are presented in Figure 3. For a more detailed view, the reader is referred to the web version of the map at https://doi.org/10.5281/zenodo.7811782. Figure 3 indicates that the northwestern part of the province has the largest number of archaeological sites, followed by the northeast.

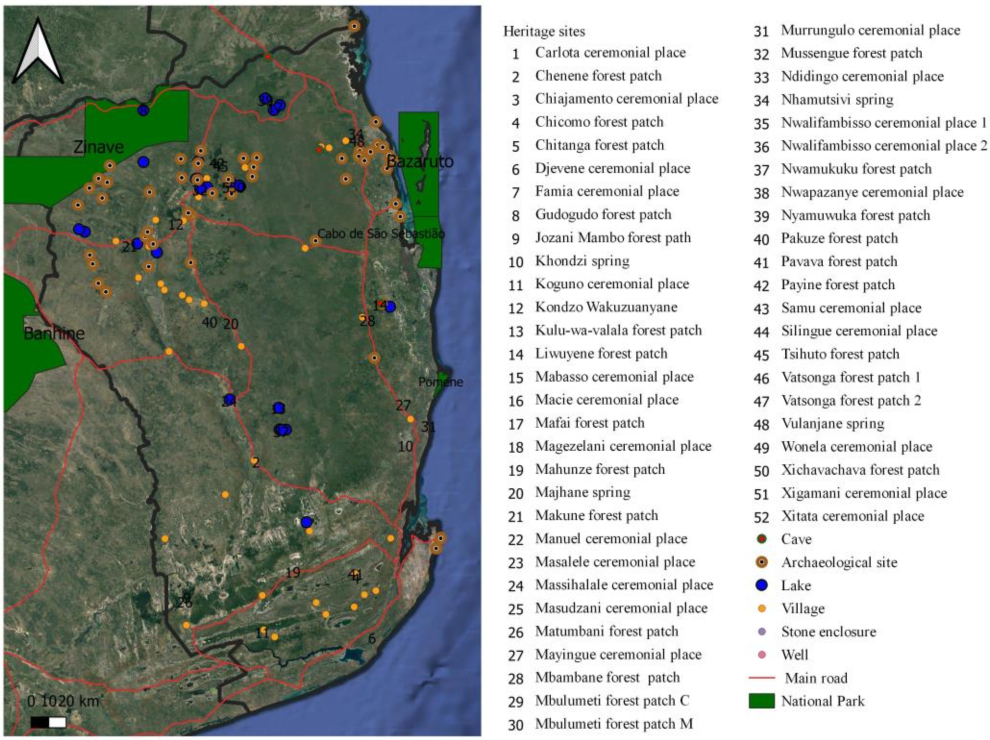

Figure 3: Identification of forest patches with cultural value and other heritage sites in Inhambane province. The background map is from Google and is available as a built-in basemap in the Quantum GIS plugin. Data about archaeological sites were derived from Adamowicz and Nhatule (2011). Data about protected areas were derived from the National Cartography and Remote Sensing Centre in Mozambique.

Fifty-two heritage sites are widely distributed in the province and follow a pattern that is linked with the distribution of the villages. Apart from one forest patch (Gudogudo) that is located inside Zinave National Park, none of the local heritage sites mapped fall within Mozambique's national conservation network. In this context, the heritage sites were incorporated in the same scripts as those used in the classification of satellite images. The scripts are available at: https://code.earthengine.google.com/fc6f1ab1e0477d069440f684dcd8ea44

3.2 Land-cover classification

The statistics for the accuracy of the land-cover classification (1984, 2007 and 2015) are presented in Table 1.Water bodies were the most accurately classified class, with both producer and consumer accuracies of more than 97%, followed by evergreen forests, open land, deciduous forest, and grassland with scattered trees.

Table 1: Confusion matrix, overall accuracy and Kappa coefficient of land-cover maps for the years 1984, 2007 and 2015.

