zef
Center for Development Research University of Bonn

Centre de Suivi Ecologique

PARI

Working Paper 244

Abdoul Aziz Diouf, Alisher Mirzabaev, Cheikh Mbow, Heike Baumüller, Zahra Didarali and Joachim von Braun

Mapping Present and Future Agroforestry in Africa

ISSN 1864-6638 Bonn, March 2025

ZEF Working Paper Series, ISSN 1864-6638
Center for Development Research, University of Bonn

Authors' addresses

Abdoul Aziz Diouf, Centre de Suivi Écologique
Email: aziz.diouf@cse.sn

Alisher Mirzabaev, International Rice Research Institute (IRRI).
Email: a.mirzabaev@cgiar.org

Cheikh Mbow, Centre de Suivi Écologique
Email: mbow@cse.sn

Heike Baumüller, Center for Development Research (ZEF), University of Bonn.
Email: hbaumueller@uni-bonn.de

Zahra Didarali, Institute for Land and Resource Economics, University of Bonn
Email: zdid@uni-bonn.de

Joachim von Braun, Center for Development Research (ZEF), University of Bonn.
Email: jvonbraun@uni-bonn.de

Mapping Present and Future Agroforestry in Africa

Abdoul Aziz Diouf, Alisher Mirzabaev, Cheikh Mbow, Heike Baumüller, Zahra Didarali and Joachim von Braun

Abstract

Agroforestry systems are vital for sustainable development in Africa, offering significant benefits such as enhanced agricultural productivity, biodiversity conservation, and climate resilience. This study provides a detailed analysis of the past, present, and potential future distributions of agroforestry across the African continent using high-resolution geospatial datasets and predictive modeling techniques. Between 2000 and 2020, agroforestry areas have expanded in some, while declining in other locations across Africa. Overall, at the continental level, net economic losses due to decline in the extent of agroforestry systems between 2000 and 2020 made up an equivalent of 14 billion USD. Economic projections point at consistently positive returns from future investments into agroforestry expansion in northern Africa, the northern part of the Sahel region, horn of Africa, and southern Africa. However, there is a strong heterogeneity across the continent in terms of economic viability of agroforestry expansion investments, requiring targeted prioritization to those areas with higher long-term returns. Projections to 2050 indicate that targeted policies and investments can not only prevent agroforestry losses under the business-as-usual trends but also help maximize benefits from agroforestry expansion where it makes the most sense.

Keywords: Agroforestry, Africa, geo-spatial mapping, Climate change, Ecosystem services, Livelihoods, Nature-based solutions, economic assessment, cost-benefit analysis

JEL codes: O13, Q2, Q23, Q24, Q28, Q54, Q55, Q56, Q57, Y10

Acknowledgements

This study was developed in the context of the Program of Accompanying Research for Agricultural Innovation (PARI), supported by the Federal German Ministry for Economic Cooperation and Development (BMZ). The close cooperation between Center for Development Research (ZEF) at Bonn University with the Centre de Suivi Ecologique in Dakar, Senegal, and their partners in various African countries is greatly appreciated.

Table of Contents

List of Figures and Tables

1 Introduction

Agroforestry is gaining recognition as an important tool for tackling both land degradation and rural development challenges. This is especially true in Africa, where 59% of the population lives in rural areas, relying heavily on natural resources for their livelihoods (World Bank, 2021). Degradation of soils, which form the productive base of rural households in Africa, is a critical problem (Barbier & Hochard, 2018). In recent decades, soil degradation has become a significant driver of poverty and food insecurity (Mirzabaev et al., 2021), and vulnerability to social and climate change (Barbier & Hochard, 2018). This degradation, largely due to unsustainable land management practices, has led to negative social, economic and ecological impacts. Addressing this through widespread agroforestry solutions is seen as a critical step towards sustainable development in Africa, particularly in the context of increasing biomass demand and climate change.

Forest and agroforestry systems deliver multiple direct and indirect benefits (Angelsen et al., 2014; (Wunder et al., 2014). Direct benefits include enhanced crop productivity through the integration of trees in cropping systems (Bado et al., 2021; Mbow et al., 2020), provision of nutritious fodder for livestock (Chakeredza et al., 2007), and improved household nutrition through the cultivation of fruit trees (Jemal et al., 2021). Agroforestry has shown to improve soil erosion attributed to the improvement of soil water regulation and soil texture, compared to conventional monoculture systems (Ngaba et al., 2024). Additionally, agroforestry reduces labor demands for fuelwood collection (Beyene et al., 2019).

Indirectly, agroforestry contributes to ecosystem services like carbon sequestration, erosion control, water regulation, nutrient cycling, and biodiversity conservation (Kuyah et al., 2019; Baumüller et al., 2020). Its climate change mitigation potential is substantial, as agroforestry systems sequester significantly more carbon than treeless systems, helping offset emissions (Tschora & Cherubini, 2020). Moreover, agroforestry supports climate adaptation by reducing soil erosion, improving moisture retention, and diversifying farmers' income sources (Mirzabaev et al., 2021). These benefits position agroforestry as a promising solution for both climate change and land degradation (IPCC, 2019).

In Africa, agroforestry has taken center stage in scientific and policy discourses. In the past, agroforestry has also experienced an increase in adoption in some parts of Africa (Garrity et al., 2010). Despite the recognized benefits of agroforestry, its uptake has not been widespread due to challenges such as lack of support for agroforestry systems through public policies (Bishaw, 2013), limited investment in the sector compared to intensified farming systems, and the failure of extension services, which limits the possibility of scaling up innovations in agroforestry for improved land use systems (Mbow et al., 2014). Further challenges include lack of technical knowledge, delayed returns on investments and insecure land tenure rights (Olsson et al., 2019; Russell & Franzel, 2004).

To effectively harness the benefits of agroforestry and build a compelling policy case for its adoption, a comprehensive understanding of its potential expansion across the African continent is essential. Identifying the costs and benefits associated with agroforestry systems is also critical. An economic assessment of costs and benefits of agroforestry can facilitate decision-making and policy action. Mirzabaev et al. (2021) have proposed an approach which demonstrates the usefulness of such assessment of costs and benefits of land restoration to guide and support policy formulation, in the Sahel and China, respectively.

While several studies have attempted to map the extent of agroforestry using various types of remote sensing data and classification techniques (Lesiv et al., 2022; Rizvi et al., 2020), inconsistencies on the definition of agroforestry exist when it comes to mapping. These methodological inconsistencies and a lack of clear classification systems for agroforestry practices complicate the assessment of their benefits (Golicz et al., 2023). Some simplified definitions refer to the main components of agroforestry such as trees, crops and/or animals (Gordon & Newman, 2018), while others are broader and refer to spatio-temporal management patterns and ecological interactions that can generate ecosystem goods and services, including socioeconomic and environmental benefits (Young, 1983).

Agroforestry systems incorporate or use naturally existing trees and shrubs in cropping and pastoral systems with the purpose of attaining synergies between these perennial and annual elements in an integrated manner (Nair, 1993b). In this study, we define agroforestry as the integration of trees, crops and/or livestock on the same management unit. To capture the diversity within African agroforestry, we focus on three main types of agroforestry: (i) Agrisilviculture, a production technique which combines the growing of agricultural crops with simultaneously raised and protected tree crops; (ii) Silvipasture, which integrates livestock, forage, and trees within a single land management unit; and (iii) Agrisilvipasture, an integrated land use system that combines agriculture, forestry, and cattle in the same unit. This typology supports a comprehensive approach to understanding the extent and function of agroforestry systems across Africa. It also avoids the pitfall of previous large scale agroforestry mapping studies typically overlays only agricultural land using cropland and percent tree cover maps, without accounting for pasture areas (Brandt et al., 2025).

Currently, no readily available data exists which provides the needed information on these dimensions of agroforestry in cropping systems at necessary detail. To our knowledge, no study to date has investigated the past, current and future of agroforestry zones at the scale of the African continent. Producing high-resolution and up-to-date maps of agroforestry and its temporal dynamics for the African continent that accurately captures all dimensions of agroforestry remains a critical gap. Previous studies such as von Maydell's (1987) work, have examined agroforestry in specific African regions, particularly dry zones, but lacked a continent-wide perspective and the incorporation of spatial analyses via remote sensing. Our study advances this field by leveraging state-of-the-art geospatial datasets, including those for tree cover (Buchhorn, Smets, et al., 2020; Hansen, 2013) animal density (Gilbert et al., 2018) and land use-land cover (C3S & CDS, 2019; ESA, 2017). In contrast to prior approaches that either downscaled or upscaled single tree cover products, we generated new tree cover maps for 2000, 2010, and 2020 by training on data from (Buchhorn, Smets, et al., 2020) and applying it to reflectance bands from Hansen (2013).

Our study contributes to the above-mentioned research gaps through four objectives. First, we aim to map and analyze the spatiotemporal dynamics of agroforestry systems across Africa in their past, present, and future distributions. Second, we assess the direct and indirect economic benefits of agroforestry to African people. Finally, we aim to evaluate the economic potential for agroforestry expansion in Africa.

2 Conceptual framework

Agroforestry systems provide a wide range of ecosystem services. For this reason, this assessment uses the total economic value (TEV) framework, assigning value to all ecosystem services provided by forests and agroforestry systems. The TEV approach classifies ecosystem services into three categories by the nature of their values: use values, non-use values, and option values (Nkonya et al., 2016). Use value consists of direct and indirect use values. The direct use values comprise marketed outputs containing priced consumption (e.g. food crops, timber products, ecological tourism, etc.) as well as un-priced benefits such as local culture and recreation. The indirect use value includes ecosystem functions and services which usually do not have market prices such as water purification, CO_2 sequestration, enhanced micro-climate, biodiversity, water level, etc. (Table 1).

Non-use value is made up of bequest, altruistic and existence values, all of which are un-priced benefits. The option value includes both marketable outputs and ecosystem services for future direct or indirect use. It is usually quite difficult to measure the non-use and indirect use values as they are rarely traded in markets.

The TEV framework considers the monetary values of all ecosystem services, both marketed ecosystem services and non-marketed ecosystem services following the classification of ecosystem services based on the Millennium Ecosystem Assessment (Millennium Ecosystem Assessment, 2005). The Millennium Ecosystem Assessment classifies ecosystem services into 22 types under provisioning, regulating, habitat, and cultural ecosystem services (Table 1). Provisioning ecosystem services are the values of food production, water provision, the extraction of medicinal, genetic, and ornamental resources, and have market prices. On the other hand, regulating, habitat, and cultural ecosystem services are mostly not traded in the markets and do not have market prices, they are non-marketed common pool ecosystem services. Their economic values are obtained through various valuation approaches such as contingent valuation, travel cost, replacement cost methods, damage cost avoided and other methods (Nkonya et al., 2016).

Table 1: Millennium Ecosystem Assessment classification of ecosystem services (Millenium Ecosystem Assessment, 2005)

Provisioning services Food, Water, Raw materials, Genetic resources, Medicinal resources, Ornamental resources	**Regulating services** Air quality regulation, Climate regulation, Disturbance moderation, Regulation of water flows, Waste treatment, Erosion prevention, Nutrient cycling, Pollination, Biological control
Habitat services Nursery service, Genetic diversity	**Cultural services** Esthetic information, Recreation, Inspiration, Spiritual experience, Cognitive development

3 Methods and Data

This study combines remote sensing, machine learning and geospatial modelling to analyze the distribution, change and projection of agroforestry systems across Africa. To estimate the direct and indirect benefits of agroforestry, we use the TEV framework.

