Working Paper

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World Agroforestry

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List of abbreviations

AGB	Aboveground biomass
ASR	Areas suitable for restoration
BSO	Breeding seedling orchard
CBD	Convention on Biological Diversity
CRGE	Climate Resilient Green Economy
CSA	Central Statistical Agency
DHS	Demographic Health Survey
EEFRI	Ethiopian Environment and Forest Research Institute
EFCCC	Environment, Forest and Climate Change Commission
ESA	European Space Agency
FAO	Food and Agriculture Organization of the United Nations
FDRE	Federal Democratic Republic of Ethiopia
FLR	Forest landscape restoration
GDP	Gross domestic product
GHG	Greenhouse gases
GPFLR	Global Partnership on Forest and Landscape Restoration
IBC	Institute of Biodiversity Conservation
ICF	Inner City Fund
ICRAF	World Agroforestry
IPCC	Intergovernmental Panel on Climate Change
IUCN	International Union for Conservation of Nature
LC	Land cover
LLC	Limited Liability Company
LRO	Landscape restoration option
MEFCC	Ministry of Environment, Forest and Climate Change
NDVI	Normalized difference vegetation index
NICFI	Norway's International Climate and Forest Initiative
PAR	Priority area for restoration
PATSPO	Provision of Adequate Tree Seed Portfolios
PET	Potential evapotranspiration
PNV	Potential natural vegetation
QGIS	Quantum Geographic Information System
RCP	Representative concentration pathway
RNE	Royal Norwegian Embassy
ROAM	Restoration Opportunities Assessment Methodology
SDG	Sustainable Development Goal

SNNP	Southern Nations, Nationalities and People's Region
UN	United Nations
UNCCD	United Nations Convention to Combat Desertification
UNEP	United Nations Environment Programme
UNFCCC	United Nations Framework Convention on Climate Change
USD	United States Dollar
WCMC	World Conservation Monitoring Centre
WRI	World Resources Institute

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Abstract

The Ethiopian government has set ambitious landscape restoration targets to achieve by 2030. Here, we describe a novel approach to identify landscapes to prioritize for tree-planting-based restoration interventions in the country. Our approach, which has several advantages compared to existing prioritization methods, starts with current land use patterns and potential natural vegetation maps, and uses a wide range of other open-access spatial datasets. The approach estimates the benefits of restoration on prioritized areas compared to a null model where no prioritization is applied. Across identified prioritized landscapes, we then quantify the expected impacts of restoration in terms of the number of households that would be reached by interventions, and by estimating carbon sequestration and soil conservation potentials. Our analysis indicated that Ethiopia has high potential for achieving enhanced restoration targets through landscape prioritization. A total of almost 17 million hectares of land prioritized for tree-based restoration by our exercise could reach 4 million rural households with interventions, with 178 million tonnes of CO_2 equivalent sequestered and 160 million tonnes of soil conserved annually. The prioritized landscapes could be restored with a combination of agroforestry, forest enrichment and woodland enrichment practices (on 31%, 8% and 61% of the total prioritized area, respectively). The Oromia region of Ethiopia was identified as a crucial location for intervention, containing almost half of the entire prioritized areas for restoration in the country. Our results provide the foundation for further studies to evaluate the potential impacts of tree-based restoration programmes in Ethiopia, and more widely, as the methods are of general application. Within Ethiopia, investigations in particular support the *ex ante* impact evaluation of the Provision of Adequate Tree Seed Portfolios project, which is developing national capacity to supply tree seed for restoration purposes. We discuss our findings in this context.

1. Introduction

1.1 Background

Ethiopia's agriculture and forestry sectors contribute 43% of GDP in total (2015 figure) and employ most of the country's population (FDRE, 2015). The forestry sector provides a wide range of timber and non-timber forest products that are sourced from the wild and cultivated. More than 80% of Ethiopia's tree plantations are grown by smallholders (FDRE, 2017a); and woodfuel and charcoal are widely used in rural and peri-urban households as an energy source (FDRE, 2017a). While crucial for energy supply, these woodfuel resources are major contributors to greenhouse gas (GHG) emissions that contribute to climate change (Bailis et al., 2015). The Ethiopian agricultural sector is currently highly vulnerable to climate change due to dependence on rainfall, low productivity and subsistence farming practices (Pistorius et al., 2017). Biodiversity loss and ecosystem degradation also have a negative effect on crop productivity and food security (FDRE, 2015). Conserving existing natural ecosystems and restoring human-made landscapes with trees are therefore urgently needed to mitigate anthropogenic effects on the environment and to safeguard ecosystem services (FDRE, 2017a).

In 2011, Ethiopia enacted a green growth strategy with the vision of becoming a middle-income country by 2025, based on a net zero increase in GHG emissions from 2010 levels. These figures are set out in the Climate Resilient Green Economy (CRGE) strategy that seeks to promote climate change adaptation and mitigation measures, while safeguarding economic growth (FDRE, 2011a, 2011b). According to CRGE estimates, in 2010, agriculture and forestry accounted for GHG emissions of a massive 50% and 37% of Ethiopia's total emissions, respectively. Therefore, on the low-carbon-path projection estimated within the CRGE, these two sectors are expected to contribute significantly to GHG emission reductions; taken together, they account for 80% of the abatement potential (FDRE, 2011b, p. 28).

As part of its commitments to a green growth strategy nationally and to support climate and biodiversity action globally, the Government of Ethiopia in 2014 pledged to restore 15 million hectares of degraded landscapes by 2030 (FDRE, 2017b). This commitment is part of pledges made to the global Bonn Challenge that intends to restore 350 million hectares of degraded lands worldwide by that date (IUCN, 2021b). Ethiopia's commitments are also part of the regional African Forest Landscape Restoration Initiative (AFR100 2021) that aims to restore 100 million hectares of land on the continent by the same 2030 date. The country is, furthermore, a major intervention zone for the African Union Great Green Wall programme, which intends to restore degraded lands across the entire width of the African continent, spanning from Senegal in the west to Djibouti in the east (UNCCD, 2021).

The above commitments involve a range of forest landscape restoration (FLR) approaches that seek to return the ecological (e.g., carbon, biodiversity, watershed protection, soil conservation), social and economic benefits of forests and trees (Mansourian et al., 2017; GPFLR, 2021; IUCN, 2021a). These approaches can be implemented over a broad range of land use types, from degraded natural forests to agricultural land, and are expected to benefit a range of stakeholders (GPFLR, 2021). The benefits achieved are expected to support the targets of various UN conventions and initiatives, such as the United Nations Convention to Combat Desertification (UNCCD); the Convention on Biological Diversity (CBD); the United Nations Framework Convention on Climate Change (UNFCCC); and the Sustainable Development Goals (SDGs).

On-the-ground realization of ambitious FLR targets in Ethiopia and globally is a major challenge (Höhl et al., 2020). One reason for this is that clearer guidance is needed on how to direct the implementation of restoration that considers both environmental and livelihood benefits (livelihood benefits are important in themselves, but also crucial for community support for restoration efforts that could fail in the absence of local stakeholder buy-in).

A recent publication by Chazdon and Guariguata (2018) provided an overview of the available decision-support tools to plan and implement fine-scale restoration interventions. One approach, developed by the International Union for Conservation of Nature (IUCN) and the World Resources Institute (WRI), is the Restoration Opportunity Assessment Methodology (ROAM) (IUCN & WRI, 2014). This was designed as a standard framework for identifying specific priority areas for FLR at a national or sub-national level. A few years ago, the WRI in collaboration with the Ministry of Environment, Forest and Climate Change (MEFCC) of Ethiopia used the ROAM approach to identify potential and priority areas for tree-based restoration in the country. The findings were subsequently published as the National Potential and Priority Maps for Tree-Based Landscape Restoration (MEFCC, 2018).

1.2 Objectives and outline of this study

Here, we have developed an alternative approach to ROAM, that is also applicable more widely, for identifying target areas for restoration in Ethiopia. Our approach has a number of differences which will be summarized later in this working paper. One important reason for our 'remapping' is that there is a lack of access to the spatial data in the above National Potential and Priority Maps. In our case, however, it is possible for users to explore our mapping results directly in digital form (link).

The reasons why we chose Ethiopia to develop and apply our methodology are two-fold: first, is the country's high forest landscape restoration target, as already mentioned above; and second, is the Provision of Adequate Tree Seed Portfolios (PATSPO) initiative that is based in Ethiopia (ICRAF, 2017). This project (2017-2021) is funded by the Norwegian International Climate and Forest Initiative (NICFI) and coordinated by World Agroforestry and the Ethiopian Environment, Forest and Climate Change Commission (EFCCC). The PATSPO initiative is developing tree seed supply capacity in Ethiopia to support the country's FLR targets. The focus on tree seed supply is due to lack of access to high-quality tree planting material which has been proven to be an important barrier to effective implementation of restoration projects in the country (Derero, 2011, 2012; IBC, 2012; Dedefo et al., 2017; Sisay et al., 2020); note that this constraint also applies globally (Jalonen et al., 2018; Lillesø et al., 2018; Roshetko et al., 2018; Höhl et al., 2020).