Land cover	EF	DF	STG	WB	OL	Consumer accuracy (%)
Year 1984						
Evergreen forest (EF)	64	3	0	0	0	96
Deciduous forest (DF)	3	42	5	0	0	89
Scattered tree grassland (STG)	0	2	54	0	3	86
Water body (WB)	0	0	1	63	0	100
Open land (OL)	0	0	3	0	96	97
Producer accuracy (%)	95	84	91	98	97	
Overall Accuracy (%)	94	Kappa Coefficient (%)				92
Year 2007						
Evergreen Forest	75	0	0	0	0	97
Deciduous Forest	2	56	14	0	0	85
Scattered tree grassland	0	9	79	0	5	79
Water body	0	0	0	78	0	100
Open land	0	1	7	0	75	94
Producer accuracy (%)	100	78	85	100	90	
Overall Accuracy (%)	90	Kappa Coefficient (%)				88
Year 2015						
Evergreen Forest	71	1	0	0	0	100
Deciduous Forest	0	66	2	0	0	99
Scattered tree grassland	0	0	46	0	9	85
Water body	0	0	0	52	0	100
Open land	0	0	6	0	54	86
Producer accuracy (%)	99	97	84	100	90	
Overall Accuracy (%)	94	Kappa Coefficient (%)				92

Scattered tree grassland was the least accurately classified land-cover class across all three years because of confusion with deciduous forest and open land. This mis-classification reflects the complex mosaics in Inhambane, which show a correlation between grassland, open land and deciduous forests. In the same table, the results for overall accuracy and kappa coefficient show that all land-cover classes being described in this study were classified with high accuracy.

Land-cover change

Images describing land-cover change from 1984 to 2015 are presented in Figures 4 and 5. Visual analysis indicates that evergreen forests are located mostly in the central, western and northeastern parts of the sub-areas (Figure 4, maps 1, 6 and 11). In comparison to the land-cover maps of 1984 and 2015, in 2007 there was an increase in the area of evergreen (map 6). Moreover, the distribution of the evergreen forests remained visible in the three maps, and there was no great change affecting the core locations of these forests (Figure 5).

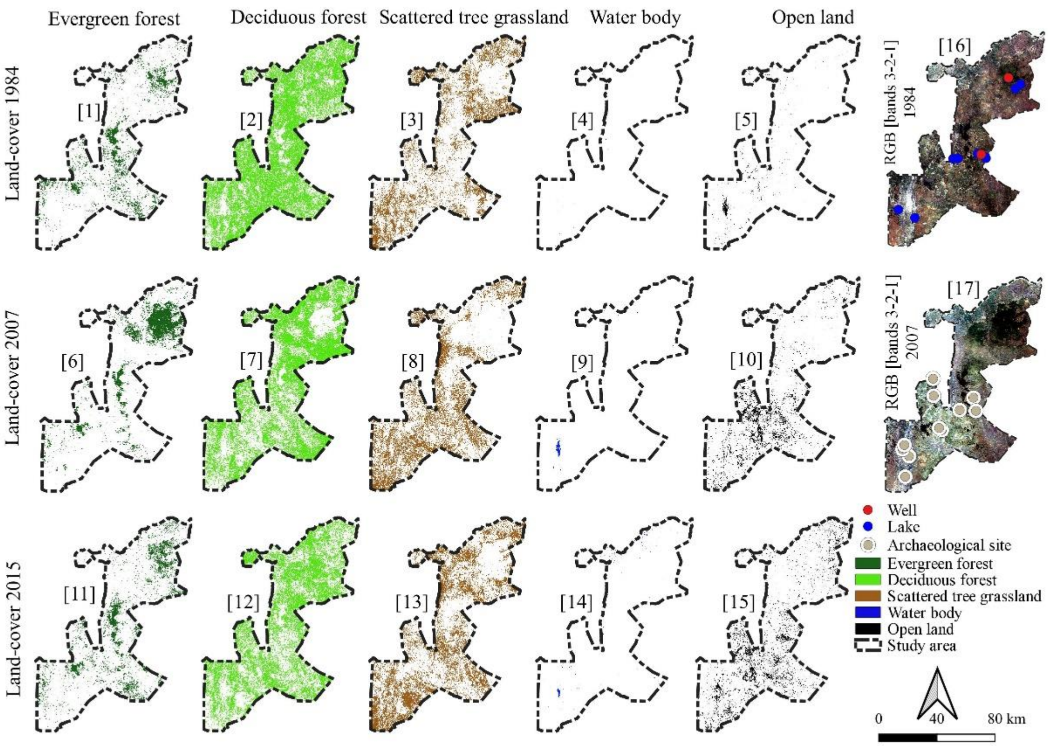

Figure 4: Maps 1–15 represent the spatial distribution of five land-cover classes in the study's sub-areas for 1984, 2007 and 2015. Maps 16–17 show information about the distribution of lakes, wells and archaeological sites in the same areas.