3.1 Mapping of agroforestry systems

The main agroforestry systems were mapped by combining different raster layers of trees, livestock and croplands in Africa for the years 2000, 2010 and 2020 – following the definition of Nair (1993a). These layers which were initially at different resolutions, were resampled to a uniform 1 km resolution using a bilinear method for trees and livestock and nearest neighbor for croplands in R. The trees and livestock layers were continuous variables, and the croplands layer was categorical. To generate presence/absence data for each study year, thresholds were applied to the respective layers: (1) livestock presence was defined by a threshold of 1 Tropical Livestock Unit (TLU) per pixel; (2) tree cover was identified where at least 1% of the pixel (equivalent to 1 ha in a 1 km^2 area) was covered by trees, following Zomer et al. (2014); and (3) crops presence was determined by the classification of all cropland pixels.

Combining these layers resulted in the identification of three primary agroforestry systems, as defined by Nair et al. (2021): agrisilviculture (trees and crops), silvipasture (trees and livestock), and agrisilvipasture (trees, crops, and livestock).

Field data for the three corresponding agroforestry classes were used to validate the agroforestry map of the year 2020 across the Africa continent. These data were rasterized to the same pixel size of 1km to allow a pixel-by-pixel comparison.

3.2 Acquisition and processing of geospatial data

Various datasets, summarized in Table 2, were used to map agroforestry and its variation across Africa for the study years 2000, 2010 and 2020. These data include layers on protected areas, wetlands, climate (i.e., rainfall and temperature), vegetation (i.e., forest cover, tree cover, croplands), topography (i.e., elevation), livestock, human population density and soil properties. These data were respectively used according to the overall methodology in three processing steps: (i) the spatial clustering of the African continent to identify the relevant countries for ground-truth data collection, (ii) the masking of areas without agroforestry and (iii) the mapping of the three main agroforestry systems.

Table 2: List of datasets and extracted features used for the Agroforestry mapping in Africa

Name	Variable(s)	Dataset / Product	Format and Resolution	Year(s)
Protected Areas	Terrestrial and Inland Waters Protected Areas	World Database on Protected Areas (UNEP-WCMC, 2021)	Polygons, Continent level	2021
Wetlands		Global Lakes and Wetlands Database (GLWD) (Lehner & Dolk, 2004)	Polygons, Continent level	2004
Climate data	Rainfall	CHIRPS dataset (Funk et al., 2015)	Raster, 0.05°	1981-2021

	Temperature	WorldClim version 2.1 dataset (Fick & Hijmans, 2017)	Raster, 1km	1975-2000
Digital Elevation Model	Elevation	Digital Elevation Model (USGS-NASA 2000)	Raster, 30m	2000
Vegetation products	Land cover	Land use and land cover (ESA, 2017 & C3S-CDS, 2019)	Raster, 300m	2000, 2010 and 2020
	Total Biomass Production	Total Biomass Production dataset of WaPOR 2.1 (FAO, 2020)	Raster, 1km	2020
	Spectral Reflectance bands	Hansen et al., (2013) Global Forest Change v1.9 (2000-2021)	Raster, 30m	2000, 2010 and 2020
	Forest cover	Forest cover fraction layer of (VITO-CGLS) (CGLS, 2019)	Raster, 100 m	2019
Livestock products	Livestock density	Gridded Livestock of the World – Latest – (GLW 3) (Robinson et al., 2014)	Raster, 10 km	2010
Continental Population	Human Population density	Africa Continental Population Datasets (CIESIN, 2018)	Raster, 1km	2000 and 2020
Continental Soil properties	Soil Organic Carbon Soil Texture	SoilGrids datasets - ISRIC Data Hub (Hengl et al., 2017)	Raster, 250m	

3.3 Geospatial data for clustering of the African Continent

Seven environmental variables were used to compute a pixel-based clustering of the African continent. The layers are presented in (Annex 1).

3.4 Masking potential areas without agroforestry

All areas without agroforestry were masked across Africa in 2000, 2010 and 2020, using four layers related to the protected areas: forests, lakes, wetlands and urban areas. The World Database on Protected Areas (WDPA) dataset (UNEP-WCMC and IUCN, personal communication, 2022) was used to mask out all protected areas potentially not involved in agroforestry. These masks of protected areas included national parks, Ramsar sites, private areas and hunter zones. The masks of forests, wetlands, settlements and water bodies were extracted from annual Land Cover maps of the European Space Agency Climate Change Initiative (ESA-CCI) (ESA, 2017), and the Copernicus Climate Change Service Data (C3S-CDS) (Copernicus, 2021) with a spatial resolution of 300m. Finally, the whole mask was applied to the agroforestry maps to exclude non-agroforestry areas for the years 2000, 2010 and 2020.

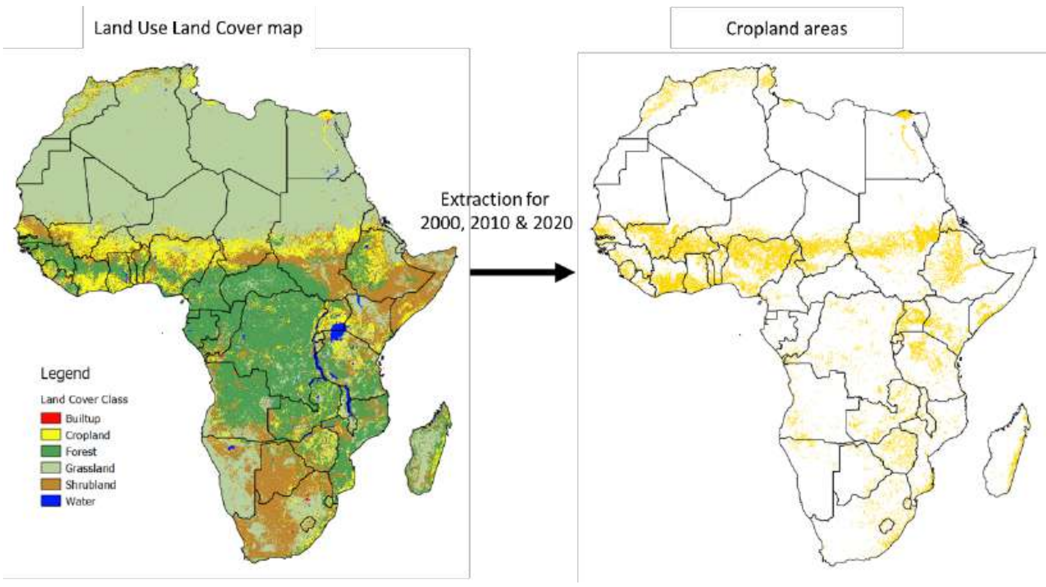
3.5 Data Extraction

Geospatial data related to the three main components of agroforestry systems, namely cropland, tree cover and livestock, were processed and extracted individually to carry out the agroforestry systems mapping.

Cropland layer

To extract the cropland layer, we utilized Land Use Land Cover (LULC) products from ESA-CCI (2017) and C3S-CDS (2021) databases. This layer included categories for rainfed, irrigated, and mosaic croplands (Figure 1). The LULC products encompass 22 classes with a spatial resolution of 300 meters. For mapping purposes, we reclassified these layers into six categories, following the Intergovernmental Panel on Climate Change (IPCC) approach, and resampled them to a resolution of 1 kilometer. The final maps and reclassified categories can be found in the supplementary materials, (Annex 2). Figure 1 illustrates the LULC map of 2020 and extracted areas/mask of non-agroforestry areas across Africa.

Figure 1: Land use and land cover map of 2020 and extracted areas/mask of non-agroforestry areas across Africa. The LULC map was simplified here into 6 major classes



Livestock production

We used the Gridded Livestock of the World - Latest - 2010 (GLW 3) database for livestock related data. This global dataset, developed by the Food and Agriculture Organization (FAO) Animal Production and Health Division in collaboration with the Oxford Environmental Research Group (Robinson et al., 2007), provides estimates for various species, including cattle, buffalo, sheep, goats, pigs, chickens, and other poultry. The GLW database facilitates global and sub-national mapping of these species, with estimates per square kilometer at an approximate resolution of 10 kilometers. The resulting maps are based on modeling empirical relationships between livestock densities and various environmental, demographic, and climatic variables within similar agro-ecological zones. The GLW 3 is the latest version generated using a Random Forest model (Gilbert et al., 2018) offers global data for the year 2010 at a spatial resolution of 0.083333 decimal degrees (roughly 10 kilometers at the equator). In this study, we focused on four species: sheep, goats, cattle, and horses. Using data from FAO Statistics, we calculated the growth rates of these species between 2010 and 2020, as well as between 2000 and 2010, using the following formula:

$$GR = \frac{(Value_{n+1} - Value_n)}{Value_n} * 100$$

Where GR is the growth rate, $Value_{n+1}$ is the livestock population of the last year and $Value_n$ is the livestock population of the first year.

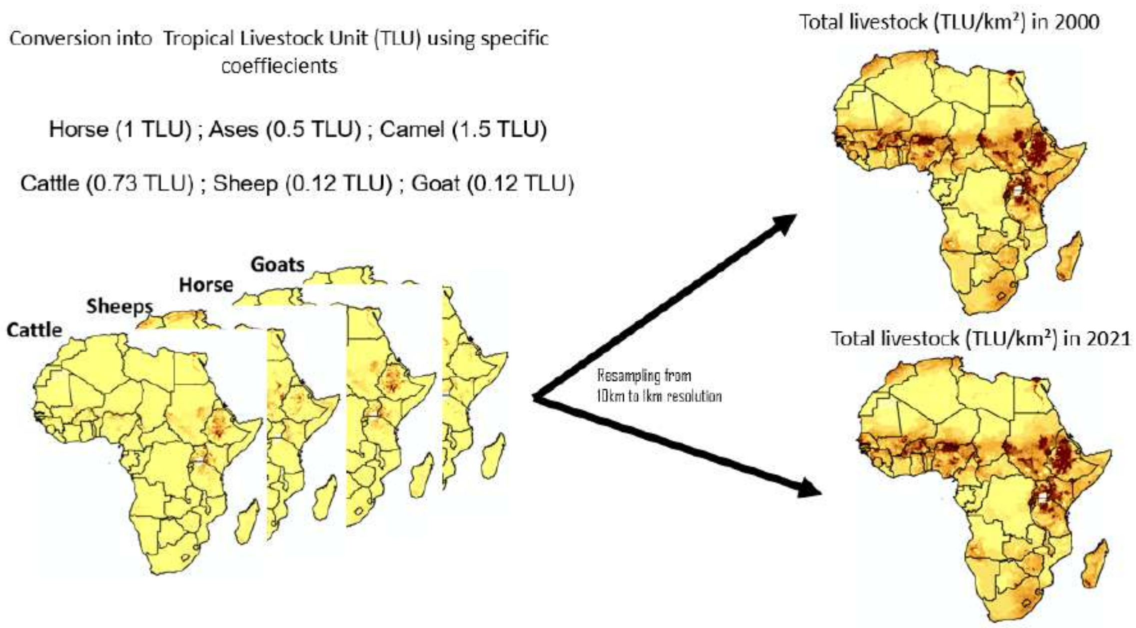
Using the growth rate of each species, the corresponding number of heads was calculated for the years 2000 (1) and 2020 (2) using the following equations:

Number of head of animals = Number in 2010 / (1+GR) (1)

Number of head of animals = Number in 2010 + (Number in 2010 * GR) (2)

These spatialized data at the scale of Africa allowed to convert the number of heads of animals into tropical livestock units (TLU) using the specific coefficient of each species. The combined data of animals is presented in Figure 2.

