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Three decades of woodland cover change in Hwedza, Zimbabwe reveals similar trajectories of woodland loss in communal and resettlement areas

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ABSTRACT

Zimbabwe has pledged to halt and reverse forest loss by 2030, which if accomplished may enhance the delivery of ecosystem services. Uncertainty over the extent of woodland cover change and the impact of land redistribution could impede progress. Through comparative analysis of communal and resettlement areas we investigated the patterns, causes and implications of land-cover change in Hwedza, Zimbabwe between 1990 and 2020. Land-cover classification of remotely sensed data reveals that Hwedza has transitioned from a trajectory of net woodland loss to net woodland gain. There is no evidence that resettlement increased deforestation compared to communal areas. Changes in off-farm income, smallholder tobacco farming, and reduced profitability of staple crops were perceived by interviewees to be important factors affecting woodland change. Due to the importance of woodland services such as fuelwood, our findings highlight the need to address the societal implications of policies aiming to reduce deforestation .

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Woodland; land cover change; resettlement; Zimbabwe; remote sensing; mixed-methods

1. Introduction

Woodland cover in Zimbabwe has declined substantially in recent decades (Kamusoko et al., 2009; Maviza & Ahmed, 2020), potentially restricting access to woodland services that are key elements in coping strategies in times of crises (Pritchard et al., 2020; Woittiez et al., 2013). Improving understanding of the patterns and causes of woodland cover change is necessary for halting forest loss in Zimbabwe (Kamusoko et al., 2009), and for appreciating the implications this might have for delivery of ecosystem services (Ryan et al., 2016).

The causes of land cover change in Zimbabwe are disputed, and while correlative explanations for land cover change are abundant, causative evidence is lacking. Remote sensing has greatly improved our knowledge of how land cover has changed in Zimbabwe over the last 30 years. Decreases in natural vegetation cover have been widespread (Matsa et al., 2020), affecting the coverage of woodland (Sibanda et al., 2016), grassland and wetland (Matsa et al., 2020). These trends echo widespread declines in woodland cover across Africa (Bodart et al., 2013; Hansen et al., 2013; Mayaux

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et al., 2013), despite woody encroachment into savannahs (Mitchard & Flintrop, 2013; Venter et al., 2018). In the face of ongoing urbanisation and agricultural expansion (De Vos et al., 2024; Jellason et al., 2021), the area under cultivation (Tendaupenyu et al., 2017) and settlements (Jombo et al., 2017) has increased. Alongside knowledge of how land cover has changed, it is necessary to provide evidence for why it has changed if policy recommendations are to be adequately informed. Zimbabwe faces two concurrent challenges: maintaining and increasing woodland resources (Goebel et al., 2000), while also addressing inequities in land ownership stemming from the colonial era (Moyo, 2011). Conflicts between land reform and environmental objectives have been discussed (Lemenih et al., 2012; Wynberg & Sowman, 2007), with some suggesting that woodland loss followed farm resettlement (Jombo et al., 2017; Sibanda et al., 2016). There are however, few comparisons of land cover change in communal and resettlement areas, and little understanding of why resettlement might have led to deforestation (Mukwada et al., 2015). These gaps make it difficult to identify policy levers to mitigate negative trade-offs between land equity and the environment.

Remote sensing is limited in its ability to provide information on the causes and implications of change (Dennis et al., 2005). Studying the land without including the people who use it fails to utilise the full potential of remote sensing data (Taubenböck et al., 2009). Integrating remote sensing and social science methods aids the production of outputs that are relevant to land users (Herrmann et al., 2014) and policy-makers (Liverman & Cuesta, 2008). Interviews can provide richly descriptive data (Merriam, 2002), giving a flexible way of gaining detailed information, and personal perspectives on the impact of land cover change.

The last four decades have been a time of substantial socioeconomic change in Zimbabwe. In 1980 Zimbabwe gained independence and the resettlement programme began; a scheme which aimed to redistribute land from the large, mainly white-owned farms, to land-poor families to redress racial and class inequalities (Moyo, 2011). The 1990s were punctuated by multiple severe droughts (Kinsey et al., 1998), which alongside the liberalisation of the maize market and changes in the role of the Grain Marketing Board, reduced farmers' access to markets and ability to grow crops (James & Kinsey, 2013). In the early 2000s the economy contracted sharply, coinciding with the implementation of the Fast-Track Land Reform, a new wave of farm resettlement (Moyo, 2011). In this period hyperinflation greatly affected farmers access to inputs and markets (James & Kinsey, 2013), and the labour opportunities available (Moyo, 2011). Re-liberalisation and dollarization of the economy in 2009 brought with it greater economic stability and the rise of contract farming (James & Kinsey, 2013). Fluctuations in socioeconomic and environmental conditions are relevant to consider when addressing land cover and changes in natural resource management systems.

Resettlement in Zimbabwe occurred in three phases over a thirty-year period (Moyo, 2011). The first occurred in the 1980s and involved purchase of land on a willing-seller willing-buyer basis (Chilunjika & Uwizeyimana, 2015; Dekker & Kinsey, 2011). While partially effective at addressing land inequities, the area of land redistributed was below government targets (Moyo, 2011). In the 1990s, the second wave of land resettlement imposed compulsory land redistributions with compensation for land acquired (Chilunjika & Uwizeyimana, 2015). In both the 1980s and 1990s settlers were required to agree with the conditions that they must not take up off-farm employment, and they could not redistribute or divide the land (Dekker & Kinsey, 2011). In the 2000s the Fast Track Land Reform took place, where farms were often seized violently without compensation (Dekker & Kinsey, 2011). While agricultural production decreased in the 2000s, trends in agricultural productivity following land resettlement need to be considered in the context of long-term changes (Moyo, 2011). Cereal productivity was undergoing long term declines since the late 1980s following economic liberalisation, and broader-scale events such as droughts had severe impacts on crop production (Moyo, 2011). Many resettled farmers were able to increase productivity despite coming from varied socioeconomic backgrounds, and from areas with different soil and rainfall conditions (Dekker & Kinsey, 2011).

The transition from forest loss to forest recovery can be understood through the lens of the forest transition theory (Mather, 1992). Forest transition theory describes the change in land cover trend from net deforestation to net reforestation (Lambin & Meyfroidt, 2010; Mather, 1992) and has been used to understand pathways to forest transition (Liu et al., 2017). A few countries have gone through a forest transition with expansion exceeding deforestation, but global rates of deforestation remain high and major technological and policy advancements would be required to achieve a global transition (Meyfroidt & Lambin, 2011). Zimbabwe is in the early phase of forest transition (Hosonuma et al., 2012), undergoing net deforestation; but, local patterns may differ from national trends (Meyfroidt & Lambin, 2011).

Miombo woodland is a dry, savanna woodland that is characterised by the dominance of *Brachystegia spiciformis, B. boehmii* and *Julbernardia globiflora* (Frost, 1996; Pritchard et al., 2019). Miombo woodlands are an essential source of provisioning services for small-holder farming communities (Grundy, 1995; Pritchard et al., 2019) and are facing high rates of land cover change (McNicol et al., 2018). Understanding trajectories of land cover change in these ecosystems is essential, but miombo woodlands are poorly characterised by large-scale mapping studies due to the challenges posed by large seasonal variation in spectral signatures and the mixture of tree and grass in miombo woodlands (McNicol et al., 2018). For this reason, accurate classification of miombo woodland often requires use of supervised classifiers with a high density of training data at a local scale (Mayes et al., 2015). Satellite imagery used to conduct land cover classification, and used to carry out classifier training and validation, is often biased towards dry seasons. During the dry season land cover classes such as bare land, cropland and grassland are particularly difficult to distinguish, but woodland can be easier to separate from grasslands due to high spectral contrast (Borges et al., 2020). Local-scale studies provide information at a scale relevant for decision-making for sustainable management of resources (Arki et al., 2020) and improve understanding of the driving factors of land cover change (Verburg et al., 2015). To understand why changes in woodland cover are happening, and to account for the complex interdependencies between socioeconomic and environmental factors, case studies are essential (Verburg et al., 2015).

Here we provide a case study of woodland cover change in Hwedza; a district covering an area of 2,560 km^2 in the Mashonaland East province of Zimbabwe (Figure 1; UN OCHA ROSEA, 2022). The average total rainfall in Hwedza is 807 mm but the vast majority of rainfall occurs in the November-March rainy season (Mugiyo et al., 2021). The annual mean temperature is 18–19°C, ranging from 11°C in winter months to 33°C in summer months (Mugiyo et al., 2021). Hwedza is in the Miombo Ecoregion of Southern Africa (Pritchard et al., 2019) and covers three agroecological zones (Manatsa et al., 2020), which summarise variation in rainfall, soil, vegetation and other variables influencing agricultural productivity. Predominantly these agroecological zones divide Hwedza into the wetter, more productive area north of Hwedza mountain (agroecological zone IIb, annual rainfall of 750-1000 mm), and the dryer, less productive area south of Hwedza mountain (agroecological zones III and IV, annual rainfall of 650-800 mm and 450-650 mm respectively), where crop production is more dependent on supplementary irrigation (Manatsa et al., 2020).