As part of the PATSPO project, we are conducting an *ex ante* impact evaluation of the environmental and livelihood benefits of making high-quality tree seed available and accessible. The current prioritization exercise described in this working paper supports this evaluation by indicating priority landscapes, the balance between different restoration interventions, and where higher tree seed quality could result in the greatest impact (see also other publications in preparation connected with PATSPO impact evaluation, e.g., van Schoubroeck et al. (2021, in prep.)).

Our methodology maps priority restoration opportunities by identifying areas of high combined potential for reaching desired socioeconomic and environmental outcomes, as it is this combination that is essential for successful implementation (Stanturf et al., 2015; Brancalion et al., 2019; FAO & WRI, 2021; IUCN, 2021d). In this approach, we first divided the study area into two restoration domains and suggested pertinent landscape restoration options which are most suited to biophysical conditions. Then we developed and applied a landscape prioritization methodology which allowed us to select landscapes with substantially higher potential for delivering restoration benefits. Finally, we evaluated the magnitude of the potential impact of restoring the prioritized areas.

2. Methods

2.1 Initial overview

This sub-section provides an overview of the methodology of our study, which is illustrated with a flowchart in Figure 1. A full description of the approaches we use will be given in subsequent sub-sections (2.2 to 2.4). In brief, our approach comprised three steps.

First, we defined the overall land area where tree (or shrub) growth is possible in Ethiopia and assigned pertinent landscape restoration options (LROs) (explained further in sub-section 2.2). In short, this was achieved by selecting specific potential natural vegetation types (PNVs) and looking at current land cover (LC). The areas suitable for tree-based restoration (ASRs) were thereby determined and divided into 'converted' (where current LC is cropland or pastureland) and 'unconverted' (where natural forest and woodland ecosystems occur) domains. The LROs, which are 'agroforestry' for 'converted' land and 'forest and woodland enrichment' for 'unconverted' land, were thereby assigned.

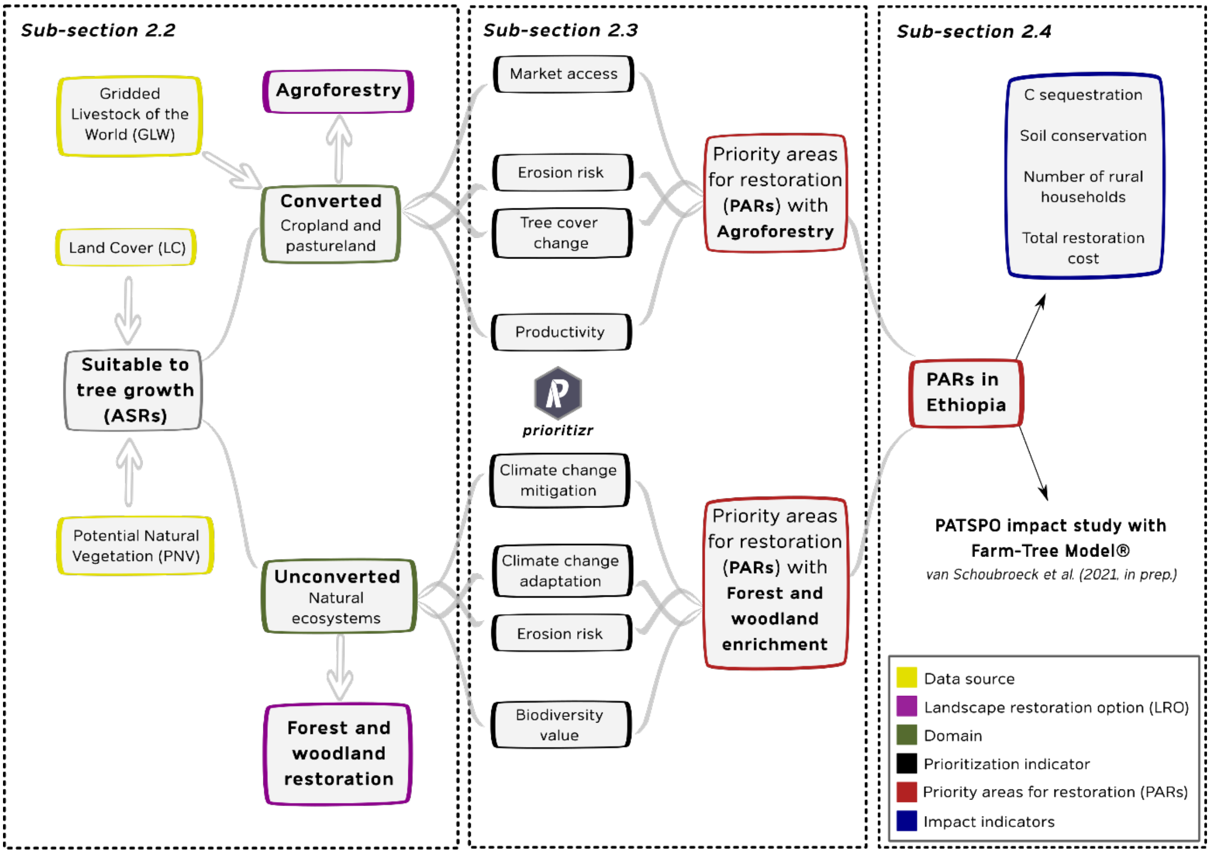

Figure 1. Flow chart of the current study's framework. The dashed outlines split the methods of our study into the relevant text sub-sections.

Second, we developed and applied a multi-indicator methodology to define priority areas for restoration (explained in detail in sub-section 2.3). The set of relevant indicators for FLR that we chose for prioritization were the following: market access, tree cover change, productivity performance, climate mitigation, climate adaptation, soil erosion risk and biodiversity value. For prioritizing within 'converted' and 'unconverted' domains, we applied different subsets of these indicators because some of the expected benefits of restoration are either different or of varying importance (although we do not consider particular restoration benefits to be *exclusively* linked to a specific domain or LRO). For each domain, the value of every applied indicator was estimated country-wide for gridded planning units and results normalized within the range of 0 to 1, based on the overall quantile distribution (higher values being associated with higher restoration benefits). For each domain, using integer linear programming, we determined the overall priority areas for restoration focus (a priority area for restoration is also known as a 'PAR') that maximizes restoration targets while minimizing the amount of space.

The assumption made was that restoration interventions should be targeted to the areas associated with the highest cumulative restoration benefits. We set a 20% relative target to specify a minimum amount of restoration benefits (or minimum proportion of indicators' distribution scaled according to total abundance in the study area) to be represented in the selected PARs. We then explored the efficiency of the above prioritization for individual indicators for each domain. We did this by comparing individual indicator values for selected planning units with those of an equal number of planning units selected at random (the 'null model') within ASRs.

Third and finally, we estimated the overall impact of implementing restoration on our PARs (as detailed in sub-section 2.4). Impact was quantified over the prioritized planning units using the indicators developed (as above) for carbon sequestration and soil conservation, with some refinement. In addition, 'rural households reached' were estimated from open-source spatial datasets and the costs of restoration calculated, supported by literature data.

2.2 Defining restoration domains and landscape restoration options

In this section, we describe how we defined 'converted' and 'unconverted' landscape domains and LROs for Ethiopia.

The geographic distributions of different PNVs in Ethiopia were first extracted from the Potential Natural Vegetation Map of Eastern and Southern Africa (van Breugel et al., 2015). This map is the most detailed of its type available, covering all of Ethiopia's vegetation types. Certain PNVs (e.g., herbaceous grassland, deserts and alpine vegetation) were then excluded from the study area in our further analysis because they were considered unsuitable for tree-based restoration activities (Figure 2A). The descriptions of PNVs which allowed us to assess whether they should or should not be included in the analysis were found in the map's accompanying documentation (Kindt et al., 2011a, 2011b, 2011c). It should be noted that these maps can also be used to provide information on suitable native tree species for restoration purposes, an important step when it comes to implementation.

Based on the most recent available LC map for Ethiopia (ESA, 2018), we then selected cropland and grassland areas to define the 'agroforestry' LRO (the 'converted' domain). To exclude natural grasslands and areas of high livestock intensity pastureland, where agroforestry practices may be unsuitable for restoration (Strassburg et al., 2020), we explored the relative geographic extent of livestock in Ethiopia using information from the latest version of the Gridded Livestock of the World dataset (Gilbert et al., 2018). Only areas where cattle density was above 0.1 and below 20 heads per hectare were considered suitable for restoration. For 'converted' landscapes, we considered agroforestry to be the pertinent tree-based LRO because these areas are managed for agriculture and (re)conversion to 'natural' ecosystems is unlikely to be feasible, and would represent a threat to the livelihoods of local communities. Agroforestry is, however, a form of cropland restoration that increases land productivity, helps reduce environmental degradation and diversifies income opportunities. In addition, it includes a wide potential (though context-specific) range of tree-based practices such as home gardens, farm boundary planting, alley cropping, small-scale woodlots and live-fencing. We then overlaid the agroforestry LRO on our PNV map and masked urban areas based on the LC classification (ESA, 2018).