Figure 2: Distribution of livestock density across Africa (Total livestock units of horses, goats, sheep and cattle)



Tree/shrub cover fraction data

To model the tree cover for the years 2000, 2010 and 2020, we used the Global Forest Change (GFC) v1.9 database (2000-2021) developed by Hansen et al. (2013) as well as the Copernicus Global Land Service (CGLS) tree and shrub cover fraction of the year 2019 (Buchhorn, Smets, et al., 2020). The reflectance bands of the GFC database were used to calculate spectral indices which constituted the main predicting variables of the tree/shrub cover while the CGLS dataset served to extract the reference data. Considering the computational requirements at the scale of our analysis (30m resolution, 3 years, the whole of Africa), we leverage the readily available and preprocessed reflectance composites for the years 2000, 2010 and 2020 from the GFC database

This tree cover modeling was undertaken due to the unavailability of the percent tree cover layers for 2010 and 2020 from the Hansen et al. (2013) dataset. To address this, we utilized the readily accessible and preprocessed reflectance composites for 2000, 2010, and 2020 from the GFC database, which provided a consistent and reliable basis for our analysis.

Forest cover fraction

The CGLS was used to identify areas with tree presence and to build a training dataset. The CGLS is a component of the Land Monitoring Core Service (LMCS) of Copernicus, the European flagship Earth observation program. This service aims to provide systematic monitoring of the land surface and has been producing annual land cover maps at 100 m resolution (CGLS_LC100) since 2015 (Buchhorn, Lesiv, et al., 2020).

3.6 Spectral indices and computation of woody cover layer

Four spectral indices were computed using the 2000, 2010 and 2021 spectral bands provided by Hansen et al. (2013). Knowing that the Landsat-8 Operational Land Imager (OLI) and the Landsat-7 Enhanced Thematic Mapper Plus (ETM+) can be used as complementary data (Li et al., 2013) and that Normalized Difference Vegetation Index (NDVI) was demonstrated to be similar between OLI and ETM+ (Huntington et al., 2016), we used the following spectral indices (see formula in Table 3):

1. The Normalized Difference Vegetation Index (NDVI) (Rouse et al., 1974) corresponds to the normalized difference of the visible red (RED) to near-infrared (NIR) reflectance and is a measure of the photosynthetic activity of vegetation. Its value ranges from -1 to 1 where high values indicate vegetation greenness, while low values indicate non-vegetated areas (Nguyen et al., 2021).
2. The Normalized Difference Infrared Index (NDII) (Hardisky et al., 1984) is the normalized difference between the NIR and the shortwave infrared (SWIR) bands. It is mainly used to account for the moisture content of the vegetation (Wilson & Norman, 2018).
3. The Normalized Difference Water Index (NDWI2) (Gao, 1996) was derived from the reflectance of the NIR and shortwave infrared (SWIR) bands. The combination of these two spectral bands improves the accuracy of determining vegetation water content by eliminating variations induced by internal leaf structure and leaf dry matter content.
4. The Modified Bare soil Index (MBI) was proposed by Nguyen et al. (2021) for the detection of bare soils using SWIR and NIR wavelengths.

Table 3: Spectral indices used in this study

Vegetation Index	Formula	Reference
Normalized Difference Vegetation Index (NDVI)	$\frac{NIR - RED}{NIR + RED}$	(Rouse et al., 1974)
Normalized Difference Infrared Index (NDII)	$\frac{NIR - SWIR}{NIR + SWIR}$	(Hardisky et al., 1984)
Normalized Difference Water Index 2 (NDWI2)	$\frac{NIR - SWIR2}{NIR + SWIR2}$	(Gao, 1996)
Modified Bare Soil Index (MBI)	$\frac{SWIR1 - SWIR2 - NIR}{SWIR1 + SWIR2 + NIR} + 0.5$	(Nguyen et al., 2021)

The woody cover mapping was carried out using Random Forest (RF) regression modeling (Breiman, 2001) via the Google Earth Engine (GEE) platform, a cloud-based computing platform that allows, at planetary scale, geospatial data retrieval, processing and analyses (Gorelick et al., 2017). The RF algorithm was used due to its proven efficiency for woody cover mapping (Anchang et al., 2020; Nagelkirk & Dahlin, 2020). The woody cover modeling was carried out in three main phases. In the first phase, data pre-processing was conducted to obtain a time series suitable for analysis. We began by importing image composites from the Global Forest Change v1.9 dataset, followed by filtering to limit the image collection to specific years, a defined study area, and target spectral bands.

The second phase focused on all image processing tasks required to obtain the satellite based explanatory variables. These involved the calculation of four vegetation indices – including (NDII, NDWI2, NDVI, MBI), and the compilation of the four spectral bands (RED, NIR, SWIR1, SWIR2) to generate a set of eight variables for each target year.

In the third and final phase, data preparation and model calibration were performed to train the RF regression model. Woody cover samples were randomly extracted from the CGLS' forest cover product of 2020 and imported into GEE as a shapefile asset. In total, 7943 sample points were extracted and randomly divided into training points (80%, 6348 points) and validation points (20%, 1595 points). Using a pixel-based approach, the RF regression model was calibrated using the GEE default number of predictors available to divide each node (mtry), and the 500 regression trees (ntree). The model's accuracy was assessed using measures such as the root mean square error (RMSE), the relative RMSE (RRMSE) and the coefficient of determination (R^2). The description of these parameters is presented in Table 4. The RF model calibrated for 2020 was subsequently applied to estimate tree cover for 2000 and 2010.

Table 4: Accuracy evaluation parameters and their formulas. N: total number of samples, Yi: measured value, Yi': estimated value and $\underline{Y}$: average of the measured values

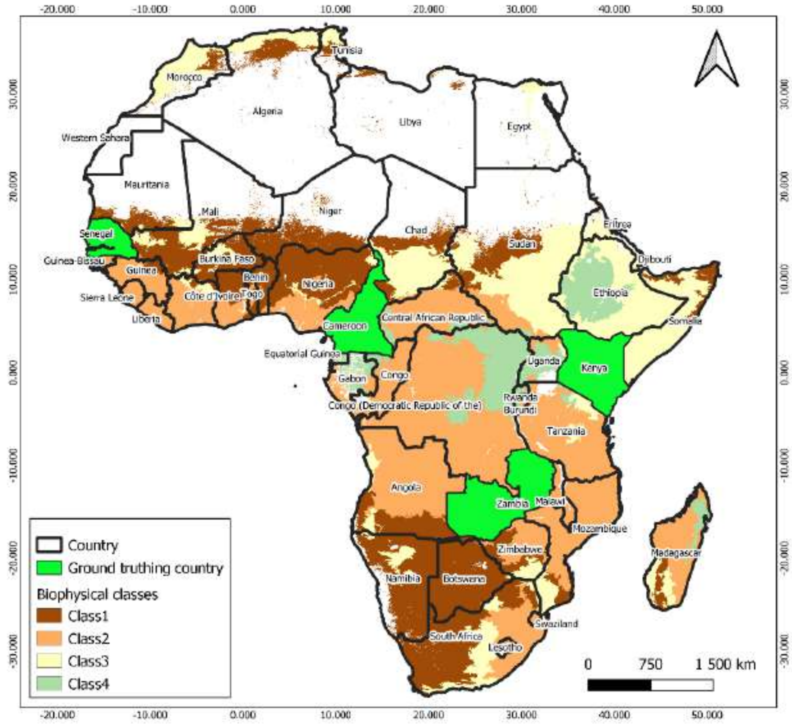
Accuracy measure	Formula
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Y_i - Y'_i)^2}{N}}$
Relative RMSE (RRMSE)	$RRMSE = \frac{RMSE}{\underline{Y}} \times 100$
Coefficient of Determination (R^2)	$R^2 = 1 - \frac{\sum_{i=1}^{N}(Y_i - Y'_i)^2}{\sum_{i=1}^{N}(Y_i - \underline{Y})^2}$

3.7 Ground reference data collection

A clustering of the African continent was done by stacking the seven environmental variables in one layer. The classification process was carried out with the k-means algorithm via the Google Earth Engine platform. According to the expected number of four countries for ground truthing, a clustering product was generated with four classes. The cluster raster was then filtered using the Sieve algorithm in QGIS with a threshold of 20,000 (i.e., pixels groups smaller than this size were merged with the surrounding class). Based on the four obtained classes, the four countries, namely Cameroon, Kenya, Senegal and Zambia, were selected for collection of ground reference data (Figure 3).

Ground truthing in this study served as a critical validation step to ensure the accuracy of agroforestry mapping across Africa. By collecting field data from four representative countries—Cameroon, Kenya, Senegal, and Zambia— we were able to verify the classification of agroforestry systems derived from remote sensing data. This process involved comparing ground observations with mapped agroforestry classes, such as agrisilviculture, silvipasture, and agrisilvipasture, to refine the model and improve its predictive accuracy. Ground truthing thus helped to mitigate potential biases in remote sensing analysis and enhanced the reliability of the spatial mapping outputs for agroforestry systems across the continent.

Figure 3: Location of countries for reference data collection



3.8 Land use-land cover data collection and processing

The LULC data were collected in each of the four selected countries where a sampling strategy based on an agro-ecological or bioclimatic zoning was used to select sites to visit (with a minimum distance of about 10 km). In each site, the different agroforestry cover types were inventoried using a digital form and/or identification sheet, depending on the country, and a Global Positioning System (GPS) device. Visited classes were fully or partially walked to create a representative polygon or to take (with GPS) several landmarks which helped to digitize a representative polygon. As a result, each visited point was categorized into the three main agroforestry classes as defined by Nair (1985, 1993a): agrisilviculture, silvipasture and agrisilvipasture. High-definition digital photos with embedded geographic coordinates were also taken to illustrate and characterize the landscapes visited.

3.9 Evaluation of the Agroforestry mapping accuracy

The accuracy of agroforestry maps was assessed using the ground reference data and based on the overall accuracy and kappa coefficient which were computed from a confusion matrix including the three agroforestry classes.