Historically, employment on large-scale commercial farms, smallholder farming of crops such as maize and millet, and mining around Wedza mountain were common sources of income (Gumbo, 1988; Pritchard et al., 2019). As a result of the resettlement programme, large-scale commercial tobacco farming was replaced by smallholder farming from the 1980s onwards (James & Kinsey, 2013). Most farm resettlement in Hwedza occurred in the first wave of resettlement in the 1980s, with some resettlement occurring during the Fast Track Land Reform Programme in the early 2000s. In Hwedza there is marked variation in land tenure arrangements, farming practices and reliance on natural resources due to the presence of both communal areas and resettlement areas (where farm resettlement beneficiaries relocated to). Due to the diversity of relationships between land tenure and livelihood, Hwedza makes an appropriate study region for this case study.

In this study we investigated whether the patterns of natural vegetation loss in Zimbabwe are also found on a subnational scale in Hwedza.

Specifically, we aimed to:

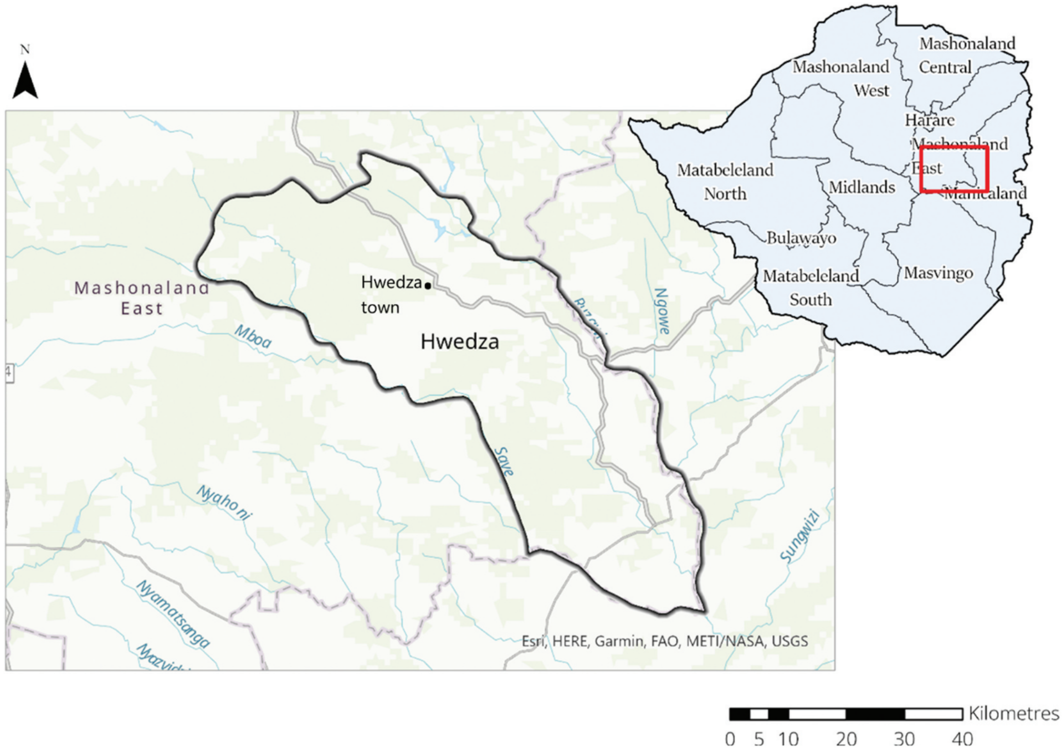

Figure 1. Location of Hwedza in Zimbabwe.

(1) Quantify woodland cover change in Hwedza between 1990 and 2020, and compare trajectories between resettlement and communal areas;
(2) Examine the implications of woodland cover change, particularly with regards to access to woodland resources; and
(3) Explore the processes underlying woodland cover change.

If patterns of woodland cover change in Hwedza align with observed changes in other areas of Zimbabwe (Sibanda et al., 2016), we expect to see a decline in woodland cover in both resettlement and communal areas. Previous studies have found loss of natural woodland cover following resettlement (Jombo et al., 2017) suggesting that loss of woodland may be greater in resettlement areas than in communal areas, but few studies compare trajectories between communal and resettlement areas. We expect that if woodland cover declines, access to woodland resources will also decline (Pritchard et al., 2019), and that land cover change will be dependent on a number of complex environmental and socioeconomic factors.

2. Materials and methods

2.1. A mixed-methods study

This project employed a mixed-methods design, utilising the complementary information sources of remotely sensed satellite imagery and interviews of key informants. The purpose of the remote sensing component was to quantify land cover change in Hwedza over a long time period in a spatially explicit manner. The interview component aimed to identify possible causes of land cover and land use change, the implications of these changes, and gain a broader understanding of socioeconomic change in Hwedza. The results of remote sensing and interviews were compared to identify areas of convergence, divergence, and complementarity between the two data sources (Nightingale, 2009).

2.2. Remote sensing

2.2.1. Study region and period

Land-cover-change analysis was conducted by creating annual land cover maps from 1990–2020, using supervised classification of Landsat data (Figure 2).

The time series was constrained between 1990 and 2020 because prior to 1990 there are few images per year in the Landsat archive. Especially in seasonal climates and mixed tree-grass ecosystems, accurate classification requires multiple images per year to allow for phenological information to be incorporated in the classification (Sweeney et al., 2015).

2.2.2. Data acquisition and preparation

Surface reflectance and elevation data were used to carry out the classification, provided by Landsat (Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 OLI) (courtesy of USGS) and NASA SRTM Digital Elevation (Nasa, 2013) respectively. Shadow and cloud pixels were excluded from Landsat data using the *pixel_qa* band.

Image processing and classification were carried out in Google Earth Engine (Gorelick et al., 2017). Yearly composites of Landsat imagery were constructed from annual medians of surface reflectance for each band, and for NDVI (Equation 1) and EVI (Equation 2).

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \tag{1}$$

Where *NDVI* is the Normalised Difference Vegetation Index, used to quantify vegetation greenness (USGS, 2020b), *NIR* is near-infrared surface reflectance and *R* is red surface reflectance.

$$EVI = G \times \frac{(NIR - R)}{(NIR + C1 \times R - C2 \times B + L)} \tag{2}$$

Where *EVI* is the Enhanced Vegetation Index and can be used to quantify vegetation greenness, however, unlike NDVI it corrects for atmospheric conditions and is more sensitive to dense vegetation (USGS, 2020a). *G* is the gain factor (2.5), *NIR* is near-infrared surface reflectance, *R* is red surface reflectance, *C*1 is the coefficient of atmospheric resistance for the red band (6), *C*2 is the coefficient of atmospheric resistance for the blue band (7.5) and *L* is a coefficient to adjust for canopy background (1). Values of *G*, *C*1, *C*2 and *L* were obtained from USGS (2020a).

Discriminating between cropland and grassland can be difficult using average reflectance alone so annual 5th and 95th percentiles of NDVI and EVI were added to aid discrimination by highlighting the seasonality of vegetation types. Using the interquartile range of NDVI and EVI instead of 5th and 95th percentiles did not improve classification accuracy.

Gaps in Landsat 7 imagery due to the Scan Line Corrector failure (USGS, 2003) were not adequately filled by creating median composites so a morphological mean filter was applied to this imagery (Cherrington, 2018). The efficacy of a morphological mean filter with different parameterisations was evaluated through visual inspection at a range of scales, adjusting the kernel type, radius and number of iterations, to give the best result. In the end, the morphological mean filter was applied with 70 iterations using a circular kernel with a radius of 1 pixel.