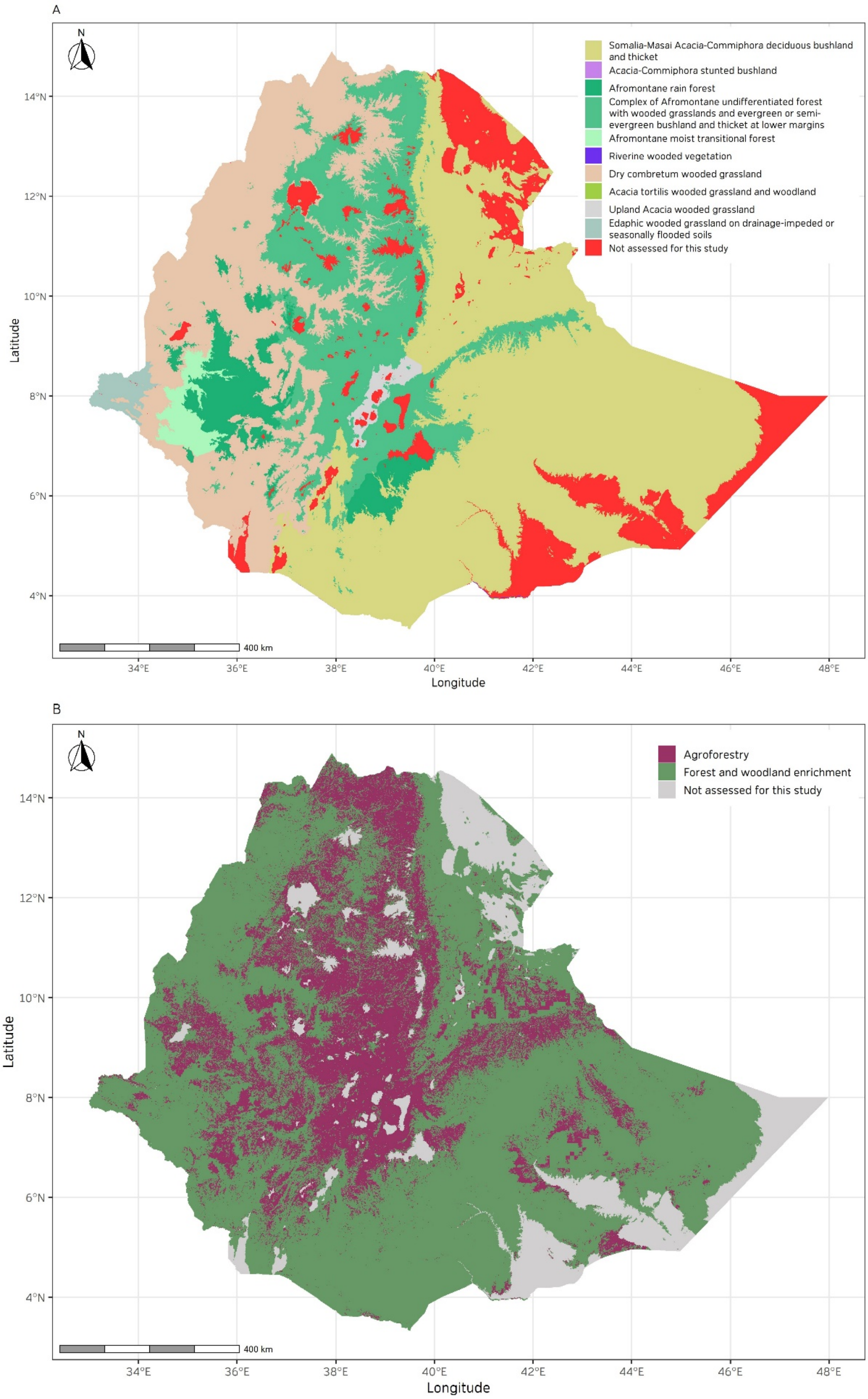

Figure 2. A) Map of potential natural vegetation types (PNVs) in Ethiopia. PNVs depicted in red are not indicated individually but were excluded from the current study (see main text); B) Areas suitable for tree-based restoration in Ethiopia, partitioned into two landscape restoration options (agroforestry; and forest and woodland enrichment).

The remaining (unmasked) area, where climax vegetation types are closed canopy forests or open canopy woodland, wooded grassland or shrubland (our ‘unconverted’ domain) was then assigned to the ‘forest and woodland enrichment’ LRO. For ‘unconverted’ landscapes, we considered enrichment to be the pertinent LRO because these are areas not under as intense anthropic pressures as ‘converted’ lands. The enrichment LRO could include a variety of potential tree-based restoration interventions depending on the social and biophysical context.

Based on this mapping, the areas suitable overall for tree-based restoration (ASRs), partitioned by the two LROs, are indicated in Figure 2B. The two LROs were set as independent areas for subsequent prioritization analysis.

2.3 Multi-indicator prioritization of priority areas for restoration

Here, we describe the development and application of our methodology for defining PARs within ASRs. We explain how we test the efficacy of prioritization for our individual indicators against a null model, and how data are combined across indicators to define the final PARs for each of the two relevant landscape domains/LROs.

We first selected seven indicators; six biophysical and one socioeconomic, that are useful for predicting cumulative restoration benefits, taking into account previous studies on restoration prioritization (e.g., Brancalion et al. (2019) and Strassburg et al. (2020)). The seven indicators are summarized in Table 1 and details provided in Box 1. They highlight which subsets of indicators (four in each case) were applied to ‘converted’ and ‘unconverted’ land domains (see also Figure 1). Since the expected benefits of restoration vary for the two domains, the subset of indicators applied to each was different.

The analysis and visualization of indicator values were performed in the R statistical environment (R Core Team, 2020) using a combination of packages including *raster* (Hijmans, 2020), *terra* (Hijmans, 2021), *sf* (Pebesma, 2018), *rgdal* (Bivand et al., 2019) and *ggplot2* (Wickham, 2016). To start with, the total study area was divided into a grid of 1,337,562 planning units; each of these corresponded in area to around 86 hectares (at the equator, i.e., a little less than 1 km squared [= 100 ha]). For each of these units, raw indicator values were extracted from datasets and used as the foundation for the analysis. Separately, for each of the two land domains (Figure 2B), the planning unit values of each of the applied indicators were normalized within the range of 0 to 1, based on the overall quantile distribution (deciles), where higher values were associated with higher restoration benefits.

For each of the two domains, an integer linear programming algorithm (Gurobi Optimization & LLC, 2021) implemented using the *prioritizr* (version 7.0.1.5) R package (Hanson et al., 2021) was then applied to prioritize areas with the highest cumulative restoration benefits. This approach identifies ‘optimal’ areas (PARs) to maximize the number of targets achieved with the lowest number of planning units. A 20% relative target was set across all indicators (that therefore have equal weights in the prioritization) to specify the minimum proportion of an indicator’s distribution that should be covered by a solution. The proportions were scaled according to the indicators’ total abundance in the study area (prioritizr, 2021). In an exercise to estimate prioritization effectiveness, individual indicator values of the prioritized planning units were compared with those of an equal number of planning units randomly selected from within ASRs (the 'null model'). This process of randomly sampling planning units was undertaken 1,000 times to produce median values. This was done separately for each of the two relevant landscape domains and the results expressed as bar plots.

Table 1. Summary of indicators applied in our study for predicting cumulative restoration benefits and assessing impact

Name of indicator	**Type of indicator**	**Key features of indicator**	**Landscape domain to which applied**	**If used for impact assessment** (see sub-section 2.4)
Biodiversity value	Biophysical	Tetrapod species richness estimated based on the habitat ranges of Ethiopian tetrapod species. It indicates the biodiversity value of the habitat.	Unconverted	
Climate change adaptation	Biophysical	Velocity of climate change based on current and future climatic conditions. It indicates to what extent adaptation measures are needed.	Unconverted	
Climate change mitigation	Biophysical	Maximum aboveground biomass (AGB) modelled with 90% quantile regression, based on an existing AGB dataset and biophysical conditions. It indicates the potential for sequestering carbon in AGB.	Unconverted	✔
Market access	Socioeconomic	Travel time to the nearest town by walking. It indicates accessibility to local markets for selling agricultural products.	Converted	
Productivity performance	Biophysical	Changes in land productivity, estimated based on the normalized difference vegetation index, from satellite images. It indicates the positive or negative trend in primary productivity.	Converted	

Name of indicator	Type of indicator	Key features of indicator	Landscape domain to which applied	If used for impact assessment (see sub-section 2.4)
Tree cover change	Biophysical	Changes in tree cover in the last two decades. It indicates where tree-based restoration could most likely happen given the history of cover change.	Converted	
Erosion risk	Biophysical	Risk of soil erosion estimated based on machine learning from satellite images. It indicates the need of soil conservation strategies to prevent soil erosion.	Unconverted and converted	✔

For further information on each indicator, see Box 1.