3.10 Change analysis, future projections and tree cover variation scenarios in agroforestry areas

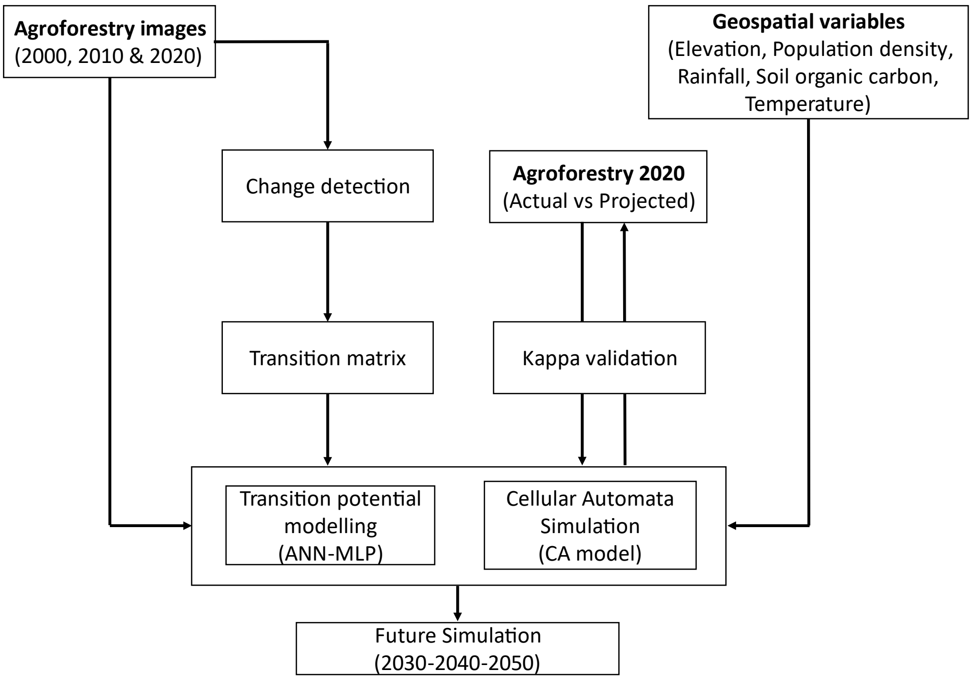
The change analysis and projection of agroforestry areas were performed using the Modules for Land Use Change Evaluation (MOLUSCE) plugin via QGIS software (Gismondi, 2013). This plugin was chosen for its effectiveness in computing post-change analysis and its suitability for modelling transition potential and future projections (El-Tantawi et al., 2019). It includes well known algorithms such as the Artificial Neural Network (ANN) and the Monte Carlo Cellular Automata (CA). The methodological workflow of the process is presented in Figure 4, and consisted of three main steps:

i) The post-change analysis including change detection into study intervals e.g. 2000 – 2010 and 2010 – 2020, which compute a post-transition probability matrix and area change of the agroforestry categories (types) between the initial and the final year

ii) The transition potential modelling was conducted using an Artificial Neural Network-Multilayer Perceptron method (ANN-MLP) with the transition probability matrix, area change and maps of elevation, population density, rainfall, soil organic carbon and temperature as predicting variables. For all study periods, the ANN-MLP process was run with 100 iterations, a neighborhood value of 3×3 pixels, a learning rate of 0.001, 12 hidden layers, and a momentum of 0.05; and

iii) The retrospective simulation of African agroforestry areas using the CA algorithm and the validation of the model using a kappa coefficient (Cohen, 1960) as well as a comparison of actual and projected agroforestry maps. This model was validated based on the simulated map of 2020 using historical layers of 2000 and 2010.

Figure 4: Overall workflow of change analysis and future projection of agroforestry system



We employed three distinct scenarios to map potential variations in agroforestry-related tree cover across Africa. Scenario 1 assumes a modest increase of 2% in tree cover by 2050, reflecting a baseline (i.e. Business as Usual) improvement related to rainfall-driven changes. This assumption was made based on Zhang et al. (2023), who observed an overall increase in woody cover across African drylands by the end of the 21st century (corresponding to 5% in average in 2100). Scenario 2 envisions a 5% increase in tree cover by 2050, representing a more ambitious yet plausible level of restoration and reforestation efforts. This scenario is aimed to express African ambitions in Nationally Determined Contributions (NDC) where more than half the countries on the continent (28 out of 54) have pledged to ecologically restore a total of 1,130,000 km^2 of land, and much of this restoration will rely on tree planting. Finally, Scenario 3 projects a substantial 10% increase, indicating a transformative scale of restoration activities. These scenarios reflect varying levels of commitment and ecological outcomes, highlighting the potential for tree cover expansion under different restoration intensities and policy implementations. Current agroforestry tree cover in Africa is estimated at 3,123,801 km^2, with significant opportunities for scaling restoration initiatives.

3.11 Economic valuation of Agroforestry systems

The TEV framework was employed to assess the value of agroforestry ecosystem services. This approach provides a comprehensive valuation by integrating both use and non-use benefits derived from these systems.

Key data sources included:

- Remote sensing and agroforestry mapping (presented above)
- Economic values of ecosystem services: Ecosystems services valuation database (ESVD), Mirzabaev et al. (2025) and primary data collection
- Costs of agroforestry establishment and maintenance: ECON-WOCAT (Mirzabaev et al. 2021) and ZEF-ELD datasets (Nkonya et al., 2016), supported by primary data collection

Values of ecosystem benefits from agroforestry systems

Based on the Ecosystems services valuation database (ESVD), Mirzabaev et al., 2025, and primary data collection, we have identified values of agroforestry ecosystem services in pastoral, cropped, and mixed systems (Annex 4), as well as of other ecosystems such as forests, grasslands, wetlands, and croplands, which were taken as the basis for economic analysis.

Costs of establishing agroforestry systems

An economic assessment of costs and benefits of agroforestry can help promote climate smart agroforestry solutions, expand the knowledge about them, and facilitate decision-making and policy action. Weighing the costs and benefits against each other enables a promotion of the most worthwhile policy choices contributing to social welfare and safeguarding the environment. We have compiled a dataset to capture the economic value of ecosystem services generated by agroforestry systems in Africa. This dataset represents the first extensive compilation of costs and benefits of agroforestry systems in Africa and contributes to closing the information gap of economic profitability of this practice.

The dataset is based on a systematic literature review (SLR) as well as focus group discussions (FGDs) conducted in selected countries across Africa. This work builds on previous ZEF research on the economics of ecosystem restoration in the Sahel by Mirzabaev et al. (2021). The SLR followed a defined review protocol with predetermined selection criteria. The review was carried out using the Scopus database. To include grey literature, a second review was conducted with Google.

The publication period for both Scopus and Google search was set to 2000-2022. The keywords for the SLR are displayed in Table 5 and contained the constant “agroforestry”, as well as terms referring to monetary values and country contexts. Additional economic data from the WOCAT SLM database (https://qcat.wocat.net/en/wocat/) was included to expand the findings. Only publications in English were considered. A total number of 750 papers was compiled. After a content review, 65 papers containing monetary values on agroforestry were retained. In addition, 33 sources on costs of agroforestry in Africa originated from the ECON-WOCAT dataset (https://qcat.wocat.net/en/wocat/), while nine sources were collected from the grey literature review. The FGDs were conducted by the Centre de Suivi Écologique (CSE) and International Centre of Insect Physiology and Ecology (ICIPE) in Senegal and Kenya in 2022, added further 102 supplementary value sources. In total, the 209 sources delivered 490 data points providing monetary information on costs and benefits of agroforestry systems in various locations in Africa (Table 6).

Table 5: List of keywords used for SLR

Agroforestry, AND economic AND costs, AND benefits, AND Africa
agroforestry, AND economic AND costs, AND benefits, AND [African country name]
agroforestry, AND income, AND Africa
agroforestry, AND income, AND [African country name]
agroforestry, AND economic, AND Africa
agroforestry, AND economic, AND [African country name]
agroforestry, AND costs, AND Africa
agroforestry, AND costs, AND [African country name]

Table 6: Compiled data from SLR and FGDs

Scopus results	750	
Scopus results after content review	Yes 65	No 685
Grey Literature	9	
Additional Data entries WOCAT	33	
FGDS Senegal	68	
FGDs Kenya	34	
Total of Sources	**209**	
Amount of Data points	**490**	

Data provided in the literature was presented in different currencies and expressed at different times, hence, a harmonization of values had to be carried out. For this purpose, two approaches can be considered. First, values will be transformed into USD and following accounting for inflation will be based on USD inflation rates. Second, inflation accounting will be performed on the local currency to bring all values to the same year and subsequently values will be converted to USD. Turner et al. (2019) recommends inflating the local currencies for non-tradable goods and services. Since most of the values recorded remain in the regional market, such as e.g., crops and timber, or are non-tradable goods like labour, the second approach was chosen. For this purpose, the World Bank's inflation and GDP deflator indicator for each country was used. Local currencies value in 2020 were then converted to USD using average exchange rates for 2020. Data harmonization resulted in all values being expressed in USD 2020 (Table 7).

Table 7: Descriptive statistics of key variables

Statistical Measure	Total Costs (USD 2020)	Establishment Costs (USD 2020)	Maintenance Costs (USD 2020)	Benefits (USD 2020)
Mean	1,081	832	345	2,799
Median	372	192	31	780
Minimum	0.02	0	0	0
Maximum	24,572	21,272	6,642	44,025

Analytical approach

Firstly, we estimated the gains and losses from changes in the areas of agroforestry systems between 2000 and 2020. This was done using the values of ecosystem services from different agroforestry systems as shown in Annex 4. Secondly, we modelled the costs and benefits of expanding agroforestry systems during the period of 2020 to 2050 under 2%, 5%, and 10% agroforestry expansion scenarios. The following parameters were considered in the modelling (Table 8). Three types of agroforestry systems—agrisilviculture, silvipasture, and agrisilvipasture—were evaluated under the same discount rate of 10% and a survival rate of planted trees at 60%. Each system is analyzed over a 30-year period, from 2020 to 2050, with the growth of each practice staged in a staggered manner: during the first five years, they are at 20% of their full potential in terms of ecosystem service delivery, during the second five years they rise to 80%, and for the remaining 20 years they operate at 100% potential.

Table 8: Parameters used in the economic modelling of agroforestry expansion

Parameters	Agroforestry in croplands (Agrisilviculture)	Agroforestry in pastures (Silvipasture)	Agroforestry in croplands+pastures (Agrisilvipasture)
Discount rate	10%	10%	10%
Survival rate	60%	60%	60%
Time horizon	30 years 2020-2050	30 years 2020-2050	30 years 2020-2050
Staggered entrance into full potential	First 5 years (20% of the full potential), 2^{nd} 5 years (80% of the potential), remaining 20 years (100% of the potential)		

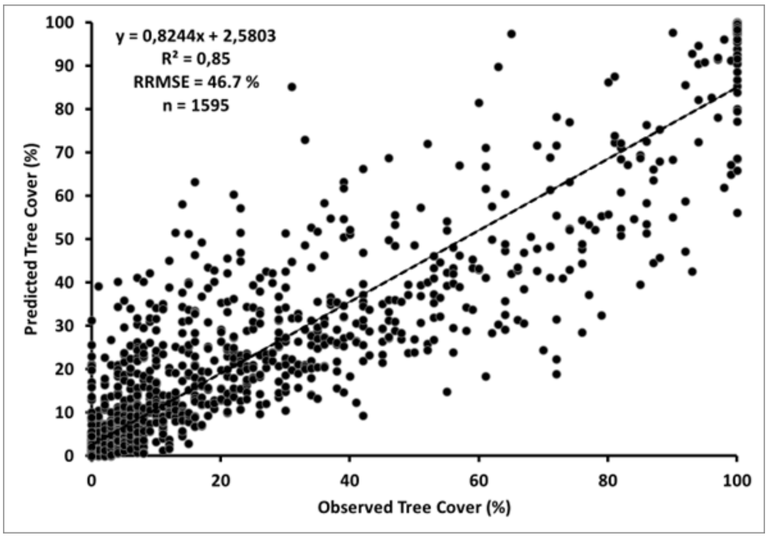
4 Results

4.1 Accuracy assessment for woody cover and agroforestry mapping

Woody cover mapping

The Random Forest model was trained using variables of the year 2020 where most of the eight predicting variables appeared to be very important for the tree cover modelling with an importance higher than 50%. The relationships between the observed and predicted tree cover showed a good prediction performance with R^2 = 0.85, RRMSE = 46.7% using 1595 testing samples which correspond to 20% of the whole dataset (Figure 5).