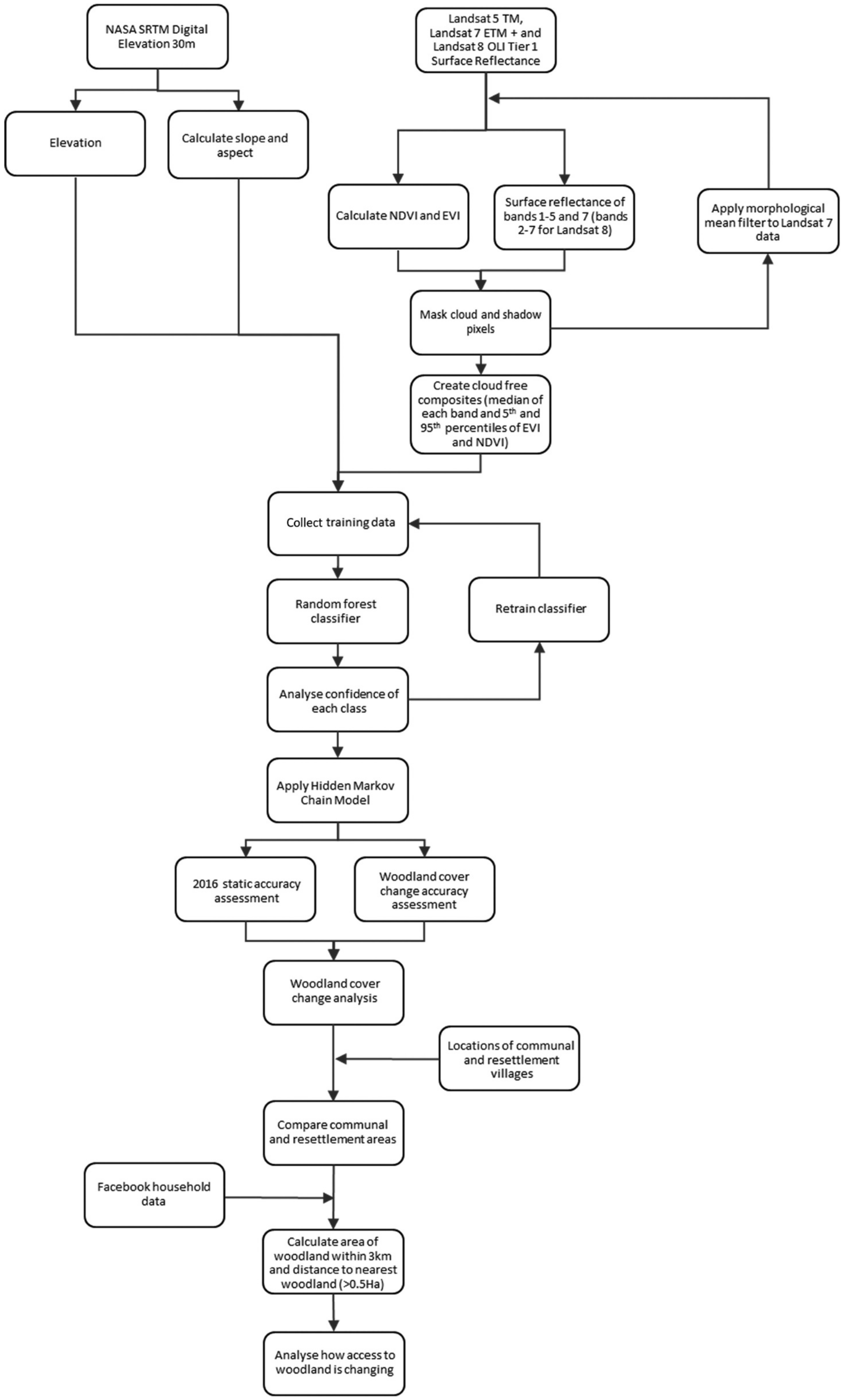

Figure 2. Summary of remote sensing methodology.

2.2.3. Gathering training data

Training data were collected by human interpretation of high-resolution optical images in Google Earth. Locations with stable land cover through the entire time series were selected to allow its use as training data for all years. High resolution satellite imagery (CNES/Airbus and Maxar Technologies) was used for identification of land cover class in recent years, but as historical imagery is rarely available this was combined with Landsat imagery to check for any land cover change. Landsat imagery allows stable pixels to be identified at medium resolution, where visual inspection can reveal where change has occurred, for example the clearing of woodland to form a rectangular field, overcoming the absence of high-resolution historical data. A total of 566 training polygons were gathered.

Initially, seven land cover classes were defined. They were, dense woodland (more than 90% tree cover), sparse woodland (between 10 and 90% tree cover), grassland (less than 10% tree cover), cropland, water, settlement, and bare ground. These classes were chosen as they divide the spectrum of land cover into broad classes of interest, hypothesised to have different environmental and social values. Dense and sparse woodland were initially classified separately to enable exploration of aggradation and degradation, but were later combined, due to high rates of confusion between these classes.

2.2.4. Classification and post classification procedure

Classification was carried out using a random forest classifier with 50 decision trees, set to output a probability of each land cover class. Increasing the number of decision trees (500) did not improve classification accuracy so the less complex classifier (with 50 decision trees) was used which gave very similar results. The output was a time series of probabilities for each pixel per land cover class. The mean out-of-bag error of the random forest classifier (before post-classification procedure) was 0.04 (standard deviation: 0.01). The out-of-bag error was not higher for classifications relying on Landsat 7 data (mean out-of-bag error: 0.03) where a morphological mean filter (Cherrington, 2018) was used to overcome gaps in imagery due to the Scan Line Corrector Failure (USGS, 2003).

Post-classification comparison of land cover maps is typically associated with poor change-detection performance, as errors in the individual maps compound and result in many spurious changes. Temporal consistency was improved using a hidden Markov Model (HMM) approach,[1] based on the methods described in Abercrombie and Friedl (2016). The HMM uses a matrix of pre-specified transitions probabilities alongside the classification certainty to suppress spurious changes through time (Hermosilla et al., 2018). This approach tends to only retain land cover transitions where the classification has a high certainty and which persist through time, and penalises changes that are considered biophysically improbable. With an absence of empirical data for Hwedza on the probability of transition between land cover classes, all change was defined as unlikely (0.01) and stability (no-change) was defined as likely (0.99), a threshold determined visually to remove the majority of spurious change while capturing known locations of forest change. The stabilised time series of land cover probabilities was produced using the 'forward-backward' algorithm (Yu & Kobayashi, 2006), and the final land cover time series used as the most probable land cover class at each time step.

2.2.5. Access to woodland

Patterns in woodland cover change were compared between communal and resettlement areas. Field arrangement was similar between resettlement and communal areas. Land was allocated to each resettled family for small holder agriculture and shared lands were available for grazing. However, in the resettlement area, farmers were generally allocated more land per farmer than the area of land available to farmers in communal areas, and resettlement area land came with the stipulation that it must be farmed. Village locations and names were scraped from the Bing Maps API (Bing Maps, 2022) using the R packages *R Curl* (Lang, 2022) and *RJSONIO* (Lang & Wallace, 2021).

Resettlement and communal villages were identified using NS's expert knowledge. Thiessen polygons were used to approximate boundaries between villages.

Differences in climate and soil between agroecological zones were expected to impact land use and could therefore influence land cover change trajectories, so we compared changes in woodland cover between areas north and south of Hwedza mountain (referred to as the northern and southern communal areas from hereon). The two agroecological zones south of Hwedza mountain were too small to analyse individually so were grouped together.

The time series of land cover classifications was used to analyse how access to woodland changed between 1990 and 2020 in the northern communal area and resettlement area (as they belong to the same agroecological zone). The distance from settlements to the nearest patch of woodland (over 0.5 ha) and the area of woodland within 3 km was measured. A minimum woodland area of 0.5 ha was used to remove very small patches of trees as it was assumed these patches would not provide comparable ecosystem services to larger areas of woodland. This analysis relied on high resolution settlement maps showing the location of individual households, produced by Meta (Facebook CIESIN, 2016). Note that these statistics cover all households in the region and are a census, not a sample.

2.2.6. Accuracy assessment

To evaluate the accuracy of produced classifications, accuracy assessment was carried out in Collect Earth (Bey et al., 2016) using the same type of imagery as used for collecting training data. The 2016 classification was assessed, chosen because coverage of high-resolution data in Collect Earth was greatest for this year. A simple random survey design was used with 479 0.5 ha sample plots. For each plot the primary land cover was identified. Overall accuracy and user's and producer's accuracies were calculated as outlined by Olofsson et al. (2014). Due to small coverage of the settlement, water and bare ground classes, the sample size was insufficient to estimate useful user's and producer's accuracy statistics for these classes.

To evaluate accuracy of change classes, a stratified random accuracy assessment of key land cover transitions between 2006 and 2011 was conducted. The time period of 2006 to 2011 was chosen as these years had the highest availability of high-resolution satellite imagery in Hwedza. Whilst change accuracy statistics may differ over a long time period, changes are more difficult to detect over a shorter time frame, so this approach may slightly underestimate change accuracy. One hundred 0.5 ha plots for six land cover transitions, between woodland, cropland, grassland, and for no change were assessed. Where insufficient imagery was available or cloud obscured land cover, plots were discarded, after which 563 validation plots remained. As woodland cover was of most interest in this study, transitions were aggregated as deforestation, woodland expansion, and no change in woodland cover, and accuracy statistics calculated (Table 1). Uncertainties are reported as 95% confidence intervals (lower bound – upper bound).