Box 1. Details of indicators applied in our study to predict cumulative restoration benefits

Biodiversity value (used as an indicator for 'unconverted' land)

This indicator of the potential biological diversity of each planning unit is based on the habitat ranges of local species. Our indicator focused on mammals, reptiles, amphibians and birds because open-source spatial data on these species' habitat ranges are the best that are available (better, e.g., than for plants and insects). Previous prioritization exercises globally have also applied such tetrapod diversity as an indicator of ecosystem biodiversity (Strassburg et al., 2020). Spatial data on our collection of tetrapods were sourced from the IUCN Red List website (IUCN, 2021c) and (for birds) from BirdLife International (BirdLife International and Handbook of the Birds of the World, 2020). The pool of tetrapod species native to Ethiopia was extracted by clipping single species global shapefile distributions to the Ethiopian border. Species ranges were then overlaid on our planning unit grid and the number of overlapping polygons counted, resulting in species richness estimates. Final values were re-scaled 0 to 1 based on the quantile distribution (1 being the highest richness). The primary justification for including biodiversity value as an indicator for prioritizing areas for forest and woodland enrichment is that tree-based restoration, when done correctly, can benefit local biodiversity by providing a favourable habitat matrix (Moguel & Toledo, 1999; Benayas et al., 2009). In Ethiopia, for example, areas covered by trees and forests provide critical habitat for a large portion of the nation's endemic flora and fauna, including endangered species (Pistorius et al., 2017). In our analysis, we have only applied the biodiversity indicator to unconverted landscapes, though it could also be used for converted landscapes restored by agroforestry practices that provide secondary habitat for at least some other species (Kanshie, 2002); (Schroth et al., 2004), though perhaps with lower overall weighting. Such an approach could be considered in the future.

Climate change adaptation (used as an indicator for 'unconverted' land)

With this indicator we estimate the relative velocity of climate change for each planning unit. It is based on the methodology of Hamann et al. (2015), where a velocity of climate change layer is computed using the metric developed by Loarie et al. (2009). Our indicator is based on the results of a principal component analysis of a sample of climatic variables similar to those used by Hamann et al. (2015). Current climate was defined as the monthly averages of maximum and minimum temperatures and average precipitations for the years 1979 to 2013 (Karger et al., 2017). Baseline and future monthly data were sourced from Chelsa high-resolution time series data (Karger et al., 2020), while present and future climate variable values were derived using the *ENVIREM* and *dismo* packages (Title & Bemmels, 2018; Hijmans et al., 2020). Future modelling was based on the period 2061 to 2080 and the RCP 4.5 pathway. This pathway is an intermediate scenario where emissions will peak by 2040 and then decline, bringing a 3°C temperature increase by 2100 (Collins et al., 2013). The first two principal components of the analysis of multiple climatic variable grids for Ethiopia explained an overall high proportion of total variance and were used for further modelling. The first component (79% of variation) mostly represented temperature variables, and the second (14% of variation) mean annual precipitation and the moisture index (Table 2). Final values of climate change velocity for planning units were re-scaled 0 to 1 based on the quantile distribution (1 indicating the highest velocity). Justification for the use of this indicator is that tree-based restoration can promote landscapes' adaptive capacities by enhancing ecosystem functionalities under multiple environmental change pressures (Trumbore et al., 2015; Mansourian et al., 2017). Promoting landscape structural diversity and the presence of microhabitats have, for example, been proven to support the safeguarding of forest biodiversity under climate change (Scheffers et al., 2014; Augustynczik et al., 2019). An increase in canopy cover by trees can also, for example, reduce the effects of extreme rainfall events (Zheng et al., 2008) that are expected to become more frequent with anthropogenic global warming (Billi et al., 2015; Myhre et al., 2019). Increased tree cover can also promote landscape connectivity that supports the adaptive migration of species in response to climate change (Noss, 2001). For current purposes, we assume that the effectiveness of tree-based interventions is greatest where climate change is happening fastest.

Table 2. Scores for the first two principal components of an analysis of a sample of climatic variables used for calculating the climate change adaptation indicator in Ethiopia

Climatic variable	PC1	PC2
Annual mean temperature	0.386	0.222
Mean temperature of warmest quarter	0.384	0.157
Mean temperature of coldest quarter	0.364	0.317
Annual precipitation	-0.291	0.600
Precipitation of warmest quarter	-0.292	0.307
Moisture index	-0.322	0.522
Growing degree days	0.386	0.221

Climate change mitigation (used as an indicator for 'unconverted' land)

With this indicator we estimate the potential gap in aboveground biomass (AGB) (and therefore carbon sequestration capability) of each planning unit, considering environmental conditions. Our indicator was developed using an approach inspired by Greve et al. (2013) and Brancalion et al. (2019). We sourced layers for aboveground biomass and biomass change from Baccini et al. (2021). Data on the baseline AGB stock from the year 2003 and on the AGB change from 2003 to 2016 were combined to obtain baseline AGB values for the year 2016. To model the relationship between the production of biomass and environmental conditions, we performed a quantile regression using a similar approach to Greve et al. (2013) that tests for trends in any part of the distribution. The 90% quantile was used to model the potential biomass that could be stored against environmental factors. Soil data were sourced from SoilGrids (Hengl et al., 2017) and bioclimatic predictors derived using the *ENVIREM package* (Title & Bemmels, 2018), based on environmental data sourced from WorldClim (Fick & Hijmans, 2017). Additionally, information on the length of the growing season was computed based on consecutive months where rainfall/potential evapotranspiration was > 0.5 and mean temperature was > 9°C (Thornton et al., 2006). Data were re-sampled to a common spatial resolution and grouped in a raster stack. A correlation matrix of dependent and independent variables was computed and variables where $\rho(X, Y) > 0.4$ with a *p-value* < 0.001 were selected. The selected variables were used as predictors of potential AGB in a multivariate linear regression, where the response variable was the baseline AGB in Ethiopia. Through a stepwise regression, the preferred model was selected by looking at the minimum Akaike information criterion value (Zhang, 2016). Predictors from the best fitting model were utilized as independent variables in the 90% quantile regression model. The final model coefficients used are reported in Table 3. The best fit to the data explained 28% of the variability in the AGB baseline (2016 figures) for the 90% quantile. The model was then used to make predictions for maximum potential AGB. Baseline AGB values were then subtracted to estimate the potential (extra) AGB that could be achieved. The final AGB gap was re-scaled 0 to 1 based on the quantile distribution (1 indicating the higher potential for carbon sequestration). Justification for this indicator is based on the observation that tree-based restoration can have significant positive impacts on landscape productivity that fixes atmospheric CO_2 (Zomer et al., 2016). Climate change mitigation is a key FLR target (IUCN, 2021e). As well as using our measure of climate change mitigation for the identification of PARs, we used this indicator as a starting point to assess the impacts of restoration (see sub-section 2.4).

Table 3. Selected variables used as predictors of potential aboveground biomass in Ethiopia. Results of the best fitting 90% quantile regression model, with relative coefficients and statistical parameters, are presented

Variates	Coefficient	Standard error	t-value	p-value
Intercept	1185.4	4.433	267.4	< 0.0001
Soil bulk density	2.3	0.044	53.1	< 0.0001
Temperature range	-10.4	0.252	-41.4	< 0.0001
PET seasonality	-0.1	0.001	-118.3	< 0.0001
Soil pH	-12.8	0.079	-162.0	< 0.0001

Tree cover change (used as an indicator for 'converted' land)

This indicator was developed from the tree cover maps of Hansen et al. (2013). Extracted values of tree cover for individual planning units were re-scaled 0 to 1 based on the quantile distribution (1 indicating the lowest current tree cover). On top of this, we overlaid information on recent tree cover loss (between 2001 and 2019), which is a surrogate for current deforestation pressures (Brancalion et al., 2019). For the locations where loss was recent, the value of our indicator was reclassified as 0, as we assume that for these recently stripped sites tree replanting is unlikely to happen due to local anthropogenic pressures which were responsible for the tree cover loss in the first place. Otherwise, our assumption is that areas of lower tree cover have higher potential for reaping the benefits of tree planting.

Productivity Performance (used as an indicator for 'converted' land)

As a measure of land productivity performance, we used the Normalized Difference Vegetation Index (NDVI). The NDVI, usually estimated by satellite using red and near infrared portions of the electromagnetic spectrum, is a common surrogate for net primary productivity (Li et al., 2004) and crop productivity (Hill & Donald, 2003). For our indicator, mean annual NDVI was computed from bi-weekly images sampled by MODIS (at 300 m) for the baseline period 2008 to 2012 and the comparison period 2013 to 2018. The values of mean NDVI were then reclassified based on percentile classes and the difference in class number between the baseline and comparison time periods computed. The analysis was performed using *Trends.Earth* (Conservation International, 2018), a semi-automatic plugin for the *QGIS software environment* (QGIS Development Team, 2021). A map of the resulting values had pixel scores ranging from -7 to 8, where values >2 were taken to indicate locations improving in productivity and <-2 to indicate locations experiencing a loss in productivity. Scores were normalized 0 to 1 based on the quantile distribution, where 1 represents the most degraded areas that we assume should be priorities for action because the potential for increasing productivity through inputs such as tree planting is greatest.

Market access (used as an indicator for 'converted' land)

Our chosen indicator is an estimate of farmers' access to local markets. It is based on global spatial data on accessibility developed by Nelson et al. (2019), where the value of each pixel is the estimated travel time in minutes to the nearest urban area (in 2015). Travel time is estimated by using a global friction surface which incorporated the best available information on transport networks and speeds, off road networks and walking speeds (Weiss et al., 2018). Of the various data layers made available by Nelson et al. (2019), we selected the layer which estimated travel times to the nearest town with a total population of ≥5,000 people for our analysis. The raster layer was re-sampled for Ethiopian planning units and scores scaled 0 to 1 based on the quantile distribution (1 indicating the greatest town/market accessibility). Our justification for this indicator is that agroforestry adoption has been observed to be positively influenced by proximity to the nearest town (Nkamleu & Manyong, 2005; Beyene et al., 2019). Specifically, access to markets has also been observed to be one of the most important variables influencing strategies of tree planting (Degrande et al., 2006) and agroforestry practice adoption (Tafere & Nigussie, 2018). Market access has also been suggested by others as a key factor to consider when designing restoration projects (FAO & WRI, 2021).