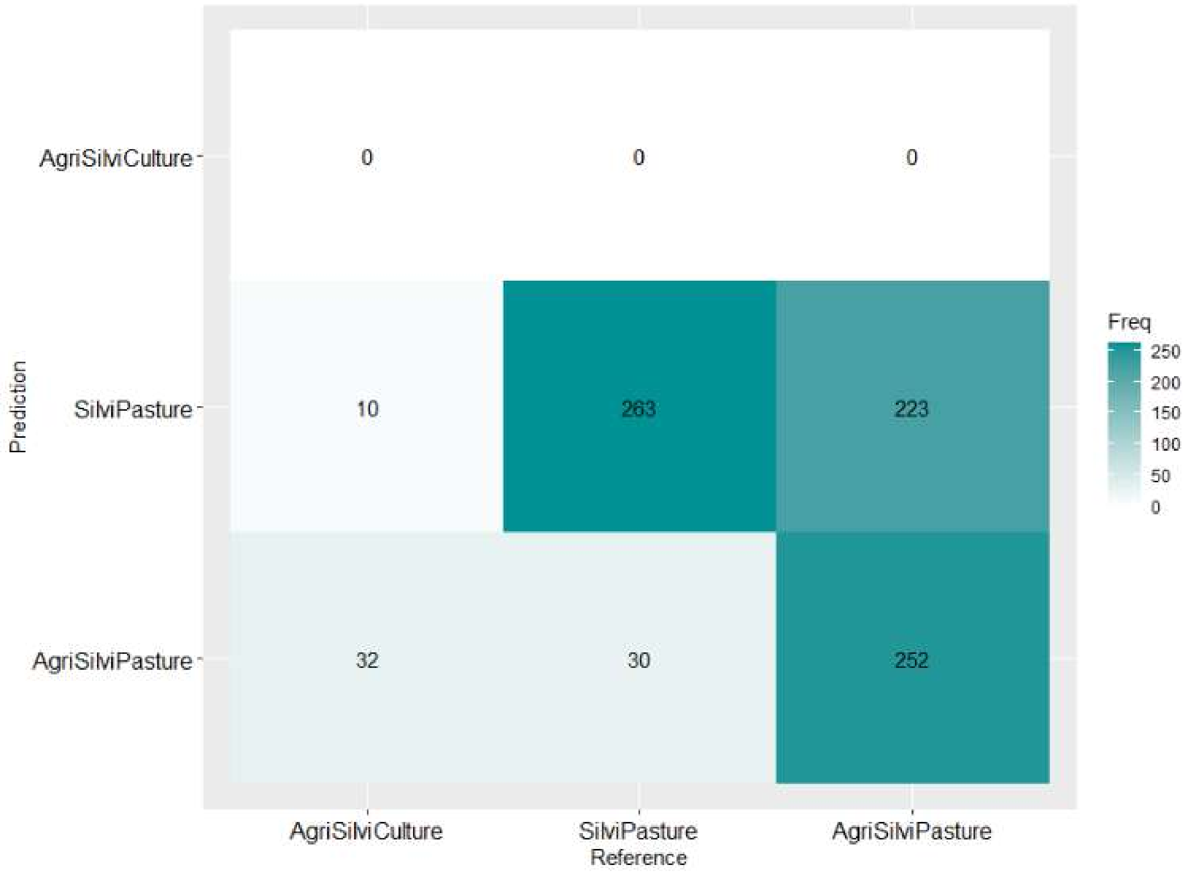
Figure 5: Relationships between observed and predicted tree cover using the Random Forest regression model



Agroforestry mapping

Agroforestry maps were validated using the ground reference data collected from Kenya and Senegal. The total reference data contained 3228 samples but due to small distance between them compared to the 1km resolution of the agroforestry map, only 810 samples were considered in this validation process (Figure 6). The overall accuracy of the mapping was about 0.64 with a kappa coefficient of 0.33. This indicates a fair agreement between the ground and predicted data as defined by Cohen (1960). However, no prediction was made for the agrisilviculture class at the scale of the validation dataset. This can be explained to the weak spatial distribution of this class and the small number of reference samples due its difficulty to be defined on the field. Some confusion was made between silvipasture and agrisilvipasture classes during the mapping. This could be related to the crop layer by (ESA, 2017) which did not capture small size and isolated croplands across the continent.

Figure 6: Confusion matrix between reference and predicted agroforestry classes



4.2 Variation of past and current African agroforestry systems

The three main agroforestry classes (silvipasture, agrisilvipasture and agrisilviculture) were mapped across the whole African continent for the years 2000, 2010 and 2020 (Figure 7). The results show a spatial predominance of silviculture, followed by agrisilvipasture and lastly, agrisilviculture across all years (Table 9). Notably, silvipasture coverage consistently decreased over the three periods, from 40.62% in 2000 to 38.98% in 2010, and 37.78% in 2020. In contrast, agrisilviculture and agrisilvipasture areas showed slight variation, maintaining around 0.04% and 9.70% coverage, respectively. These trends were further underscored by the annual rate of change (Table 9), which showed a decrease across agrisilviculture (-0.52%), silvipasture (-0.35%), and agrisilvipasture (-0.15%).

Figure 7: Map of the three main agroforestry classes in Africa in (a) 2000, (b) 2010 and (c) 2020

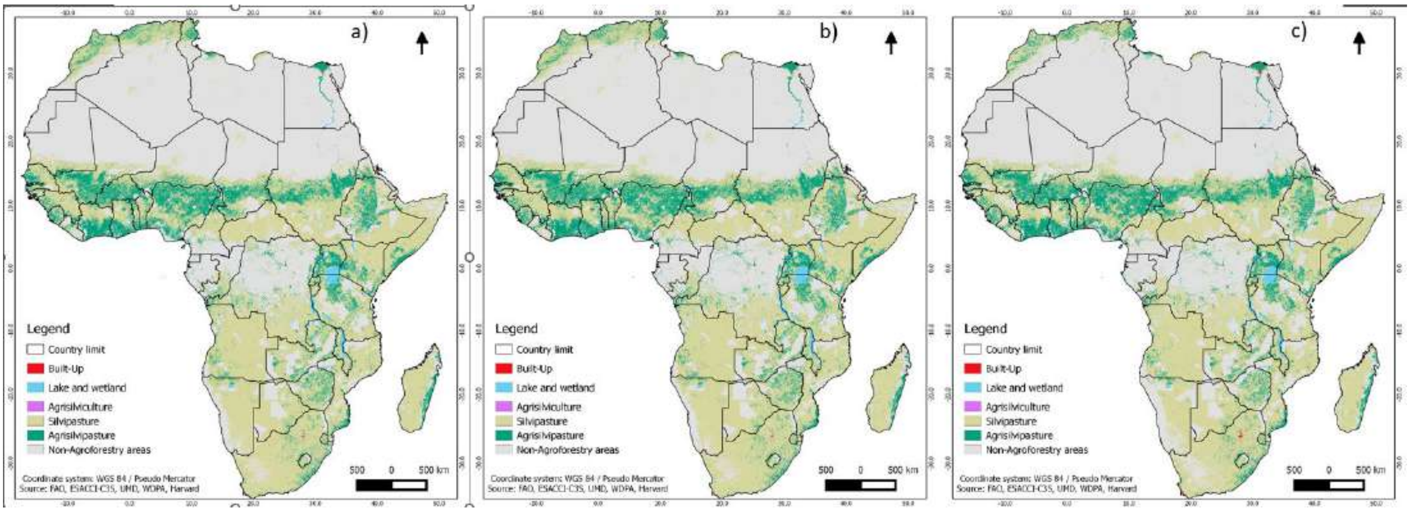


Table 9: Agroforestry area statistics and annual rate of change between 2000 and 2020

Agroforestry Class	**2000**		**2010**		**2020**		**Annual Rate of Change**	
	sq. km	**%**	**sq. km**	**%**	**sq. km**	**%**	**sq. km**	**%**
Non-Agroforestry	16,581,306	49.47	17,186,075	51.28	17,637,731	52.62	52,821.25	0.32
Agrisilviculture	12,832	0.04	12,069	0.04	11,488	0.03	-67.2	-0.52
Silvipasture	13,613,790	40.62	13,066,419	38.98	12,661,263	37.78	-47,626.35	-0.35
Agrisilvipasture	3,309,331	9.87	3,252,696	9.70	3,206,777	9.57	-5127.7	-0.15

4.3 Change variation into agroforestry systems

The evolution of agroforestry areas between 2000-2020 is presented in the change map in Figure 8 (see Annex 3 for changes between 2020-2030 and 2030-2040). Our results reveal limited changes in agroforestry (see non-agroforestry layer), indicating a small change in land use during the last two decades. Among the changes observed, the loss of agroforestry areas outweighed its gains, as highlighted in Figure 8 and Table 10. Notable losses were concentrated in the Sahara, Horn of Africa, and southwestern Namibia and South Africa. In contrast, gains in agroforestry, particularly agrisilviculture, were observed along the southern boundary of the Sahara Desert.

Silvipasture emerged as the most dynamic land-use category, experiencing the highest turnover in both losses and gains. Overall, these maps indicate a decrease in agroforestry areas by 2020 compared to 2000, with pronounced declines near the Sahara and the northern Sahelian belt.