2.3. Interviews

We aimed to interview a wide range of key informants. To achieve this despite COVID-19 restrictions, the interviews were conducted by either Kerry Stewart who was based in the United Kingdom (UK) via telephone or video call, or by Nyaradzo Shayanewako, a locally based researcher, who conducted interviews in person or by telephone or video call. Nine key informants were interviewed, identified

Table 1. Transitions included when aggregating accuracy assessment results by woodland change classes.

Woodland change class	Transitions included
No change	No change, grassland to cropland, cropland to grassland
Deforestation	Woodland to grassland, woodland to cropland
Expansion	Grassland to woodland, cropland to woodland

through purposive sampling to provide diverse views. First, we made contact with researchers known to have experience in the subject area and with village heads from numerous villages. After conducting these interviews, we identified other people in each community who might provide a complementary perspective through snowball sampling (Palinkas et al., 2015). We deliberately sampled participants with a wide range of perspectives to obtain diverse views on land cover change. Interviewees were from a range of occupations including researchers, farmers, village heads, teachers and nightwatchmen, and included people familiar with both the northern communal area and the resettlement area. We did not interview participants from the southern communal area, so interview results only pertain to the northern communal area and the resettlement area. With this number of interviews, we aimed to gather perspectives on the causes of land cover change and the implications of these changes, rather than provide an independent assessment of the extent of land cover change in Hwedza. Ethics approval was obtained from the GeoScience Ethics Committee, University of Edinburgh. Participants were informed of the aims and possible outcomes of the study, and how their data would be handled and anonymised. Participants were asked for their consent to be interviewed and recorded (audio) before every interview.

In 30–60 minute, semi-structured interviews, participants were asked about land use/cover change, access to natural resources, how land use compares between the northern communal area and resettlement area and other factors influencing social change. Semi-structured interviews were used to enable comparison between interviews whilst giving flexibility to explore some topics in greater depth. KS and NS carried out interviews in the participants' first language (English or Shona) and then transcribed them into English for coding.

Interviews were coded into phrases of similar meaning (DeCuir-Gunby et al., 2011). Connections between codes were explored and the results summarised. With limited numbers of interviews, it was not possible to be sure that all perspectives had been heard, or that the views presented were representative of the wider population. Therefore, interview data presented in this study are intended to contextualise results obtained from earth observation data and identify possible causes of land cover change that could be used to inform hypothesis setting in future.

In addition to interviews, perceptions of population change were compared to changes in population recorded by the Zimbabwe population census (UN OCHA ROSEA, 2022; The World Bank, 2019; ZIMSTAT, 2022), between 2002 and 2012, and between 2012 and 2022. For each ward the difference in population density between 2002 and 2012, and between 2012 and 2022 was calculated, as a percentage of the population density in 2002 and 2012 respectively. The difference between northern communal area wards surrounding the mountain, and northern communal area wards not surrounding the mountain, were assessed for both time periods using one-tailed, two-sample t-tests.

Our positionality impacts how we perceive the world (Jacobson & Mustafa, 2019). Our research team included both insiders (NS) and outsiders (KS, CR, SB) (sensu Merton, 1972) providing both advantages and disadvantages to the research process (Gary & Holmes, 2020). A researcher's position on the insider-outsider spectrum is not fixed and depends on a number of factors including the participant, so in some cases, particularly when interviewing a researcher, KS may be more of an insider than an outsider. Conversely, NS was mostly an insider, so these advantages and disadvantages are reversed.

Throughout this project we have aimed to remain aware of the impact that our positionality will have on the research design, data collection and dissemination of results, and to explicitly tackle biases we hold, in order to progress closer towards empathetic neutrality (Gary & Holmes, 2020).

3. Results

3.1. Land cover change

In 2016 there was a sharp divide between the wooded South of Hwedza and the more agricultural North (Figure 3). Hwedza has a dynamic land cover system, with 27% of pixels exhibiting change between 1990 and 2020 (see Figure A2 in the appendix), and 2% of pixels undergoing change more than once over that period. The majority of change occurred among woodland, cropland and grassland, making up 97% of changes. Due to low accuracy of cropland-to-grassland and grassland-to-cropland transitions (Table S1, see Appendix) we have focused on woodland cover change. Changes in cropland and grassland cover are detailed in the appendix.

Woodland cover showed little net change (<1%) between 1990 and 2020, but gross changes in woodland cover were large (Figure 4, 28% of woodland cover in 1990). Net and gross changes in land cover obscure temporal and spatial aspects of land cover transitions that occurred in the district. Notably, Hwedza underwent a woodland transition between 1990 and 2020, meaning that the trajectory of woodland cover change switched from net woodland loss to net woodland gain. Woodland cover decreased from 963 km^2 to 933 km^2 between 1990 and 2009 then increased to 963 km^2 by 2020 (Figure 4).

Woodland cover change varied between the north and south of Hwedza (Figures 5 and 6). In the south of Hwedza (all communal areas) woodland cover increased by 5% between 1990 and 2020 whereas in the northern communal areas and resettlement area woodland cover was lost (9% and 14% decrease in woodland cover for the northern communal area and resettlement area respectively). Between 1990 and 2005 the northern communal area and the resettlement area showed similar trends in changing woodland cover. Following 2005, woodland cover increased in the northern communal area but fluctuated in the resettlement area (Figure 6).

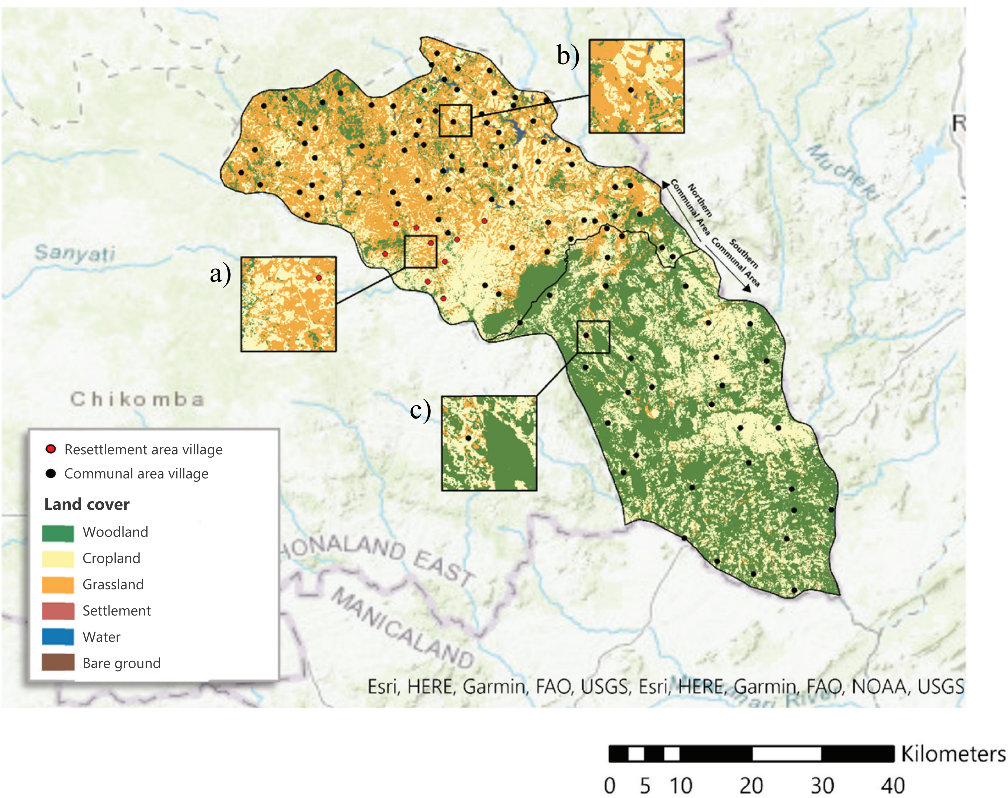

Figure 3. Land cover in 2016 in Hwedza district, based on random forest classification of landsat imagery and a hidden Markov model. Village locations were scraped from bing maps API (Bing Maps, 2022). a) shows a matrix of grassland and cropland cover around a resettlement village, b) shows grassland and cropland cover around a northern communal area village (north), and c) shows large woodland patches around a southern communal area village.