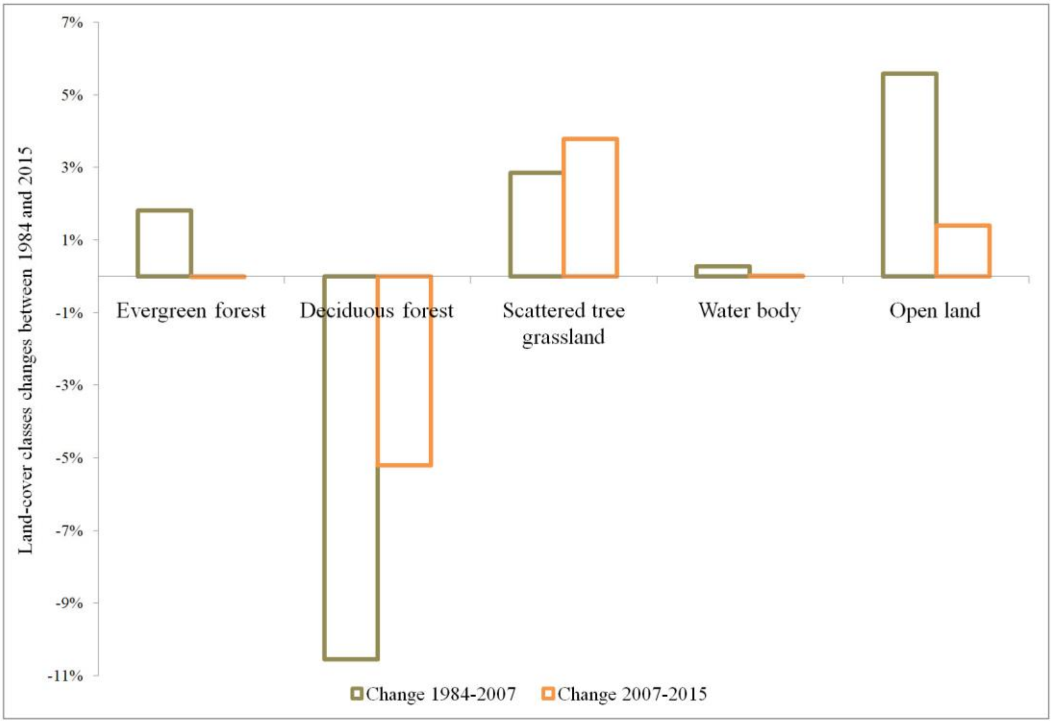

Figure 5: Results of land-cover change analysis between 1984 and 2015 in the study's sub-areas.

Deciduous forests are the main land-cover class during the whole timeframe; they are distributed throughout the sub-areas of the study (Figure 4, maps 2, 7 and 12). However, it can be noted that the 2007 map shows an expansion of scattered tree grassland areas and a decrease of deciduous forests (see also Figure 5). Interestingly, also in 2007, in the northeast there is an increase of deciduous forests surrounding evergreen forest (Figure 4, map 12). This pattern changed by 2015: a visual analysis shows that most of the areas are fragmented, reflecting an increase of scattered tree grassland and open land areas (Figure 4, map 13).

Although in the 1984 map areas of open land are visible only in the southeast, representing a dried-up lake (Figure 4, map 5), from 1984 to 2007 there is a clear appearance of areas of open land in the central part of the map, which continued to be visible in the 2015 map (Figure 5, and Figure 4 maps 5, 10 and 15). Open-land areas reflect the presence of settlements. In this case, the open areas are surrounding evergreen forest, scattered tree grassland and deciduous forests. True colour images from Landsat 5 employed to produce land-cover maps were then used for a basemap to represent ancillary data (maps 16 and 17). These data show lakes and wells distributed widely across archaeological sites that are concentrated in the central and southern parts of the study areas.

Statistical analyses of land-cover change

Statistics describing land-cover changes between 1984 and 2015 are presented in Table 2. Evergreen forests represented 10% of the total land (6,603.82km^2) in 1984. From 2007 to

2015, this class registered an increase in 2% and maintained overall stability during the entire period under analysis.