Erosion risk (used as an indicator for 'unconverted' and 'converted' lands)

Our chosen indicator estimates potential soil loss within planning units. It is based on a global dataset of erosion risk sourced from Vågen and Winowiecki (2019). Data on soil erosion (t ha^{-1} y^{-1}) were re-sampled to match our planning unit grid size and the values scaled 0 to 1 based on the quantile distribution (1 indicating the greatest soil erosion risk). Justification for this indicator is that soil erosion has multiple negative impacts, including on crop productivity (Lal & Moldenhauer, 1987) and the global carbon budget (Lal, 2003), while tree cover can significantly reduce soil erosion and runoff (Bennett, 1940). The assumption is that tree-based restoration can have the largest benefits where erosion risk is highest. As well as using soil erosion risk for the identification of PARs, we used this indicator as a basis to assess the impacts of restoration (see sub-section 2.4).

2.4 Measuring the impacts of restoration

Here, we describe how we estimate the overall impact that implementing restoration on our finally selected PARs, identified according to the methods described above, would have. This is based on carbon sequestration and soil conservation, and through an additional approach based on 'rural households reached'. We also estimate the costs of restoration.

Once PARs for both 'converted' and 'unconverted' landscape domains had been identified, we estimated the potential impacts of their restoration based on our LROs of agroforestry and forest and woodland enrichment. We used the metrics already described above for both climate change mitigation (carbon sequestration) and soil erosion risk (soil conservation) as a starting point, but with some modifications, as described below.

For the estimation of potential carbon sequestration on prioritized planning units in the 'unconverted' domain, previously calculated AGB values were used (see sub-section 2.3). An estimate of sequestration for 'converted' landscapes prioritized planning units restored by agroforestry was, however, also added. In this case, we assumed an average 10% tree cover increase over baseline values, and a linear relationship between tree cover and AGB increase (Zomer et al., 2016). For both domains, we also added an estimate of belowground biomass accumulation for prioritized planning units, measured as 25% of the extra AGB (Cairns et al., 1997). We then assumed the carbon fraction of dry matter was according to IPCC (2003) estimates.

For the estimation of potential soil conservation, we took values of erosion risk as already calculated for prioritized planning units for 'converted' and 'unconverted' domains (sub-section 2.3) and computed median values aggregated by PNV type. We set 14% of the erosion risk as the maximum increase in soil conservation achievable by intervention (Hengsdijk et al., 2005).

We then used data from a combination of sources to estimate the number of rural households reached by intervention across PARs. Data on Ethiopian population densities for 2020 were obtained from

WorldPop (WorldPop, 2020), and the percentage of the population of Ethiopia that is rural from the latest World Bank indicators (The World Bank, 2019). The population density layer was then adjusted by the percentage of the population that is rural to obtain a spatial estimate of rural population density. The geographic extent of urban areas was sourced from the land cover map (see sub-section 2.2) and masked in our analysis. The rural population density layer was then divided by the average household size per woreda (woreda = administrative unit) (CSA & ICF, 2016) to produce the final rural household density layer. The number of households captured within our PARs was then calculated.

Finally, to estimate the opportunity costs (forgone benefits of current agricultural practices) for the restoration of prioritized 'converted' lands, we considered cropland and pastureland separately. For the former, we used values of crop production in the HarvestChoice database (International Food Policy Research Institute, 2020) to estimate the net present value (NPV) of prioritized planning units over a 40-year period, applying a discount rate of 5% and assuming a profit margin of 20% (Strassburg et al., 2020). For pastureland, the opportunity cost was estimated based on cattle stocking levels in the Gridded Livestock of the World v2.0 dataset (Gilbert et al., 2018), combined with average animal ages, weights and values of carcases at slaughter in Ethiopia (Senbeta & Megersa, 2019; Tefera et al., 2019). Again, the NPV for each prioritized planning unit was estimated over a 40-year horizon. The restoration costs of restoring landscapes for the 'unconverted' land domain's prioritized planning units were sourced from a previous study estimating improved forest management costs in Ethiopia (Pistorius et al., 2017). Opportunity costs for the 'unconverted' domain were not quantified because restoration intervention is not expected to displace the existing practices (e.g., charcoal production, harvesting of non-timber forest products). Our methods for costings clearly only provide an incomplete picture, but they represent a starting point for encompassing 'converted' and 'unconverted' lands into estimates.

3. Results

3.1 Effectiveness of indicators for planning unit prioritization

The geographic distribution of normalized values for each of our individual indicators is presented in the Appendix. Figure 3 provides a summary for each of our two land domains on the effectiveness of our planning unit prioritization processes. The box plots show the original values of individual indicators (not normalized in this case for better comparison) for planning units that were prioritized by our multi-indicator approach compared to the values for an equal random sample of planning units. The plots demonstrate that the extent of effectiveness of prioritization varied for the different indicators and domains, but that in all cases prioritization provided clear benefits.

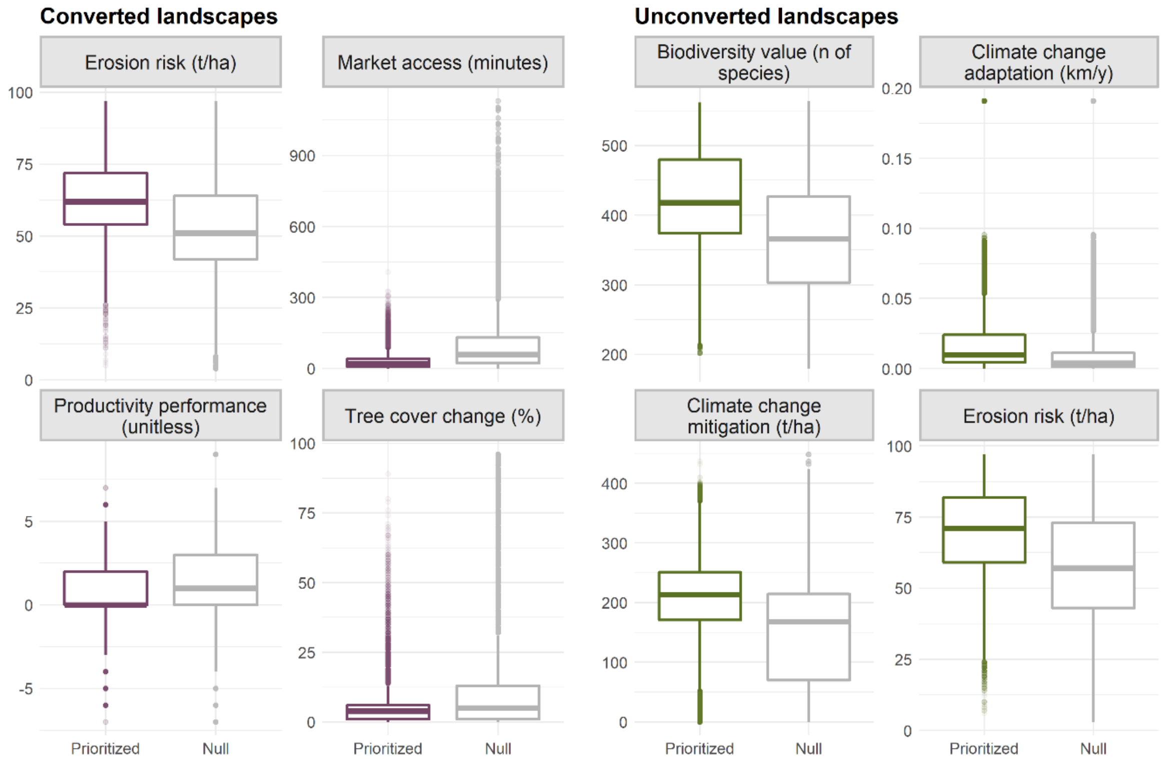

Figure 3. Box plots comparing the distribution of indicator values for prioritized versus randomly sampled (null scenario) planning units in the two domains ('converted' and 'unconverted'). Results are shown for each of the four indicators applied to each domain for the identification of overall priority areas for restoration in Ethiopia (indicators are explained in Box 1). Lower and upper box limits correspond to the first (25%) and third (75%) quartiles of the distribution, and the middle line corresponds to the median value of the distribution.

3.2 Locations of priority areas for restoration

The extent of the geographical areas identified for our two LROs were 29 million hectares (M ha) for agroforestry and 73 M ha for forest and woodland enrichment (Figure 2B; 10 and 63 M ha for forests and woodlands, respectively, though these are not differentiated in the figure). These hectarages together mean that our identified ASRs, before prioritization, amounted to 89% of Ethiopia's land area.

Figure 4 presents the spatial distribution of the final PARs within each of the two LROs, based on our multi-indicator prioritization approach (for interested readers, this map can be compared with the individual indicator maps in the Appendix already mentioned). The spatial distribution of the PARs indicated that the highest restoration benefits were predicted for the Ethiopian highlands (compare Figure 4 with the vegetation patterns of Figure 2A). In addition, a large portion of the PARs (for 'unconverted' landscapes) were located in Borena zone (Oromia region) in the Southern lowlands, and for 'converted' and 'unconverted' landscapes in Harerge and Shewa zones (also in the Oromia region). For 'converted' landscapes, our model predicted high restoration benefits across the Tigray region.