Figure 8: Change map of agroforestry between 2000 – 2020

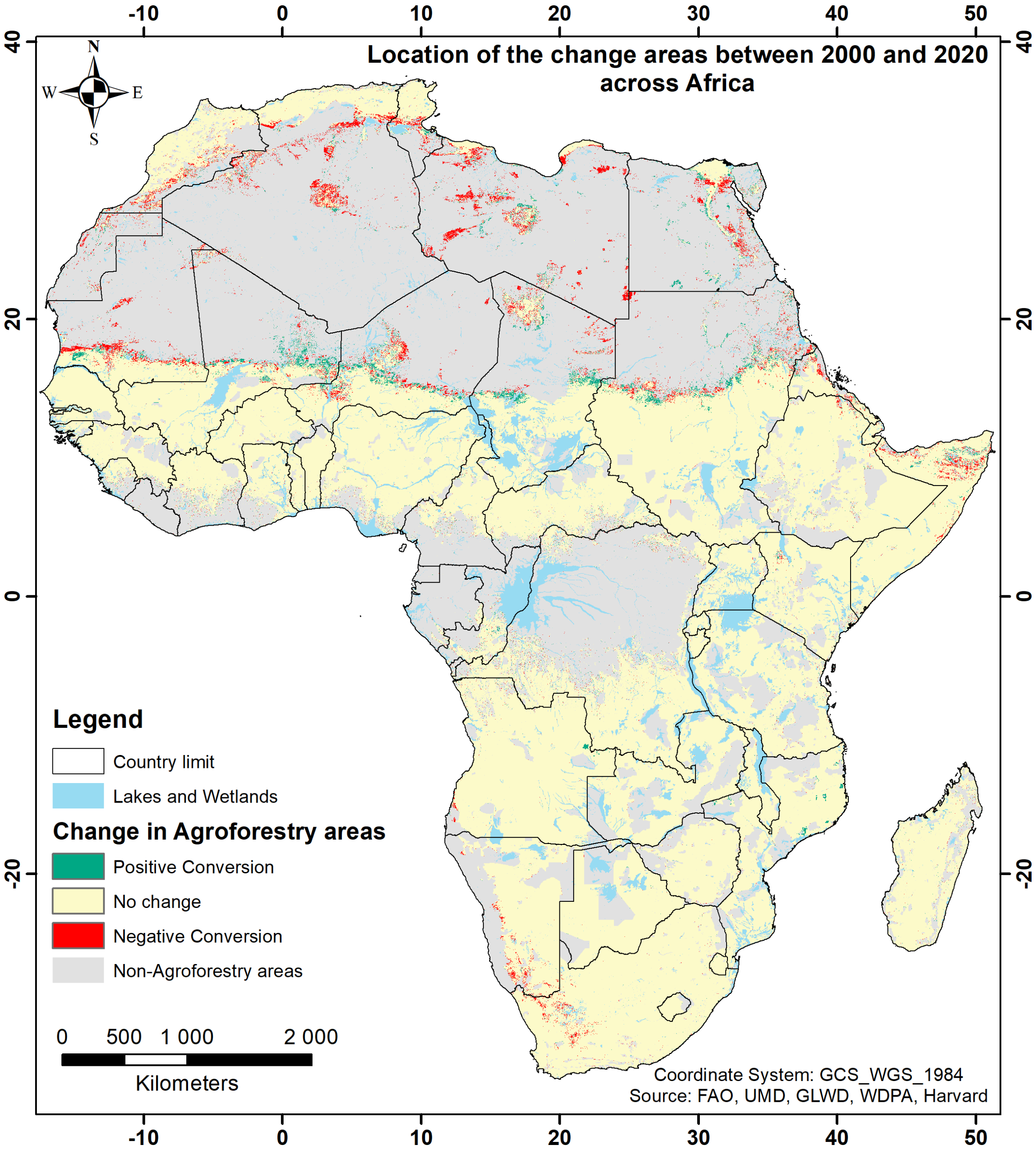


Table 10: Matrix of land use changes among agroforestry classes

Agroforestry Class	Non-Agroforestry	Agrisilviculture	Silvipasture	Agrisilvipasture
Non-Agroforestry	0.00	0.06	14.54	1.32
Agrisilviculture	0.10	0.00	0.01	0.01
Silvipasture	53.95	0.00	0.00	12.21
Agrisilvipasture	6.09	0.00	11.73	0.00

4.4 Performance of the Cellular Automata projection model

The performance of the Cellular Automata projection model was assessed by comparing the predicted and the reference map of 2020. Table 11 presents validation statistics and the predicted and observed agroforestry maps of the year 2020. The predicted map of 2020 was obtained using the CA model based on maps of 2000 and 2010 along with the predicting spatial variables and applying the ANN-MLP for the transition potential model (validation kappa of 0.91).

The final dataset contained a total of 33,517,259 pixels where 32,918,935 pixels were correctly classified, giving an overall accuracy of 94.88%, and an overall kappa of 0.91. The non-agroforestry class showed the highest misclassification with -0.89% followed by the Silvipasture class with 0.74% and the Agrisilviculture class with 0.14%. Negligible errors were observed for the Agrisilviculture class with 0.002%. of pixel being misclassified.

Table 11: Statistics of reference and projected agroforestry classification pixels for 2020

Agroforestry Class	Reference		Projected		% of Correctness	Kappa Value	
	sq. km	%	sq. km	%		ANN-MLP	CA-Validation
Non-Agroforestry	17,637,731	52.62	17,338,569	51.73	94.88	0.91	0.91
Agrisilviculture	11,488	0.03	12,053	0.04			
Silvipasture	12,661,263	37.78	12,913,984	38.53			
Agrisilvipasture	3,206,777	9.57	3,252,653	9.70			

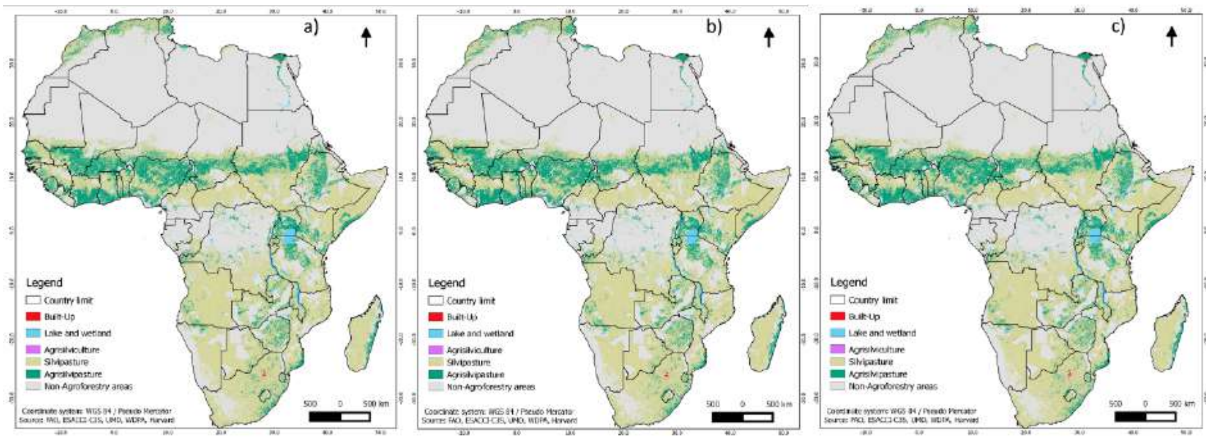
4.5 Agroforestry projection

Agroforestry areas of the year 2030, 2040 and 2050 were projected using CA models based on maps of corresponding periods along with predicting spatial variables and applying the ANN-MLP for the transition probability modelling. Two date maps from 2010-2020, 2020-2030 and 2030-2040 were used to project the agroforestry areas for the years 2030, 2040 and 2050, respectively. The area statistics with kappa validation of the transition model are presented in Table 12 while the projection maps of the year 2030, 2040 and 2050 are presented in Figure 9 and changes in Figure 10. Silvipasture areas exhibited a continuous decline across the three forecast years, decreasing from 36.32% to 35.61% and subsequently to 35.10%. Correspondingly, non-agroforestry areas expanded, accounting for 54.08%, 54.79%, and 55.29% across the same timeframes. Meanwhile, agrisilviculture and agrisilvipasture areas remained relatively stable, constituting approximately 0.03% and 9.57%, respectively, throughout the projection period.

Table 12: Statistics of projected agroforestry areas for 2030, 2040 and 2050

Agroforestry Class	**2030**			**2040**			**2050**		
	sq. km	**%**	**kappa**	**sq. km**	**%**	**kappa**	**sq. km**	**%**	**kappa**
Non-Agroforestry	18127185	54.08	0.84	18363480	54.79	0.90	18533125	55.29	0.99
Agrisilvi-culture	11429	0.03		11429	0.03		11426	0.03	
Silvipasture	12171875	36.32		11935585	35.61		11765944	35.10	
Agrisilvi-pasture	3206770	9.57		3206765	9.57		3206764	9.57	
Total	33517259	100.00		33517259	100.00		33517259	100.00	

Figure 9: Projected Agroforestry areas in Africa for the year a) 2030, b) 2040 and c) 2050.

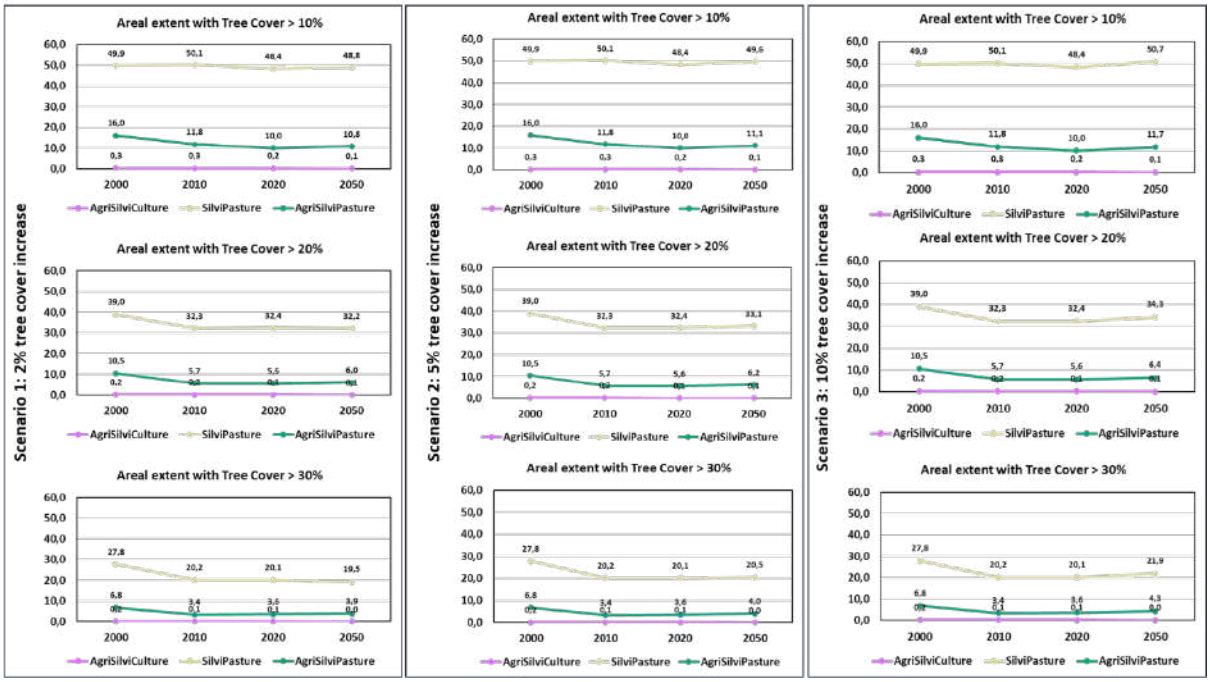


An overall decrease was observed between 2000 and 2020 for all tree cover categories in agroforestry areas. This decrease was particularly higher between 2000 and 2010 for the categories >20% and >30% with the silvipasture and agrisilvipasture classes. For the same period 2000-2010, a slight increase was noted for tree cover above 10% with the silvipasture class.

For the three scenarios, a slight decrease was observed by 2050 for the agrisilviculture class considering the tree cover categories >10% and >30%. No variation was noted for >20% category for the same agroforestry class. This indicates that, despite the restoration effort that could be made under scenario 3, the agrisilviculture class will no longer develop. The same behaviour was observed for the silvipasture class under the baseline Scenario 1 with the categories >20% and >30% (Figure 10).