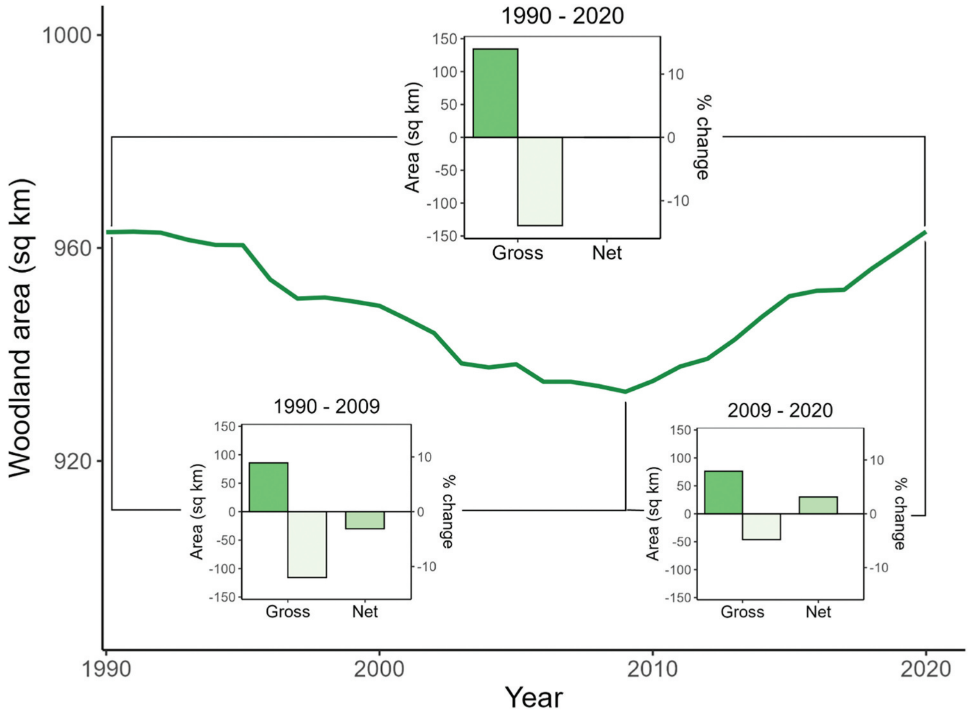

Figure 4. Change in woodland cover in Hwedza between 1990 and 2020, showing gross and net change in woodland cover (area in square kilometers and percentage change relative to 1990 woodland cover) between 1990 and 2009 (year of minimum woodland cover), 2009 and 2020, and 1990 and 2020.

As woodland cover decreased in both the northern communal area and resettlement area, we assessed how this affected household access to woodland. Despite a 9% reduction in woodland cover, there were no substantial changes in the proximity and quantity of woodland surrounding northern communal area households between 1990 and 2020 (Figure 7). In the northern communal area, the mean area of woodland within 3 km of each household was 538 ± 459 ha (± indicates SD) in 1990 and 577 ± 479 ha in 2020. Mean distance to the nearest woodland patch (>0.5 ha) also remained similar between 1990 and 2020 (229 ± 280 m in 1990 and 207 ± 221 m in 2020). As access to woodland statistics covered all households rather than a sample, SDs are given to indicate the variability in the population and not to enable an assessment of significant differences.

Unlike in the northern communal area, in the resettlement area there was a substantial decrease in the quantity of woodland surrounding households. The area of woodland within 3 km of households in the resettlement area decreased from 200 ± 138 ha in 1990 to 146 ± 93 ha in 2020. Despite this, households in the resettlement area were nearer to woodland patches in 2020 (mean minimum distance to woodland patches: 337 ± 203 m) than 1990 (mean minimum distance to woodland patches: 436 ± 441 m) the resettlement area. Households became nearer to woodland patches despite a decrease in woodland cover, due to an increase in fragmentation of woodland patches across Hwedza (see Appendix).

Due to both pre-1990 differences and the 1990–2020 trends, woodland cover in 2020 was substantially higher in the northern communal area (woodland was 21% of land area) than the resettlement area (11%). This higher woodland coverage was associated with greater quantity and proximity of woodland for households in the northern communal area, although there was great variability.

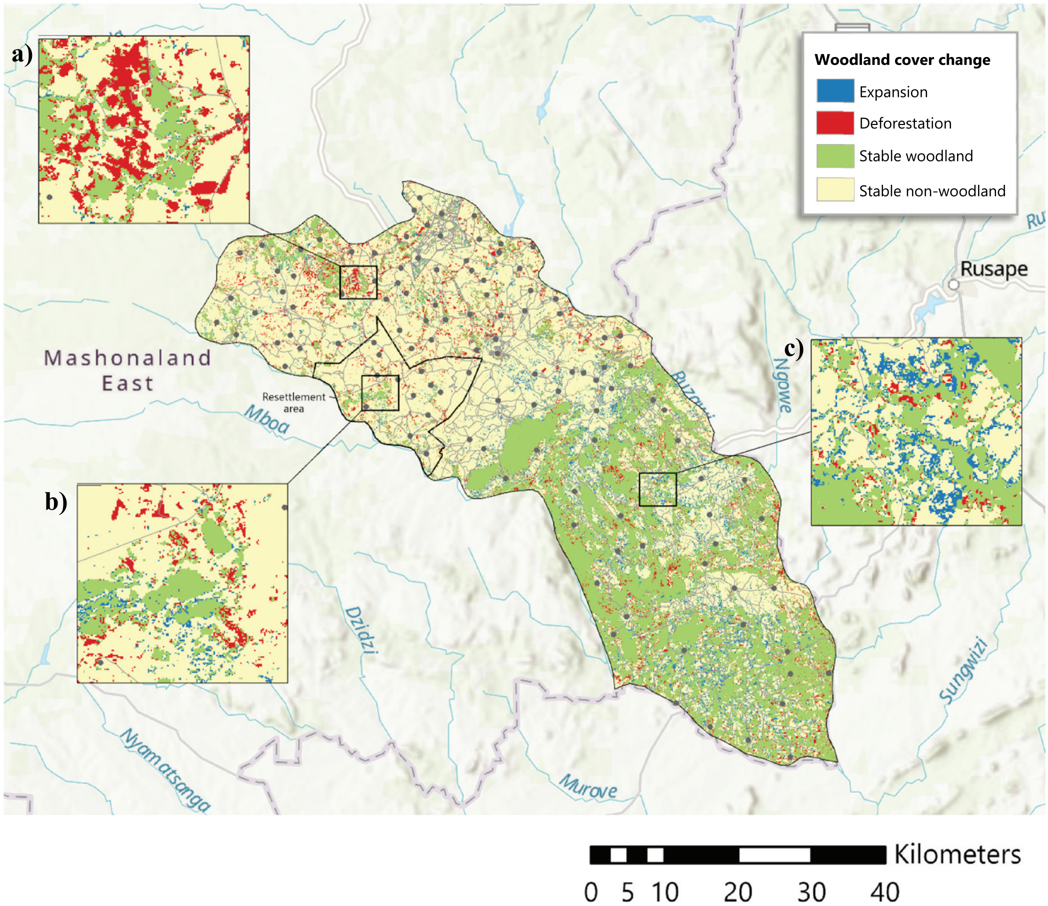

Figure 5. Map of woodland cover change between 1990 and 2020 in Hwedza based on random forest classification of landsat imagery and a hidden Markov model. Focus areas show a) an area of marked deforestation in the northern communal area, b) matrix of deforestation and woodland expansion in resettlement area and c) woodland expansion in southern communal area. Due to the dynamic land cover system, woodland expansion and deforestation were widespread across the communal and resettlement areas. Basemaps from Esri, TomTom, Garmin, Foursquare, METI/NASA, USGS, NGA and FAO.

3.2. Accuracy assessment

3.2.1. 2016 classification

The 2016 classification (Figure 3) had an overall accuracy of 66% (95% CI: 62–70%, $n = 479$) (Table 2). The user's accuracy of cropland (48%) and producer's accuracy of grassland (49%) were low, relative to other classes, due to confusion between these two land cover classes. Confusion between cropland and grassland did not impact woodland cover classification however, which had high user's and producer's accuracy (79% and 77% respectively).