In contrast, a low occurrence of PARs was observed for the Gambela and Benishangul-Gumuz regions in the western part of the country, where most intact extant natural forest patches are located. A low density of PARs was also observed in the Afar and Somali regions of north-eastern and south-eastern Ethiopia, respectively. The areas we deemed unsuitable for tree-based restoration, i.e., outside our ASRs and therefore not assessed for restoration prioritization in this study, are mostly distributed within these two regions.

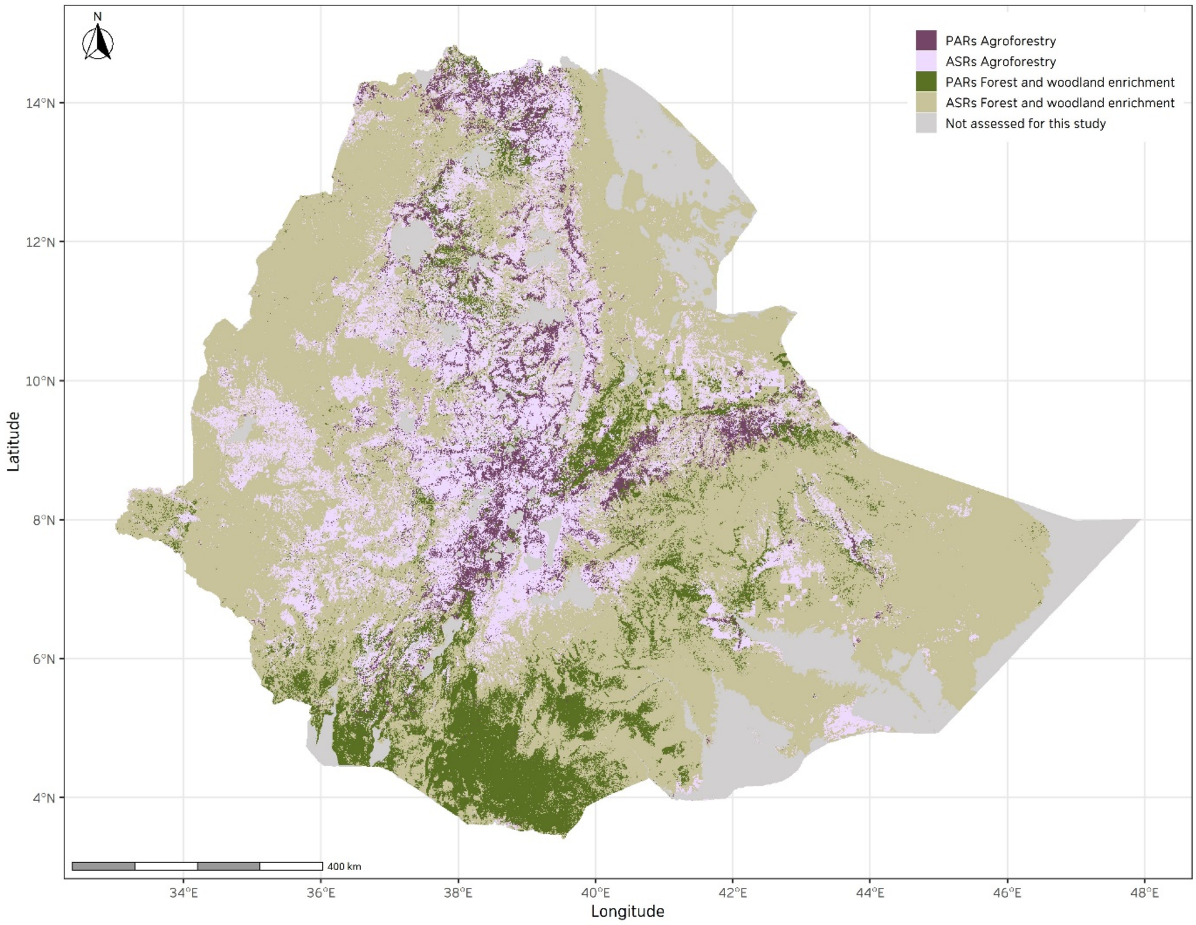

Figure 4. Spatial distribution of all suitable areas and priority areas for the restoration of 'converted' and 'unconverted' landscapes with tree-based approaches in Ethiopia (priority areas [PARs in the key] are a subset of all suitable areas [ASRs in the key]).

Further information summarizing PARs is presented in Table 4. About two-thirds of total PAR coverage was assigned to the forest and woodland enrichment LRO (11.6 M ha) and a third to the agroforestry LRO (5.3 M ha, adding up to 16.9 M ha of PARs in total). Within the forest and woodland enrichment LRO, around 11% of planning units assigned as PAR were located in forest PNVs and the remainder in woodland (or shrubland) PNVs (separate calculations from Table 4, details available on request). The proportion of land coverage of PARs as a proportion of all ASRs varied slightly by LRO, being 19% for agroforestry and 16% for forest and woodland enrichment.

Table 4. Total areas suitable for tree-based restoration (ASRs) and priority areas for restoration (PARs) for Ethiopia, by domain/landscape restoration option

Domain	LRO	ASRs (million ha)	PARs (million ha)	Percent (PARs/ASRs)
'Converted'	Agroforestry	28.3	5.3	19%
'Unconverted'	Forest and woodland enrichment	71.6	11.6	16%

Figure 5 summarizes how PARs split across Ethiopia's regions by LRO/landscape domain. About 8 M ha in total (5.8 M ha for the forest and woodland enrichment LRO and 2.2 M ha for agroforestry) of PARs were assigned to the Oromia region, which represented 25% of the land area of this region as a whole. A similar proportion of the Southern Nations, Nationalities and Peoples (SNNP) region was covered by PARs, though the overall land area involved, while still relatively large, was reduced to about 2.6 M ha, due to this region being smaller in total area than the Oromia region. Whereas for most regions it was the forest and woodland enrichment LRO that had most of the PAR coverage, in

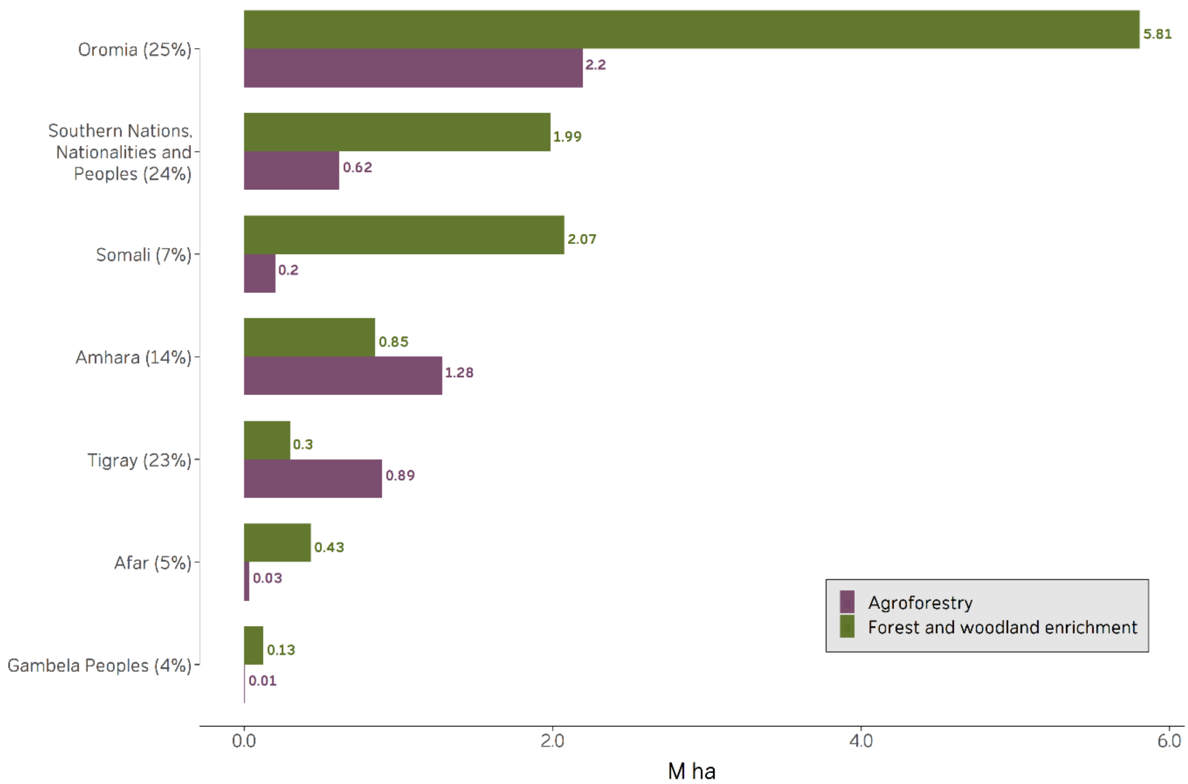

Figure 5. Bar chart showing priority areas for restoration (PARs, in M ha) within a selection of Ethiopia's regions, identified by landscape restoration option. On the vertical axis the percentage of the total land area of the region covered by PARs is given. Regions with only small land areas assigned as PARs are not included in the chart.