Table 2: Change of land-cover classes between 1984 and 2015 in the study's sub-areas

Land-cover classes	1984		2007		2015	
	km2	%	km2	%	km2	%
Evergreen Forest	682.23	10.33	802.65	12.15	803.15	12.16
Deciduous Forest	4,099.48	62.08	3,403.46	51.54	3,059.55	46.33
Scattered tree grassland	1,730.20	26.20	1,918.32	29.05	2,168.30	32.83
Water body	5.91	0.09	24.16	0.37	24.88	0.38
Open land	86.00	1.30	455.23	6.89	547.93	8.30
Total area	6,603.82	100	6,603.82	100	6,603.82	100

Deciduous forest was the dominant land-cover class in 1984 (62%). This class remained the most dominant and was always followed by areas of grassland with scattered trees (occupying 26% in 1984 and 33% in 2015). Water bodies are the smallest land-cover class, taking up less than 1% of the land during the whole period. In 1984, 1.3% of the land was open areas. This increased significantly in the following years. In 2015, open areas were estimated to cover around 8.3% of the study's sub-areas. Overall, there was also a decrease of deciduous forest areas.

3.3 Zooming in on forest patches of Chitanga and Luido villages

In Chitanga village, most of the heritage sites are located in deciduous forests. However, the burial place of Chitanga (the village's founding father) is located in the evergreen forest named after him. Chitanga village has ten heritage sites, of which four are locally protected forest patches; all have burial places (Figure 6). A close view of the land-cover map of Chitanga in 1984 shows a landscape covered mostly by deciduous forests. During the period under analysis there was a change in the vegetation composition, but most of the areas of evergreen forest are still visible in the 2015 map. In the maps of 2007 and 2015, there are increases of scattered trees and grassland areas. In both maps (2007 and 2015), areas of open land are clearly visible; these contain many ceremonial places.

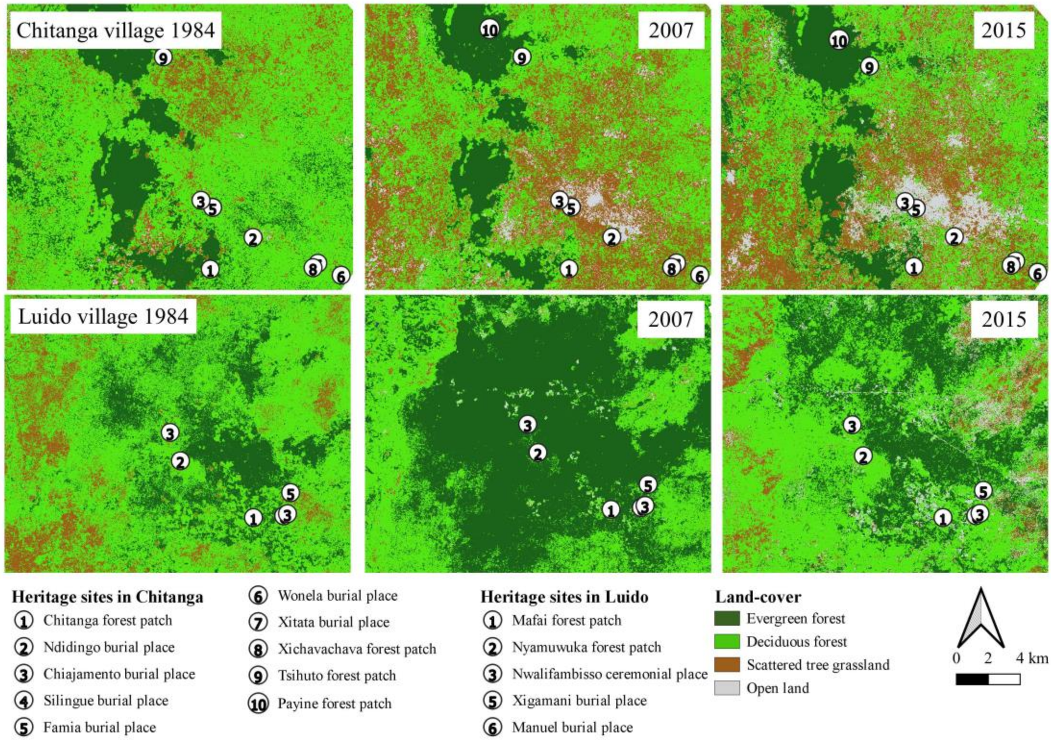

Figure 6: Close view of the location of heritage sites in Chitanga and Luido villages. Forest patches and burial (and ceremonial) places are placed in the context of land-cover maps.

In the case of Luido community, in 1984 there were areas of grassland with scattered trees. These areas were reduced by the expansion of evergreen forest in 2007. Culturally, Luido possesses two forests (Mafai and Nyamuwuka). Although local narratives describe these as different forests, a visual analysis shows them as part of the same ecosystem. Compared to Chitanga forest, Luido registered much greater change in land cover, from land covered mostly by deciduous trees (1984) to evergreen (2007) and then deciduous (2015). Most of the heritage sites in Luido are located in the core areas of the forest.