3.2.2. Woodland change accuracy assessment (2006–2011)

The overall accuracy of the 2006–2011 woodland cover change map was 97% (95–99%, $n = 563$), although user's and producer's accuracy varied between change classes (Table 3) and were low for woodland expansion, which was often confused with no change. Of the 563 reference plots, 111 showed evidence of deforestation in the high resolution satellite imagery (the reference data) compared to 172 which were classified as deforestation in the change map (Table 3). 51 reference plots showed evidence of expansion whereas 159 plots were classified as expansion in the change

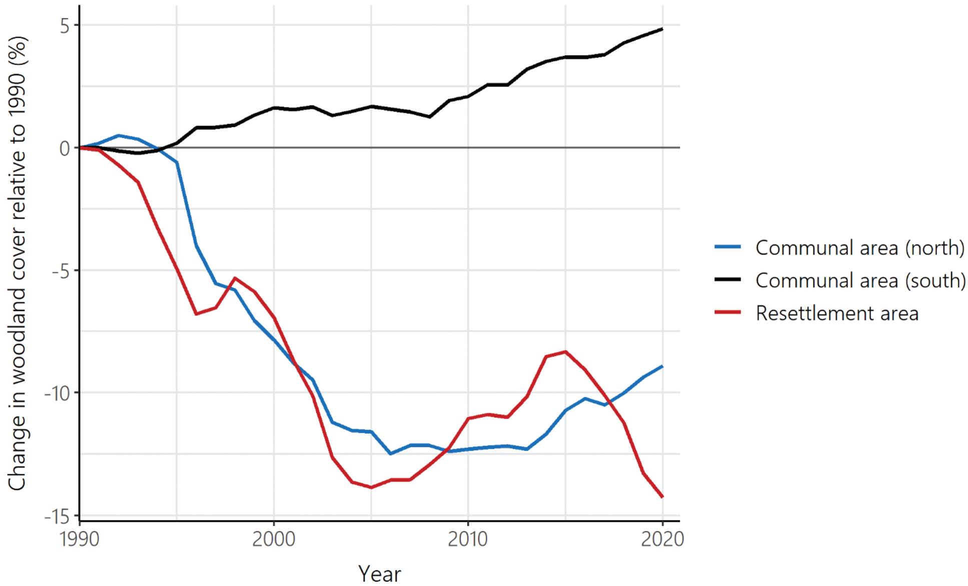

Figure 6. Change in woodland cover (%) between 1990 and 2020 in the communal areas and the resettlement area. Resettlement and communal villages were identified using NS's expert knowledge, and Thiessen polygons were used to approximate boundaries among villages.

map. This suggests that between 2006 and 2011 the change map underestimated deforestation (relative to the reference class) and overestimated expansion. It was not possible to adjust change statistics to reflect the underestimation of deforestation and overestimation of expansion between 2006 and 2011, due to uncertainties with projecting accuracy statistics to other points in the time series.

Nevertheless large, long-standing changes in woodland cover appeared to be classified with greater accuracy than small, temporary changes. Visual inspection (in comparison to historical high resolution satellite imagery) revealed the change map was effective at identifying changes where the change was sustained over a long time period and was less good at identifying changes that occurred over a small area or were temporary (Figure 8). Where land cover was a mixture of land cover types, change map accuracy appeared especially low. These limitations are inherent when simplifying the complexity of land cover into discrete classes and were considered when interpreting the results.

3.3. The woodland transition: results from interviews

Interviewees reported a scarcity of woodland resources in both the resettlement area and the northern communal area.

Four of the five participants that had knowledge of the resettlement area stated that wood availability was causing problems for residents in various ways and all six referred to the declining availability of wood and other environmental resources (key response 1, key responses can be found in Table 4). Removal of trees has violated traditional taboos in some places, removing fruit trees and trees of cultural importance (key response 2 and 3).

Shortage of wood has increased collection time, the travel time to get to wood resources and the cost of wood (key response 4). Due to the requirement for firewood in many aspects of daily life (key response 5), a reduction in wood availability had implications for farmers' wellbeing (key response 6).

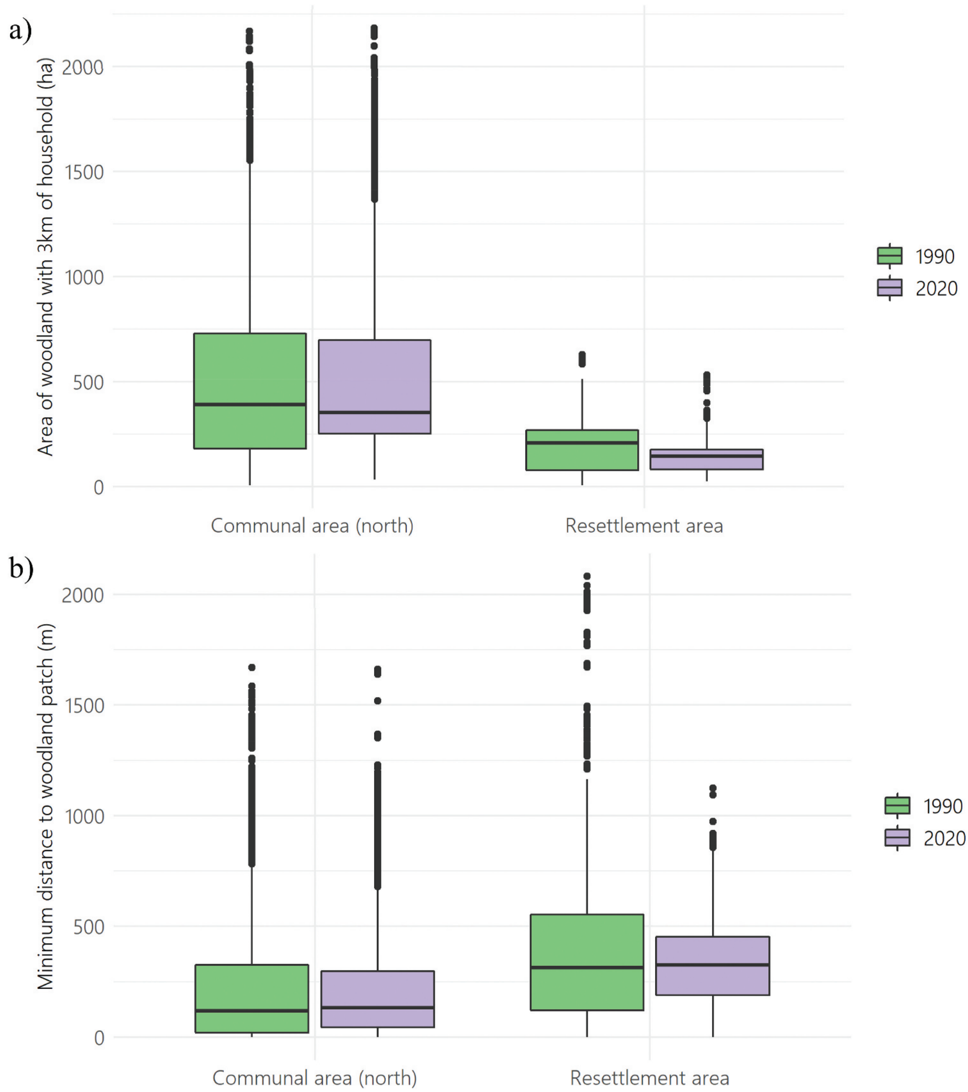

Figure 7. a) Area of woodland within 3 km of the household, and b) minimum distance from household to woodland patch >0.5 ha in 1990 and 2020 in communal (North) and resettlement areas.

Table 2. Confusion matrix of 2016 classification accuracy assessment. Only areas that showed no change between 2010 and 2020 were included. Brackets show the 95% confidence interval for the accuracies.

Reference class Map class	Woodland *n* = 212	Cropland *n* = 142	Grassland *n* = 122	Map area km^2	User's accuracy, %
Woodland, *n* = 206	167	7	38	860	79 (73–85)
Cropland, *n* = 93	20	69	53	472	48 (40–54)
Grassland, *n* = 177	19	17	86	838	70 (62–78)
Producer's accuracy, %	77 (71–83)	77 (69–86)	49 (42–56)		Overall accuracy: 66 (62–70)

Loss of trees was linked by farmers and village heads to reduction in rainfall, both due to the ecosystem services provided by trees and the reduction in cultural rain-making ceremonies (a northern communal area farmer, resettlement village head, and northern communal area village

Table 3. Confusion matrix of class-by-class woodland change map (2006–2011) accuracy assessment. Brackets show the 95% confidence interval for the bias-corrected area estimates and accuracies.

Reference class Map class	No change (n = 401)	Deforestation (n = 111)	Expansion (n = 51)	Map area (km^2)	Bias-corrected area estimate (km^2)	User's accuracy (%)
No change (n = 232)	227	4	1	2496	2477 (2430–2524)	98 (96–100)
Deforestation (n = 172)	71	101	0	31	62 (20–104)	59 (52–66)
Expansion (n = 159)	103	6	50	34	21 (0–43)	31 (24–38)
Producer's accuracy (%)	99 (98–100)	29 (21–37)	50 (49–51)			Overall accuracy: 97 (95–99)

head linked reduction in rainfall to rain-making ceremonies and a resettlement village head linked reduction in rainfall to fewer trees).