Amhara and Tigray regions it was PARs in the agroforestry LRO that dominated. The Afar and Gambela Peoples regions only contained small totals for PARs of 0.5 M ha or less, and these also constituted a small proportion of the two regions' total land areas (5% or less). The Addis Ababa, Benishangul-Gumuz, Dire Dawa and Harari regions were not included in Figure 5, as none of them contributed more than 100 thousand ha in PARs.

Figure 6 shows how PARs split across LC classes and PNVs for Ethiopia by LRO. For the agroforestry LRO, 98% of PARs were located in cropland and only 2% in grassland, while the dominant PNV was Afromontane undifferentiated forest (57% of PARs), followed by Acacia-Commiphora deciduous bushland (21%) and then dry combretum wooded grassland (15%). For the forest and woodland enrichment LRO, 76% of PARs were located in shrub cover areas, 16% in tree cover areas and 7% in grassland, while the dominant PNV was Acacia-Commiphora deciduous bushland (70%), followed by dry combretum wooded grassland (17%) and then Afromontane undifferentiated forest (11%). There was, therefore, a difference in rank ordering of the dominant PNVs between the two LROs.

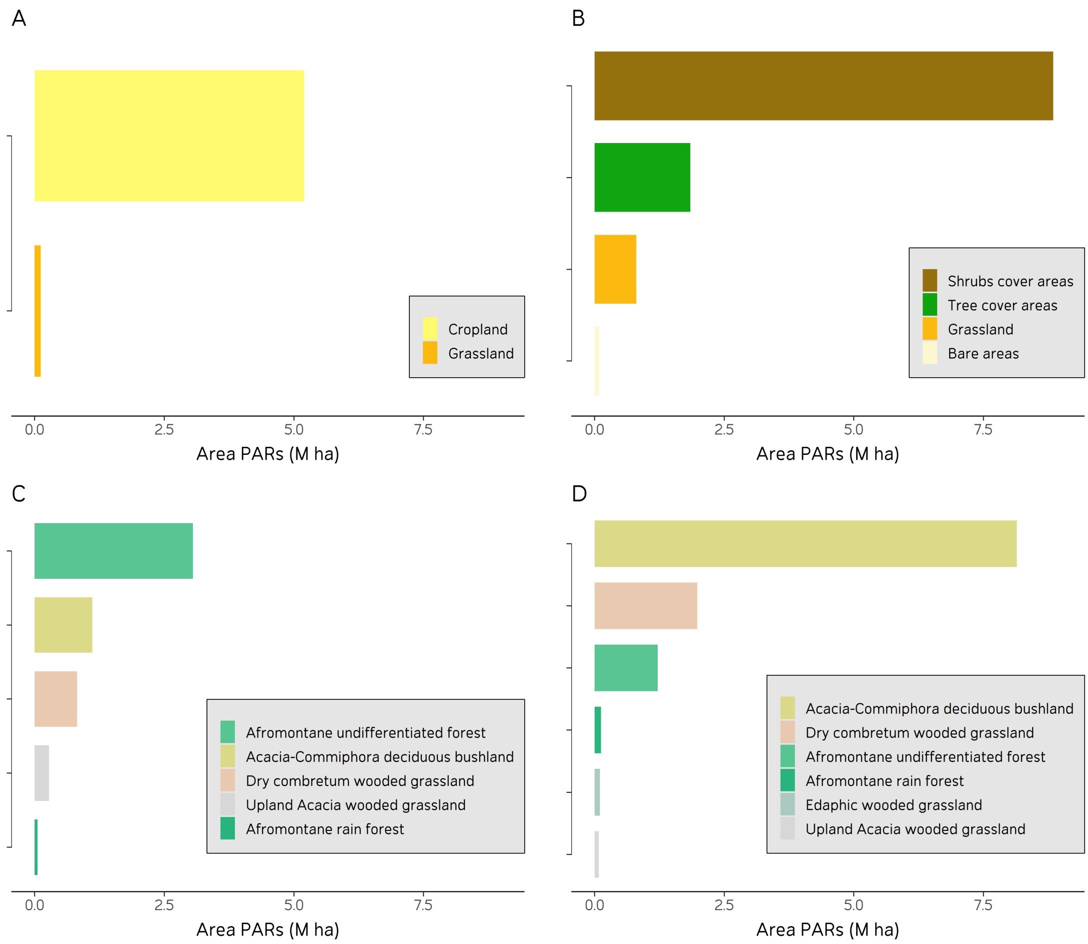

Figure 6. Land cover classes (A and B) and potential natural vegetation types (PNVs) (C and D) for prioritized areas for restoration in agroforestry (A and C) and forest and woodland (B and D) LROs in Ethiopia. PNVs with a total area of less than 50 thousand ha were not included in plots.

3.3 The predicted impacts of implementing restoration on PARs

Table 5 summarizes the potential impacts of implementing restoration on our defined PARs. The estimates of extra soil conserved were 8.7 and 9.6 t ha^{-1} y^{-1} for agroforestry, and forest and woodland enrichment, respectively. Extra C-sequestration was estimated to be approximately 0.3 and 2.8 tC ha^{-1} y^{-1} for agroforestry, and forest and woodland enrichment, respectively. In addition, the estimate was that 2.8 and 1.2 million households would potentially benefit from implementation of tree-based restoration for agroforestry, and forest and woodland enrichment, respectively.

In terms of our calculated costs associated with restoration, these were estimated at USD 368 and 281 ha^{-1} for agroforestry, and forest and woodland enrichment, respectively (for agroforestry the calculation is the opportunity cost, whereas for forest and woodland enrichment this represents the actual restoration cost, as detailed in sub-section 2.4).

Summing figures over PARs, restoration was expected to contribute annually to the extra conservation of 160 megatonnes (Mt) of soil and the extra sequestration of 50 Mt of carbon, this last figure corresponding to approximately 178 Mt of CO_2 eq. Conversely, the total cost we calculated associated with restoring the identified PARs amounted to an estimated USD 5.2 billion.

Table 5. Impact metrics and costs associated with priority areas for restoration in Ethiopia

LRO	Extra soil conserved (t ha^{-1} y^{-1})		Extra C-sequestration (t ha^{-1} y^{-1})		Cost of intervention (USD ha^{-1})		Rural households reached (n)
	mean	SD	mean	SD	mean	SD	
Agroforestry	8.7	0.9	0.3	0.1	368	424	2,791,703
Forest and woodland enrichment	9.6	2.2	2.8	0.5	281*	-	1,172,344

4. Discussion

In this working paper, we have described a new multi-indicator approach that applies an integer linear programming algorithm for the identification of priority areas for tree-based restoration (PARs). The method was inspired by previous studies of Brancalion et al. (2019) and Strassburg et al. (2020), who both developed and applied a multi-indicator approach to restoration planning. We have applied our new approach to Ethiopia, where a comparison of our thus-designated PAR planning units with randomly sampled units for a range of indicators has shown the effectiveness of the method. The total PARs determined, of 16.9 M ha, approximates Ethiopia's pledged areas of degraded landscapes for restoration of 15 M ha in total by 2030 (FDRE, 2017b), and our exercise thus provides a useful guide in determining restoration priorities at an appropriate magnitude.

Our new approach constitutes a parallel and sometimes advantageous one compared to past prioritization methods. Previous work using the ROAM approach (IUCN & WRI, 2014) to set priorities for restoration in Ethiopia (MEFCC, 2018) was significantly different in method from our current approach in several features, as summarized in Table 6. Advantages of our current approach include its ability to rely on open-access datasets that can easily be updated for the analysis as newer versions become available, its low cost, our linkage of the approach to impact assessment, and the ability to replicate it elsewhere. This last feature is highly desirable when regional initiatives (in the case of Africa, initiatives such as AFR100) are considered that would greatly benefit from the use of a standardized prioritization approach. We estimate our method requires comparable analytical skills to ROAM, but its lower cost of implementation is a significant benefit.

Table 6. Comparison between our study and a previously published study on defining priority restoration opportunities in Ethiopia

Feature	**A) MEFCC & WRI (2018)**	**B) Our study**	**Comment**
Repeatability	︾	︽	A) Vague description of methodology; not repeatable. B) Logical methodology accompanied by a thorough description; repeatable.
Ground-truthing	︽	︾	A) Identified priority areas verified with field data collection so that an accuracy value could be assigned to the analysis. B) Efficiency of the prioritization verified through comparison with a 'null model', but no ground-truthing is carried out.
Data	︾	︽	A) Included outdated and limited-access datasets. B) Based on open-source datasets that can be easily updated.
Impact assessment	︾	︽	A) Does not estimate the impact of implementing restoration actions. B) Impact estimation based on the indicators developed for prioritization and some additional open-source global datasets.
Priority areas	︽	︽	A) Three different priority levels identified, down to the lowest administrative unit level. B) One priority level identified, down to the planning unit level (~1km^2).
Restoration interventions	︽	︾	A) Numerous interventions are described, and their feasibility assessed in relation to the country's biophysical conditions, although results are not displayed spatially. B) Fewer interventions are distinguished, but these are displayed spatially.
Participation	︽	︾	A) Involved numerous stakeholders, who gathered in workshops to write the methodology and conceptualize the study. B) Not equally inclusive of stakeholders.