In general, ambitious restoration effort adopted under Scenario 2 or Scenario 3 could allow significant improvement of tree cover in agrisilvipasture and silvipasture areas by 2050.

Figure 10: Tree cover increasing scenarios in African agroforestry areas by 2050



4.6 Investment costs and returns from restoration scenarios

Figure 11 and Figure 12 show the financial impacts of agroforestry expansion and loss across subregions in Africa. North Africa achieved the biggest positive gains in terms of the expansion of agroforestry in pastoral systems (about 2.8 billion USD) and also recorded the highest level of net losses which equaled -12 billion USD. West Africa was the only sub-region with a net gain. Overall, at the continental level, net economic losses due to decline in the extent of agroforestry systems between 2000 and 2020 made up an equivalent of 14 billion USD.

Figure 11: Agroforestry expansion and loss by subregions in Africa during 2000-2020

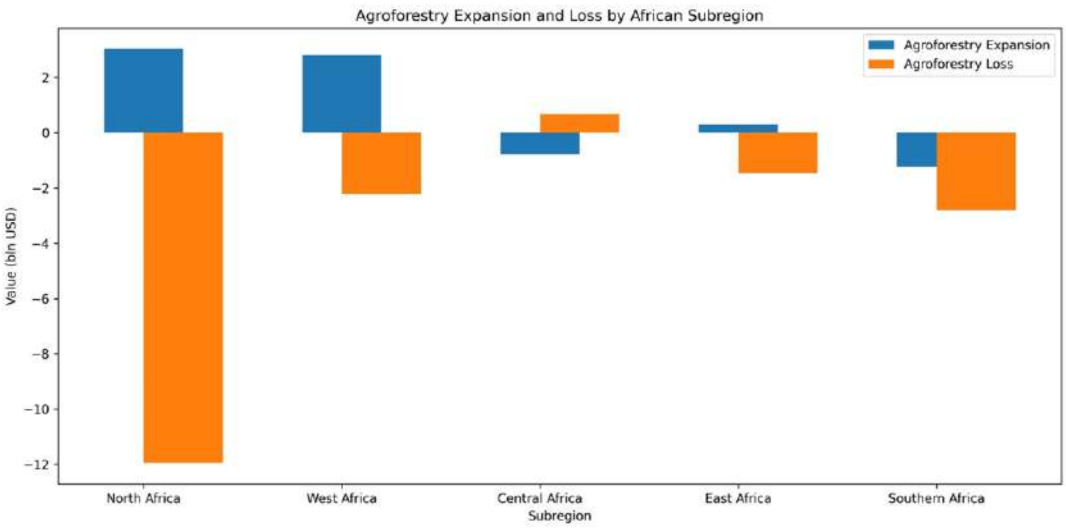
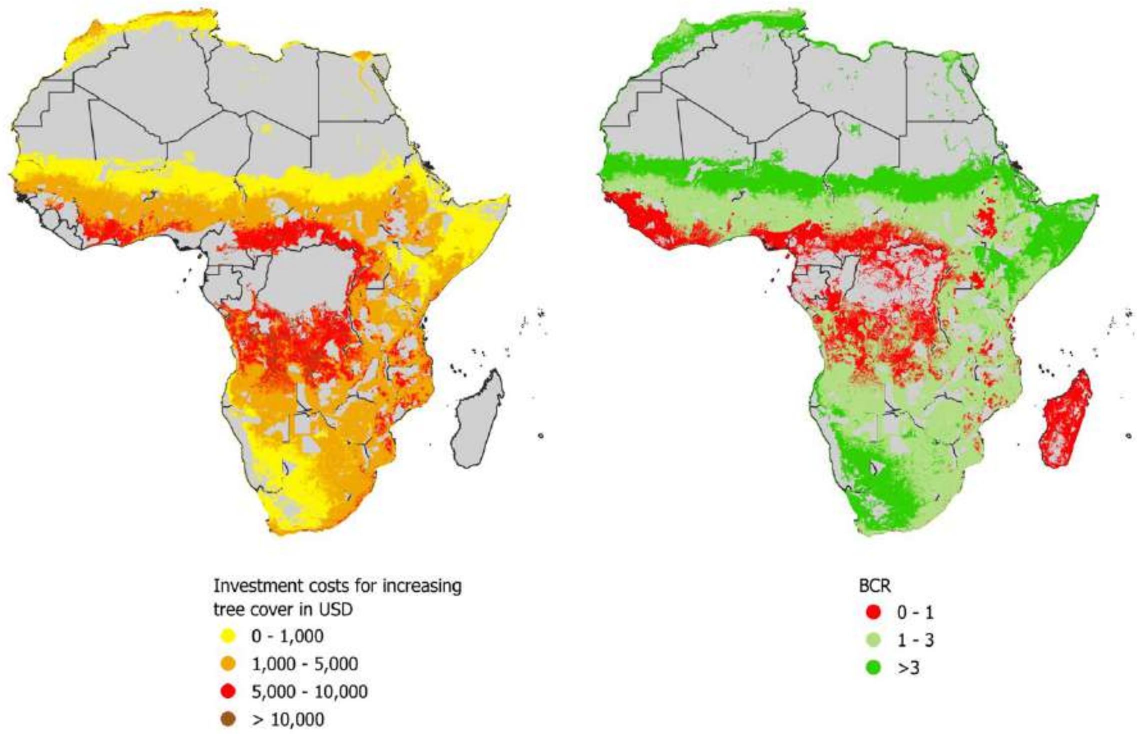


Figure 12: Investment costs and returns from annual 2% agroforestry increase



Economic viability varies substantially depending on the scale of expansion. For a modest annual increase of 2%, the total investment cost of 38.8 billion USD generates a return of 55.7 billion USD, with high-return regions concentrated in Northern and Eastern Africa. However, in parts of Central Africa, which exhibit lower BCRs, agroforestry expansion faces challenges in terms of economic viability (Figure 12). Further scenarios of 5% and 10% expansion of agroforestry systems across the continent reinforce these trends (Figures 13 and 14). Under these scenarios, expansion of agroforestry systems still provides positive economic returns in most areas across northern Africa, the northern part of the Sahel region, horn of Africa, and southern Africa, while investments into expansion of agroforestry systems do not yield positive returns in southern Sahel, central Africa, and parts of Eastern Africa. These findings show that careful targeting and prioritization of efforts is needed towards those areas which exhibit higher returns from agroforestry expansion.

Figure 13: Investment costs and economic viability of agroforestry expansion across Africa (5% scenario)

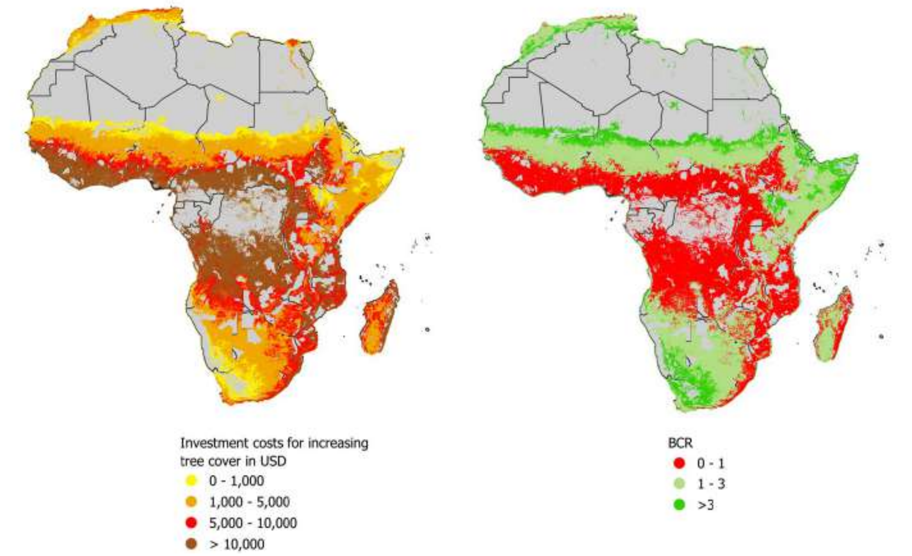
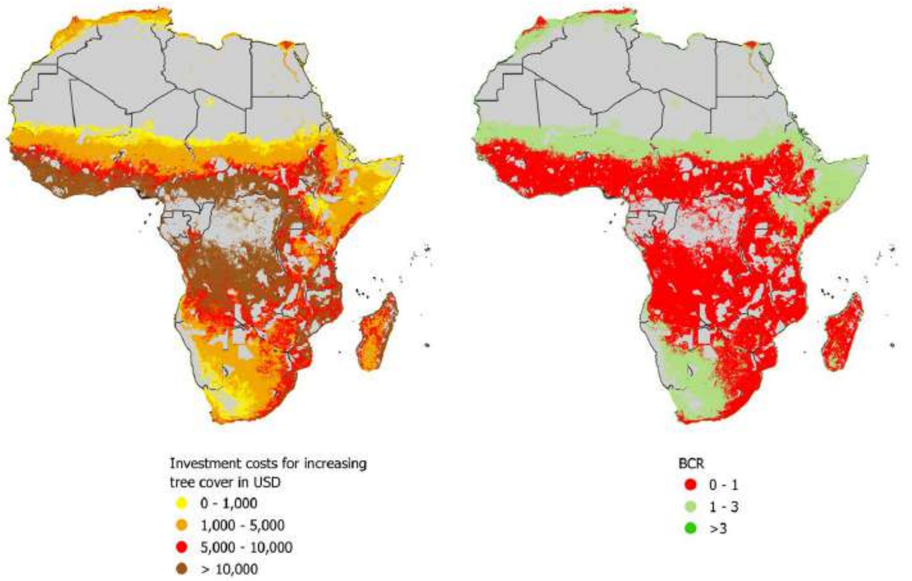


Figure 14: Investment costs and economic viability of agroforestry expansion across Africa (10% scenario)



5 Discussion

5.1 Suited approach for mapping agroforestry across Africa

The overlaying of different raster layers of trees, livestock and crops extent enabled us to map the main agroforestry systems across the African continent as defined by Nair (1993a). A random forest model was trained and applied on reflectance bands from Hansen (2013) to obtain tree cover maps of the year 2000, 2010 and 2020. Most predictor variables significantly contributed to tree cover mapping accuracy, except for NIR and the MBI, each under 50% importance. The NDII proved the most critical variable, likely due to its effectiveness in tracking vegetation moisture—a key factor for Africa's largely grazed landscapes (Wilson and Norman, 2018). While the model's performance was fair (R^2 = 0.85; RRMSE = 46.7%), it successfully illustrated spatio-temporal changes in tree cover, aligning with earlier work (Hansen, 2013).

The spatiotemporal change analysis of the African agroforestry areas showed decreases between 2000 and 2020 at annual rate of change of -0.52% (agrisilviculture), -0.35% (silvipasture) and -0.15% (agrisilvipasture). Simulations toward the year 2030, 2040 and 2050 with the MOLUSCE plugin into the QGIS software predicted continued declines in agroforestry areas under the business-as-usual trends. This decrease in agroforestry areas is mainly related to the reduction of tree cover in agricultural lands as observed by Zomer et al. (2016) who found that the largest decreases in per hectare biomass carbon were found in countries in West and Central Africa from 2000 to 2010.