Many interviewees linked decline in wood resources to tobacco farming in resettlement areas (tobacco needs a large amount of wood for curing), with other factors, such as increase in population also reportedly playing a role (key response 7).

In the northern communal area woodland resources were also reported to be limited. Of the five people interviewed with knowledge of communal areas, four stated there was low availability of wood resources and one said wood resources were limited in the most deforested areas (key response 8).

Only one interviewee, a farmer who lives close to the well-wooded Hwedza mountain, stated that access to environmental resources had not changed and that there was enough firewood (key response 9). As the mountain is considered a sacred place, woodland on and around the mountain may have greater protection.

Use of firewood was not always associated with cutting down trees, and dead wood was reported to be an important source of firewood (key response 10).

Mining activity, increased population, and increasing reliance on environmental resources were linked to decline in wood resources in the northern communal area by several interviewees (key response 11 and 12).

Population increase was linked to an influx of people coming to communal areas for gold panning (key response 13). According to the Zimbabwe population census (ROSEA, UN OCHA, 2022; The World Bank, 2019; ZIMSTAT, 2022), the population of Hwedza did increase between 2002 and 2012, and again between 2012 and 2022. Despite this, communal area wards around the mountain, where gold extraction was expected to be most prevalent, did not show a greater increase in population than other northern communal area wards ($p > 0.05$, $n = 6$, for both 2002–2012 and 2012–2022).

In the northern communal area, off-farm employment was an important source of income with people travelling to cities for work and engaging in gold-panning (key response 14). Changes in off-farm employment and rainfall patterns were linked to a decline in profitability of staple crops (key response 15, 16 and 17).

Cultivating tobacco offered an alternative to staple crops in the resettlement area and for some was very profitable. Farm sizes in the northern communal areas were reportedly smaller than farm sizes in the resettlement area, and had fewer government inputs. Low land availability and few government inputs was linked to reduced harvests in the communal area relative to the resettlement area by one resettlement farmer (key response 18). Many communal and resettlement farmers said that this difference if farm sizes was why communal farmers were not able to engage in tobacco farming and agriculture has become less profitable (key response 19).

Tobacco growing is not only an opportunity for resettlement households but also for many it is a necessity. Lack of off-farm employment and encouragement from the government to farm (a

Table 4. Key responses from interviews.

Key response	Response by	Quote
1	Village head from a resettlement area	*'We found thick forests and other natural resources when we got here, but I can tell you 10 years from now, we will start experiencing shortages in some of the natural resources'*
2	Farmer from a resettlement area	*'Tobacco growing has destroyed all trees, even fruit trees'*
3	Farmer and village head of a resettlement area	*'We have sacred trees like the Muchakata tree* [*Parinari curatellifolia*] *where all our cultural rain making ceremonies are held. These sacred trees have been cut down as well'*
4	Farmer from a resettlement area	*'We now take 2–3 hours to collect firewood and we have to travel 6–10 km to and from places with firewood. It is expensive to buy firewood these days'*
5	Farmer from a resettlement area	*'Firewood is life because we cook, heat our homes, cure tobacco and treat brick kilns using firewood.'*
6	Farmer from a resettlement area	*'… our life has become difficult to lead because we no longer have firewood, wild fruit and herbs'*
7	Farmer	*'Our trees have been cut down by tobacco farmers and overpopulation has caused a high demand for firewood'*
8	Communal area resident	*'"We no longer have the trees. All trees have been cut down. We steal the firewood at times … Our way of living is no longer good because we cannot access environmental resources."'*
9	Farmer from a communal area	*'We still have enough firewood, wild fruits, herbs etc. … It's easy to get firewood from the mountains … We gather firewood from the mountain which is 200 m away; we don't go far.'*
10	Teacher from a communal area	'. A communal area teacher reported: *"When people collect firewood they collect the dead firewood that is on the floor, but if they don't get enough of that they can also cut down some trees to augment their pile of firewood.'."*
11	Village head from a communal area	*'"The miners do cut down trees, even fruit trees, when they strengthen the mine tunnels, so we no longer have firewood or wild fruit. … Above all, poverty has negatively affected our natural resources. All families now depend on the environment for a living"'.*
12	Farmer from a communal area	*'… overpopulation has caused the scarcity of natural resources.'*
13	Village head from a communal area	*'"The gold panning has attracted people from far and wide. We now live with strangers who might be criminals for all we know.'"*
14	Teacher from a communal area	*'" … most of the men are into gold panning, and since they spend most of their time gold panning, they are using less and less land'."* (teacher, communal area).
15	Farmer from a resettlement area	*'"We used to grow maize, groundnuts, roundnuts, rapoko [millet], sunflowers and other crops. The price of selling maize got very low as from 1996 and at times we were not paid for our maize in time. … When the price of maize fell and the Grain Marketing Board failed to pay us in time, we then went into tobacco farming.'"* (resettlement farmer).
16	Village head	*'"We have had poor rains and our cattle have died so we are poor now."'*
17	Farmer	*'"Poor rainfalls have caused poor yields as well, resulting in farmers abandoning farming.'"*
18	Farmer from a resettlement area	*'We farm differently from the communal farmers. … We have the land. The government helps with the inputs often and we are supervised in our farming by Agritex [extension] officers. In the communal areas, the land is inherited. The farming done is not supervised and they rarely get government inputs, so they harvest far less than us.'*
19	Farmer from a resettlement area	*'"In communal areas, the farmers have limited land and do not take farming seriously. As a result, they don't grow tobacco but go for gold mining instead. In the resettlement area, we have the land, we get inputs at times, we get loans so as to buy inputs and we are growing tobacco most of us so as to get money"'.*
20	Farmer from a resettlement area	*'Lack of employment forced our children to go into farming as a source of income, and tobacco is a good cash crop.'*
21	Farmer from a resettlement area	*'"Here in the resettlement area, we are farmers. We are forced to do farming. We get our money from farming. Our children are encouraged to become farmers as well.'"*

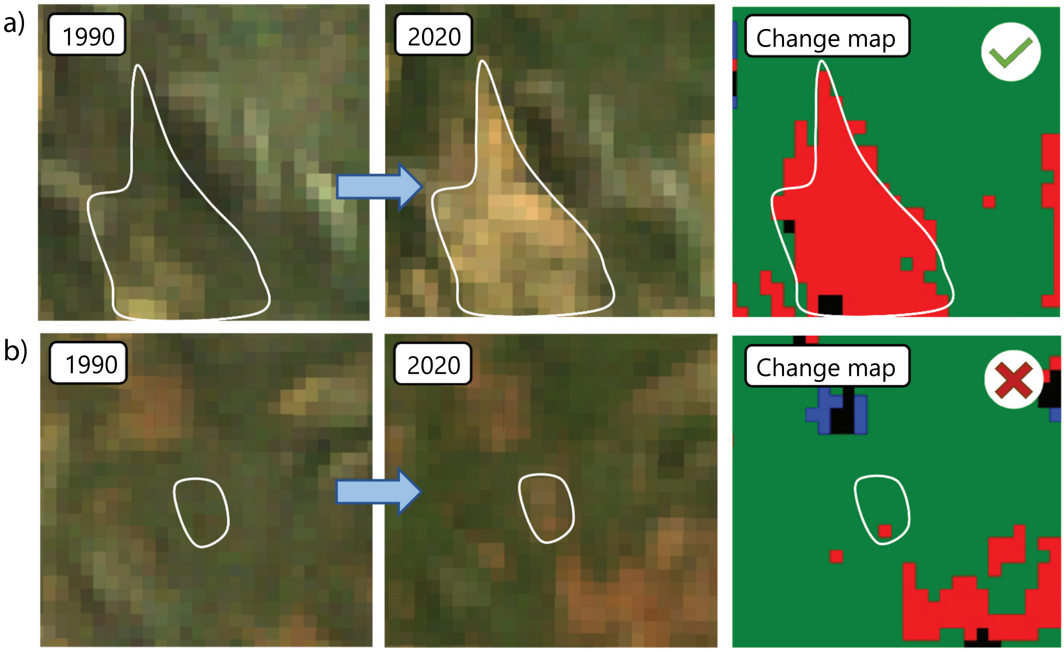

Figure 8. Examples of woodland to non-woodland change observed from landsat data. In a) woodland loss occurred over a larger area and was successfully identified by our classification. In b) woodland change occurred over a much smaller area, and loss was not successfully identified for all but one of the pixels (both 1990 and 2020 were mostly classified as woodland). Yearly composites of Landsat images (1990 and 2020) are displayed in RGB. In the change maps green indicates pixels classified as woodland in both 1990 and 2020 (stable, woodland), blue indicates pixels classified as non-woodland in 1990 and woodland in 2020 (woodland gain), red indicates pixels classified as woodland in 1990 and non-woodland in 2020 (woodland loss) and black indicates pixels classified as non-woodland in both 1990 and 2020 (stable, non-woodland).

stipulation for first generation land resettlement recipients) means some farmers feel there is no choice but to go into tobacco farming (key response 20 and 21).