Feature	A) MEFCC & WRI (2018)	B) Our study	Comment
Cost	︾	︽	A) High. The process involved numerous actors (governmental and research institutions) and design phases, with in-person workshops to gather expertise. Additional funds had to be allocated to carry out fieldwork for the ground-truthing exercise. B) Low. Process handled internally by the analyzers, based on remote work without fieldwork or face-to-face design phases.

The results of our prioritization exercise for Ethiopia showed that around half of the total PARs were located in the Oromia region, which we therefore suggest is a location of key importance for the Ethiopian government to consider for reaching the nations' restoration targets. An initial comparison with protected area maps (results not shown) also suggests that 14% of our identified PARs fall within the borders of protected areas (UNEP-WCMC & IUCN, 2021). Since these are under different governance regimes from the remaining 86% of PARs, restoration actions in them may require especially careful mediation with local and regional stakeholders.

A feature of our prioritization approach is that it is underpinned by an assessment of baseline habitat PNVs to exclude from consideration non-woody ecosystems where tree planting could cause harm to local biodiversity (Phifer et al., 2017). Africa's native grassy ecosystems, for example, are under major threat, in some cases due to inappropriate targeting for afforestation (Bond et al., 2019). Their planting with trees not only damages biodiversity, but may not be effective in fixing carbon (Lewis et al., 2019). In our analysis, our choice of PNVs to which tree-based restoration measures could be targeted may over-emphasize tree-based opportunities, but a useful feature of our approach is that it is easy to repeat the calculations with different (smaller) target sets of PNVs, if so desired. Our current analysis is unequivocal in revealing that the majority of PARs were once forested areas for 'converted' landscapes, with about 3 M ha of Afromontane forest cleared for agricultural use. This corresponds with other Ethiopian studies which indicate that the extent of agricultural expansion has been dependent on forest loss (Bishaw, 2001; Deribew & Dalacho, 2019; Tadesse et al., 2020).

A useful feature of the documentation of the PNV maps that we used as a starting point for our analysis is the list of native tree species provided for each PNV (van Breugel et al., 2015). This information provides an initial guide for which trees to focus on (a tool for this purpose in Ethiopia has just become available (Kindt et al., 2021b)) when designing appropriate agroforestry, and forest and woodland enrichment, implementation measures. There are a number of advantages in focusing on local tree species during implementation, which include adaptation to the environment (further information for trees in Ethiopia in this regard is available from (Kindt et al., 2021a)) and the protection of biodiversity.

The actual implementation of restoration on PARs is of course a complex and context-specific process in which it is essential to work with local communities (Höhl et al., 2020) and take into account a range of national targets and government strategies, and PARs could be further prioritized for different purposes. Our analysis thus only represents a starting point. It could, for example, be built on, using our methodological pipeline, to consider the connectivity between PARs (Hanson et al., 2021), which could provide biodiversity and logistical benefits, though some analyses would require significantly longer run times. At a simple level, logistically, isolated prioritized planning units would of course likely be of lower importance from an implementation perspective (see link).

As already alluded to above, we are involved in the PATSPO initiative that focuses on tree seed supply for the effective implementation of restoration projects in Ethiopia. The PATSPO project is doing this by describing existing tree seed sources, establishing new ones, and planting breeding seedling orchards for tree improvement and as high-quality adapted seed sources. The current prioritization exercise, combined with information on tree species' distribution, helps inform which trees should be the focus of PATSPO's seed supply efforts, and indicates where the building of tree 'seed system' infrastructure is most needed in Ethiopia for restoration implementation (according to current results, especially in the Oromia region).

Our evaluation of impacts of restoration on PARs in the current study, which were significant, also provides the starting point for an *ex ante* impact evaluation of the environmental and livelihood benefits of the PATSPO project. The impact assessment of PATSPO, which considers not only the availability and accessibility of tree seed *per se,* but what additional benefits using *higher quality* tree seeds and seedlings bring, is currently underway, guided by our current findings (van Schoubroeck et al. (2021, in prep.)). This analysis will include estimating economic benefits for smallholder farmers and local communities, as understanding how they benefit from restoration is crucial in predicting restoration success.

Our impact numbers presented in the current study suggest that restoring 16.9 M ha of PARs would sequester 178 Mt CO_2 eq. annually, which is approximately four times the abatement potential assumed for forest management, reforestation, afforestation and pastureland improvement activities in Ethiopia's CRGE strategy (FDRE, 2011b). Our estimate of annual sequestration potential for unconverted landscapes of 2.8 tC ha^{-1} y^{-1}, equivalent to 10.1 tCO_2e ha^{-1} y^{-1}, has an estimated cost of around USD 10 per tCO_2e, if it is considered that planted trees will subtract CO_2e from the atmosphere for a period of 30 years.

5. Conclusion

We have devised a new method for setting priority areas for tree-based restoration (PARs) and applied it to Ethiopia. Our multi-indicator, linear programming approach identified a total of 16.9 M ha of PARs in Ethiopia, with about two-thirds in 'unconverted' landscapes that can be targeted with forest and woodland enrichment-based restoration, and one-third in 'converted' landscapes that can be targeted with agroforestry. The prioritization approach we have used estimates the benefits of restoration compared to a null model of no prioritization, and indicates the impacts of restoration interventions. Our approach, which has several advantages compared to existing prioritization methods, can be applied widely.

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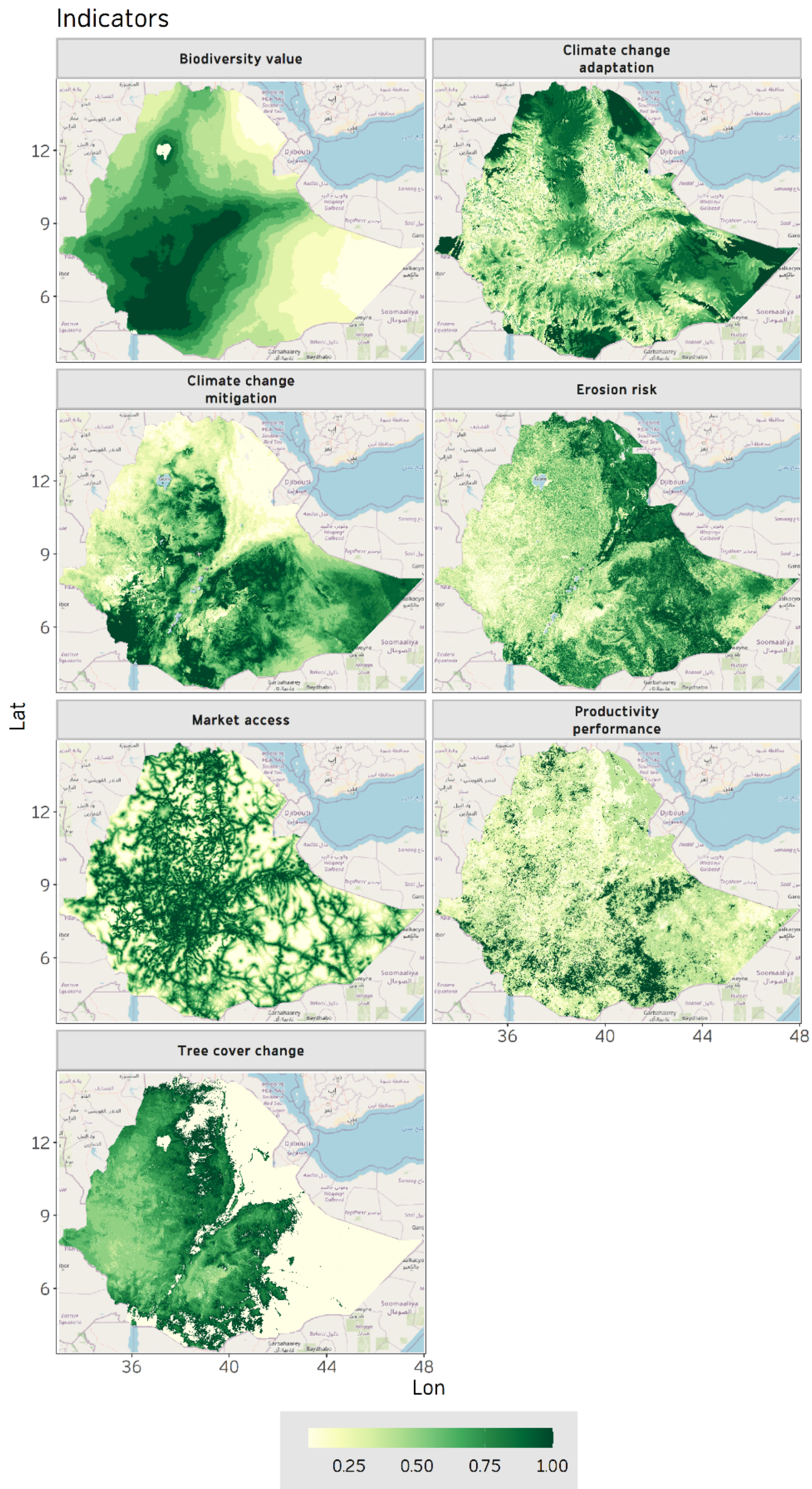
Appendix



The geographic distributions of normalized values for the seven individual indicators used to define priority areas for tree-based restoration in Ethiopia, based on a multi-indicator approach (see Box 1 for detailed information on indicators).

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