Several scholars have identified locally protected forests as single heritage sites (e.g., Virtanen, 2002; Cruz, 2014; Simbine, 2020). None of these scholars carried out a spatiotemporal analysis of land-cover change in the protected forests. Thus the present research stands as a pilot study for understanding land-cover changes of locally protected areas more broadly, and the results presented here can serve as a roadmap for a much larger analysis of local heritage sites in Inhambane province.

4 Conclusions

Gaps in knowledge of local heritage sites, land use and land cover result in part from not integrating different methods and approaches, or not exploiting their synergies (geoinformatics, geonarratives, satellite images, and remote sensing techniques). Without local knowledge, mapping forest patches with cultural values is impossible, as is locating a particular heritage site in the forest using satellite images. This scenario makes patches with cultural values invisible to policy makers. As a consequence, decisions taken only in accordance with land-cover and land-use maps, without the integration of local knowledge, might translate into policies that superimpose those maps on local communities' perspectives on forest use (see discussion in Fairhead & Leach, 1996; Yuliani et al., 2022). As well as mapping local heritage sites, this paper aims to contribute to closing that gap. The combination of methods used here made it possible to identify and map local heritage sites in Inhambane. Combining those data with local knowledge in a process of engaging local people's 'spatial knowledge or perception' (Kwan, 2008), an analysis of relatively recent land-cover changes targeting heritage sites was made possible.

Mapping heritage sites in Inhambane revealed that local uses of forests by communities as burial and ceremonial places, as described by early scholars, continue. Locally, these forests are considered heritage sites and are actively managed by the communities. In the face of current pressures on forests, the reasonably stable boundaries of forests patches, as evidenced by land-cover maps, show that the conservation of local heritage has a positive effect on the continued existence of forests. Considering that swidden agriculture is widely practised in Inhambane and a plethora of local human needs depend on forests products, forests that are both outside formally protected areas and without a recognized cultural value are likely to be felled. It is to be hoped that the results from this study will help policy makers and practitioners to integrate such culturally important places in the network of formally protected areas in Mozambique.

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References

Abdo, Z. A., & Prakash, S. (2020). A Review Paper on Monitoring Environmental Consequences of Land Cover Dynamics with The Help of Geo-informatics Technologies. Geosfera Indonesia, 5(3), 364–389.

Adamowicz, L., & Nhatule, E. (2011). Environment and social impact assessment for the proposed exploration in EPC area "A". Maputo, Mozambique: Archaeological Circle of Cultural Heritage.

Agapiou, A. (2017). Remote sensing heritage in a petabyte-scale : satellite data and heritage Earth Engine © applications. International Journal of Digital Earth, 10(1), 85–102.

Basheer, S., Wang, X., Farooque, A. A., Nawaz, R. A., Liu, K., Adekanmbi, T., & Liu, S. (2022). Comparison of Land Use Land Cover Classifiers Using Different Satellite Imagery and Machine Learning Techniques. Remote Sensing, 14(4978), 1–18.

Bey, A., Jetimane, J., Nogueira, S., Ribeiro, N., Sitoe, A., & Meyfroidt, P. (2020). Mapping smallholder and large-scale cropland dynamics with a flexible classification system and pixel-based composites in an emerging frontier of Mozambique. Remote Sensing of Environment, 239 (111611), 1–17.

Clarke, G. P. (1998). A new regional centre of endemism in Africa (Chapter 4). In C.R. Huxley, J.M. Lock &D, F, Cutler (Eds.), Chorology, Taxonomy and Ecology of the Floras of Africa and Madagascar. Kew, UK: Royal Botanic Gardens.

Cruz, M. D. (2014). The Nature of Culture: Sites, Ancestors, and Trees in the Archaeology of Southern Mozambique. In N. Ferris, R. Harrison, &M. V. Wilcox (Eds.), Rethinking Colonial Pasts through Archaeology. Oxford, UK: Oxford University Press.

Darbyshire, I., Timberlake, J., Osborne, J., Rokni, S., Matimele, H., Langa, C., ... &Wursten, B. (2019). The endemic plants of Mozambique: Diversity and conservation status. PhytoKeys, 136, 45–96.

Deribew, K. T., & Dalacho, D. W. (2019). Land use and forest cover dynamics in the North - eastern Addis Ababa, central highlands of Ethiopia. Environmental Systems Research, 8(8), 1–18.