Overall, interviews suggest that access to woodland resources is limiting in both the northern communal area and the resettlement area but the patterns and causes of land cover change differ between the two. Government inputs in the resettlement area and increased availability of land (relative to the northern communal area) has provided an opportunity to adopt small-scale tobacco farming, but in the northern communal areas decline in profitability of staple crops alongside insufficient land and government inputs to sustain tobacco farming has led many to seek alternative means of income, such as gold panning.

4. Discussion

In contrast to reports of continued woodland loss across Zimbabwe (Kamusoko et al., 2009; Maviza & Ahmed, 2020), there was no regional decline in woodland cover across Hwedza between 1990 and 2020 (marginal net increase in woodland cover of < 1%). We found evidence for both deforestation and expansion in Hwedza, with total expansion exceeding the rate of deforestation from 2009 onwards. Due to high uncertainty in grassland and cropland cover change, it was not clear whether the increase in woodland cover since 2009 occurred due to afforestation of cropland area, or woody encroachment on grasslands, and further exploration of cropland and grassland cover change in this area would be a useful topic for future study. While the reported woodland transition in Hwedza may make a positive contribution to Zimbabwe's deforestation targets, it is important that woodland transitions are accompanied by delivery of ecosystem services (Pritchard et al., 2019).

Interview data suggest that woodland resources declined in both the northern communal and resettlement areas between 1990 and 2020, and that this had a negative impact on livelihoods. It was less clear however, whether availability of woodland resources was linked to woodland cover, as results from remote sensing (access to woodland) differed from those reported in interviews (availability of firewood). Interview data suggest that cutting down trees was a last resort, where dead wood resources had been exhausted. As such, it is possible that woodlands appear intact but provide little or no firewood to nearby households. Highly transformed woodlands are capable of providing ecosystem services (Pritchard et al., 2019) and resource-saving practices are used in times of scarcity (Goebel et al., 2000), which may weaken or negate a correlation between woodland cover and ecosystem service delivery. Results from remote sensing and interviews revealed the variability in access to woodland resources. This finding was supported by Elliott and Kinsey (2003), who suggest that, in resettlement areas, availability of woodland resources is becoming more divergent over time. Local variation may obscure broader trends in woodland cover and resource availability. The uncertainty and complexity surrounding linkages between woodland cover and natural resource availability suggest that research should consider the quality (Lambin & Meyfroidt, 2010) and spatial pattern of woodland cover (Wolfersberger et al., 2015), as well as the area.

While there was evidence of deforestation in the resettlement area, our findings challenge the narrative that resettlement has led to net woodland loss (Matsa & Muringaniza, 2011). Trends between the northern communal area and resettlement area were broadly in agreement and there was no evidence that resettlement led to additional deforestation above that already occurring in the northern communal area. Despite this, woodland cover in the resettlement area was lower than the northern communal area in 1990 (the start of the time series), so we cannot rule out deforestation following the first wave of resettlement in 1980, before the start of the study period. Our findings suggest that conclusions about the association between resettlement and changes in woodland cover should only be drawn if supported by comparative analyses of land cover trends and interview data to better understand the processes driving woodland cover changes. Interview data suggested that there were large differences between the resettlement area and northern communal area in income sources, firewood use, and the factors constraining livelihoods, so considering land tenure arrangements is important for understanding how woodland cover might respond to new policy interventions.

This study was not without its limitations. Only nine key informants were interviewed, and interview participation was not stratified by ethnic group, religion or political affiliation. As such, it is possible that ethnic minorities or people with minority beliefs were underrepresented. No participants were interviewed from the southern communal area, so our study does not reveal the causes and implications of woodland cover change in this area. Land cover relations in the southern communal area might differ from the northern communal area due to the different agroecological zone and land cover trajectories. Carrying out interviews over telephone and video, and in two languages means that some nuance of understanding may have been lost. Population increases linked to gold panning were not reflected in census data. This could be due to the small number of wards compared, and high variability in population changes among wards, or because population changes due to gold panning are highly localised, or temporally variable. Taken together these limitations mean that interview data presented here can be used to contextualise land cover patterns obtained from earth observation data but are not a representative cross-section of opinions and perspectives held across Hwedza. Future research which uses an in-depth household survey might allow broader exploration of the processes of change, and thorough analysis of how household use of woodland resources is changing.

The woodland cover trends reported here come with some uncertainties. There was high overall accuracy, but the accuracy of deforestation and expansion classes was lower. This is in part due to challenges associated with long-term land cover classifications in savannah ecosystems (Abdi et al., 2022). Lower availability of imagery in wet seasons and towards the start of the study period (Almeida de Souza et al., 2020), errors in cloud masking (Huang et al., 2010), the presence of novel spectral signatures such as fire scars (Maponga et al., 2017), and challenges in identifying historical training data, all contribute to uncertainty in mapping land cover change. In addition, the accuracy assessment conducted was strict, requiring that the map not only correctly identify change, but also that it identify the correct year of this change and the correct land cover classes on each side of this change. This is particularly difficult with rare land cover classes (Bogner et al., 2018) (as is the case for most change classes). Due to the apparent reduced accuracy of small change areas, small fragments of woodland loss and gain may have been missed, although this may partly be accounted for in our woodland access assessment by excluding small areas of woodland. The Hidden Markov Model was used to improve change classification accuracy but in future this could be taken a step further, by assessing all possibly transition matrices and their relative impact on classification accuracy to identify likely and unlikely changes between classes (rather than only change and no-change as applied here). Despite the limitations discussed, previous studies provide external validation of our findings, as the rate of woodland loss in the resettlement area during the 1990s is comparable to that reported by Elliott and Kinsey (2003) between 1981 and 1998.

Under current conditions, woodland loss in the northern communal and resettlement areas is expected by most interviewees to continue, with detrimental impacts on some resource availability. Our results demonstrate the need for attention to the overarching drivers which push people in both communal and resettlement areas to cut trees, such as lack of alternative livelihood opportunities. They also demonstrate that increasing equity in land distribution while also improving woodland cover will require attention to harmful incentives, such as preventing off-farm work, and greater clarity over tree and woodland tenure rights. Interviews revealed that even trees once protected from deforestation, such as those with high spiritual value, are now being utilised. Thus, the development of policies around net zero deforestation and forest landscape restoration faces large challenges, not least that most livelihoods in the area utilise trees for energy and timber. New interventions will need to consider current differences in use of natural resources, income sources and constraints on livelihoods between communal and resettlement areas. Due to the co-dependency among income sources, land availability and land cover change, sustainable resource management and conservation cannot be viewed independently of broader socioeconomic objectives.

Overall, the broad spatial and temporal scale of remotely sensed data with high spatial and temporal resolution was crucial to the findings presented here. The remotely sensed data permitted the detection of a woodland transition in Hwedza that was previously unreported and revealed that resettlement is not associated with continued deforestation above that already occurring in the northern communal area. Integration with interview data allowed the processes underlying land cover change to be understood, and common narratives surrounding resettlement and deforestation to be challenged. Future research could build on our approach by augmenting optical land cover classification with other remote-sensing approaches, such as classification of radar data or object-based approaches, to improve understanding of grassland and cropland change, alongside a large-scale household survey to provide a representative cross-section of perspectives on land cover change across Hwedza. Our findings highlight the importance of understanding the underlying drivers of woodland cover change, such as uncertainties or weaknesses in woodland tenure arrangements, and lack of alternative employment opportunities which pushes people into high natural resource intensity livelihood strategies. The need for wood for fuel and timber may pose challenges to forest landscape restoration and emphasises the need for future research on the social impacts of policies for reducing deforestation.

Note

1. Available at: https://bitbucket.org/sambowers/hmm/

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Data availability statement

The data used in this study are publicly available from Landsat (https://www.usgs.gov/landsat-missions/landsat-data-access, courtesy of USGS), NASA (https://doi.org/10.5067/MEaSUREs/SRTM/SRTMGL1.003, NASA JPL, 2013), Google Earth (https://earth.google.com/, courtesy of CNES and Maxar Technologies), Facebook CIESIN (https://ciesin.columbia.edu/data/hrsl/, Facebook CIESIN, 2016) and Bing Maps (https://www.bing.com/maps). Interview transcripts have not been published to protect participant anonymity.

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