Ekblom, A., Notelid, M., & Witter, R. (2017). Negotiating identity and heritage through authorised vernacular history, Limpopo National Park. Journal of Social Archaeology, 17(1), 49–68.

Fairhead, J., & Leach, M. (1996). Misreading the African landscape: society and ecology in a forest-savanna mosaic. Cambridge, UK: Cambridge University Press.

FAO. (2020). Global Forest Resources Assessment 2020 - Report- Mozambique. Rome: FAO.

Hu, Y., & Hu, Y. (2019). Land Cover Changes and Their Driving Mechanisms in Central Asia from 2001 to 2017 Supported by Google Earth Engine. Remote Sensing, 11(554), 1–21.

Izidine, S., Siebert, S. J., Van Wyk, A. E., & Zobolo, A. M. (2008). Taboo and Political Authority in Conservation Policy: A Case Study of the Licuati Forest in Maputaland, Mozambique. Journal for the Study of Religion, Nature and Culture, 2(3), 373–390.

Junod, H. A. (1927). The Life of a South African tribe (second edition). London, UK: Macmillan.

Kwan, M. (2008). From oral histories to visual narratives: re- presenting the post-September 11 experiences of the Muslim women in the USA. Social & Cultural Geography, 9(6), 653–669.

Kwan, M. P., & Ding, G. (2008). Geo-Narrative: Extending Geographic Information Systems for Narrative Analysis in Qualitative and Mixed-Method Research. The Professional Geographer, 60(4), 443–465.

Masayi, N. N., Omondi, P., & Tsingalia, M. (2021). Assessment of land use and land cover changes in Kenya's Mt . Elgon forest ecosystem. African Journal of Ecology, 59, 988–1003.

Moçambique (2010). Plano estategico da provincia de Inhambane (Strategic plan of Inhambane Province). Maputo, Mozambique: Governo da Província de Inhambane.

Mozambique (2017). Profile of Inhambane province. Maputo, Mozambique: Governo da Província de Inhambane.

Ochungo, P., Khalaf, N., Merlo, S., Beldados, A., Mbogori, F. N. M., Tiki, W., & Lane, P. J. (2022). Remote Sensing for Biocultural Heritage Preservation in an African Semi-Arid Region: A Case Study of Indigenous Wells in Northern Kenya and Southern Ethiopia. Remote Sensing, 14(314), 1–23.

Ryan, C. M., Berry, N. J., & Joshi, N. (2014). Quantifying the causes of deforestation and degradation and creating transparent REDD baselines : A method and case study from central Mozambique. Applied Geography, 53, 45–54.

Sedano, F., Lisboa, S. N., Duncanson, L., Ribeiro, N., Sitoe, A., Sahajpal, R., Hurtt, G., & Tucker, C. J. (2020). Monitoring forest degradation from charcoal production with historical Landsat imagery. A case study in southern Mozambique. Environmental Research Letters, 15(1), 1–12.

Simbine, M.G.Z. (2020). 'Instituições Informais e Contribuições da Natureza para as pessoas: Subsídios para a Conservação das Florestas Sagradas em Moçambique' (Informal Institutions and Nature's Contributions to People: Guidance for Conserving Sacred Forests in Mozambique).University of Campinas.

Straka, T. M., Mischo, M., Petrick, K. J. S., & Kowarik, I. (2022). Urban Cemeteries as Shared Habitats for People and Nature : Reasons for Visit, Comforting Experiences of Nature, and Preferences for Cultural and Natural Features. Land, 11(1237), 1–21.

Virtanen, P. (2002). The Role of Customary Institutions in the Conservation of Biodiversity: Sacred Forests in Mozambique. Environmental Values, 11(2), 227–241.

Wilson, A. (2022). The use of remote sensing and digital tools for cultural heritage management and archaeological research. Levant, 53(3), 384–388.

Wondie, M., Schneider, W., Melesse, A. M., & Teketay, D. (2011). Spatial and Temporal Land Cover Changes in the Simen Mountains National Park, a World Heritage Site in Northwestern Ethiopia. Remote Sensing, 3, 752–766.

Yang, Y., Yang, D., Wang, X., Zhang, Z., & Nawaz, Z. (2021). Testing Accuracy of Land Cover Classification Algorithms in the Qilian Mountains Based on GEE Cloud Platform. Remote Sensing, 13(5064), 1–25.

Yuliani, E. L., Moeliono, M., Labarani, A., Fisher, M. R., Tias, P. A., & Sunderland, T. (2022). Relational values of forests : Value- conflicts between local communities and external programmes in Sulawesi. People and Nature, 1–17.