The decline in agroforestry is shown in studies for other world regions. India experienced a severe decline in large agroforestry trees, with approximately 11% of large trees disappearing by 2018, attributed to changing cultivation practices that view trees as detrimental to crop yields (Brandt et al., 2024). In Europe, agroforestry areas decreased by 47% from 2009 to 2018, primarily due to reduced outdoor grazing and livestock numbers (Rubio-Delgado et al., 2023). Declining resin productivity and rising timber prices are prompting farmers to cut mature agroforests in Sumatra, Indonesia, although tree planting activities continue. This suggests a shift in land use driven by economic factors (Kusters et al., 2008).

As agroforestry systems are increasingly recognized for their contributions to food security, biodiversity conservation, and climate change mitigation, the contraction of these systems may signal missed opportunities for sustainable development. Further, the comparison with global trends shows that Africa's challenges mirror those observed elsewhere, driven by shifts in agricultural practices and grazing intensity.

Future projections to 2050 suggest a continuation of these trends unless targeted interventions are implemented. The projected increase in non-agroforestry areas, combined with the stabilization of agrisilviculture and agrisilvipasture, underscores the need for policies that actively promote agroforestry expansion, particularly in regions where economic and ecological benefits are substantial.

5.2 Economic valuation of agroforestry

The findings underscore the significant variability in economic outcomes associated with agroforestry expansion across Africa, emphasizing the need for regionally tailored strategies to optimize investment returns.

Agroforestry landscapes in Africa are very heterogenous. Agroforestry expansion is very profitable in many parts of Africa but not in each and every context. Current levels of agroforestry adoption in Africa can be significantly expanded, especially in cropping systems. Nevertheless, there are some economic, institutional and policy barriers that are currently hindering more rapid and wider adoption of agroforestry practices.

Compared to other forms of technological innovations, such as new crop varieties or adoption of chemical fertilizers, agroforestry innovations are more complex, requiring the management of at least two species (crops and trees) and their interactions (Baumüller et al., 2020; Nair, 1993). This calls for supporting agroforestry expansion through targeted training and extension. National extension agencies need to be helped by non-governmental organizations in extending agroforestry-related training programs to farmers and pastoralists. More investments are needed to be directed to research and development for finetuning the existing agroforestry solutions to specific conditions of various settings across Africa (Bartlett, 2021). More attention needs to be given to socio-economic monitoring and assessments of agroforestry adoption and its ensuing impacts on rural livelihoods and sustainable development dimensions.

A major challenge for farmers wishing to adopt agroforestry practices is that it requires longer planning horizons (Mbow et al., 2020). When fully matured, agroforestry systems will allow farmers to save on fertilizer costs by increasing soil nitrogen and soil organic matter through improved carbon sequestration (Bayala et al., 2018). The profits from adopting agroforestry will reach their full amounts only after trees have matured – which takes considerable time. In some cases, it will take up to 10 years to reach break-even relative to initial investments (Mirzabaev et al., 2021). De Guisti et al. (2019) show that agroforestry was not considered as more profitable than cropping systems without trees in Kenya, however, farmers still invested in agroforestry as a source of fuelwood and a way of saving to deal with future risks. Fuelwood sourcing was also a major factor for agroforestry adoption in Malawi (Toth et al., 2019). This situation calls for public and development partner investments because the public goods values of ecosystem services provided by agroforestry practices will not attract private investments at sufficient scale unless there are further incentives established, such as through carbon farming and trading systems (Mirzabaev et al., 2021).

To promote agroforestry effectively, land use regulations should be fine-tuned with an agroforestry-oriented perspective. This does not necessarily require the creation of new government agencies dedicated solely to agroforestry. Instead, it calls for improved coordination mechanisms among existing government institutions, particularly those in the agricultural and forestry sectors, to facilitate and streamline agroforestry development (Bartlett, 2021; Baumüller et al., 2020).

A lack of secure land tenure is a significant barrier to the expansion of agroforestry practices (Olsson et al., 2019). This challenge is exacerbated in regions where government regulations prohibit the cutting of trees, even on privately owned agroforestry plantations, creating disincentives for landowners to invest in such systems (Baumüller et al., 2020). Conversely, investments in agroforestry can enhance land tenure security, particularly for female land users (Benjamin et al., 2021). For example, in Malawi, female land users in male-headed households were found to be more likely to invest in agroforestry practices, such as planting trees, compared to their counterparts in female-headed households. This behavior reflects a strategy to assert and secure their access rights to land in relation to their husbands' rights (Benjamin et al., 2021).

The expansion of agroforestry in Africa can be accompanied by developing modern value webs for agroforestry products as part of African strategies for bioeconomy development (Callo-Concha et al., 2020; Dietz et al., 2018; Oguntuase and Adu, 2021). Increasing use of agroforestry biomass for bioeconomy development should be accompanied by accelerated innovations increasing the productivity of agroforestry systems in order to avoid negative impacts on food security and sustainable natural resource use (von Braun, 2018).

5.3 Limitations

1. While high-resolution datasets were used, the uniform 1 km resolution may not fully capture fine-scale variations in agroforestry systems, especially in heterogeneous landscapes. This could affect the precision of mapping smaller-scale agroforestry practices.
2. Ground reference data were collected from only four countries (Cameroon, Kenya, Senegal, and Zambia), which may not fully represent the diversity of agroforestry systems across the entire African continent.
3. Data layers for different variables (e.g., tree cover, livestock density, and cropland) are derived from different time periods and sources. This could lead to mismatches and inaccuracies in temporal analyses.
4. The economic valuation relies on benefit transfer approaches using available datasets, with currently unavoidable uncertainty in terms of capturing costs and benefits for those locations for which no data is available for model calibration.
5. The CA projection model assumes uniform transition probabilities across regions, potentially oversimplifying complex socio-economic and environmental drivers of agroforestry dynamics.

6 Conclusion

Agroforestry systems represent a large share of land use in Africa. They play a crucial role in sustainable development, offering a wide array of direct and indirect benefits, from food security and biodiversity preservation to enhanced climate resilience. While we identify potentials of agroforestry growth, our findings reveal a decline in agroforestry areas over recent decades, leading to net losses that were equivalent to 14 billion US dollars over the period of 2000 to 2020. Projections indicate that this trend may continue, with agroforestry areas expected to decline further, unless policy action is taken for safeguarding and restoring agroforestry systems.

The economic benefits of agroforestry underscore its value as a high-return investment for Africa. Regions with robust agroforestry systems demonstrate increased agricultural productivity, diversified income sources, and improved resilience against climate variability. These economic returns, however, are spatially variable. For agroforestry to meet its full potential, strategic investments and supportive policies must be prioritized, focusing on enhancing adoption in profitable areas and overcoming institutional and economic barriers.

In many rural African settings, institutional factors such as land tenure insecurity, lack of agroforestry research and extension support, and lack of access to long-term funding serve as major barriers for agroforestry expansion. To provide an enabling environment for the development of agroforestry systems in Africa, national policy needs to revise land use regulations (including for communal lands) as well as the institutional frameworks through an agroforestry lens. Development partners can play a critical role in promoting agroforestry in Africa by capacity building and strengthening, expanding access to finance, as well as supporting research for developing and refining agroforestry options.

Ultimately, these results highlight the critical need for agroforestry to be integral to Africa's environmental and economic strategies. Through a tailored approach to policy and investment, agroforestry can drive substantial economic, social, and ecological gains, supporting Africa's sustainable development trajectory in the face of climate challenges.

References

Anchang, J. Y., Prihodko, L., Ji, W., Kumar, S. S., Ross, C. W., Yu, Q., Lind, B., Sarr, M. A., Diouf, A. A., & Hanan, N. P. (2020). Toward Operational Mapping of Woody Canopy Cover in Tropical Savannas Using Google Earth Engine. Frontiers in Environmental Science, 8, 1–17. https://doi.org/10.3389/fenvs.2020.00004

Angelsen, A., Jagger, P., Babigumira, R., Belcher, B., Hogarth, N. J., Bauch, S., Börner, J., Smith-Hall, C., & Wunder, S. (2014). Environmental Income and Rural Livelihoods: A Global-Comparative Analysis. World Development, 64, S12–S28. https://doi.org/10.1016/j.worlddev.2014.03.006

Bado, B. V., Whitbread, A., & Sanoussi Manzo, M. L. (2021). Improving agricultural productivity using agroforestry systems: Performance of millet, cowpea, and ziziphus-based cropping systems in West Africa Sahel. Agriculture, Ecosystems & Environment, 305, 107175. https://doi.org/10.1016/j.agee.2020.107175

Barbier, E. B., & Hochard, J. P. (2018). The impacts of climate change on the poor in disadvantaged regions. Review of Environmental Economics and Policy, 12(1), 26–47. https://doi.org/10.1093/reep/rex023

Bartlett, A. G. (2021). Exploring transformational outcomes from donor investments in agroforestry research for development. Agroforestry Systems, 95(8), 1251–1264. https://doi.org/10.1007/s10457-020-00516-3

Bayala, J., Kalinganire, A., Sileshi, G., & Tondoh, J. E. (2018). Soil Organic Carbon and Nitrogen in Agroforestry Systems in Sub-Saharan Africa: A Review | SpringerLink. https://link.springer.com/chapter/10.1007/978-3-319-58789-9_4

Baumüller, H., von Braun, J., Admassie, A., Badiane, O., Baraké, E., Börner, J., Bozic, I., Chichaibelu, B.B., Daum, T., Gatiso, T. (2020). From Potentials to Reality: Transforming Africa's Food Production. ZEF Policy Brief No. 35. Center for Development Research (ZEF), University of Bonn. https://doi.org/10.22032/dbt.48033

Benjamin, E. O., Ola, O., Sauer, J., & Buchenrieder, G. (2021). Interaction between agroforestry and women's land tenure security in sub-Saharan Africa: A matrilocal perspective. Forest Policy and Economics, 133, 102617. https://doi.org/10.1016/j.forpol.2021.102617

Beyene, A. D., Mekonnen, A., Randall, B., & Deribe, R. (2019). Household Level Determinants of Agroforestry Practices Adoption in Rural Ethiopia. Forests, Trees and Livelihoods, 28(3), 194–213. https://doi.org/10.1080/14728028.2019.1620137

Bishaw, B. (2013). Farmers' strategies for Adapting to Mitigating Climate Variability and Change through Agroforestry in Ethiopia and Kenya.

Brandt, M., Chave, J., Li, S., et al. (2025). High-resolution sensors and deep learning models for tree resource monitoring. Nature Reviews Electrical Engineering, 2(1), 13–26. https://doi.org/10.1038/s44287-024-00116-8

Breiman, L. (2001). Random Forests. Machine Learning, 45, 5–32. https://doi.org/10.1007/978-3-030-62008-0_35

Buchhorn, M., Lesiv, M., Tsendbazar, N.-E., Herold, M., Bertels, L., & Smets, B. (2020). Copernicus Global Land Cover Layers—Collection 2. Remote Sensing, 12(6), 1044. https://doi.org/10.3390/rs12061044

Buchhorn, M., Smets, B., Bertels, L., Roo, B. D., Lesiv, M., Tsendbazar, N.-E., Herold, M., & Fritz, S. (2020b). Copernicus Global Land Service: Land Cover 100m: Collection 3: Epoch 2019: Globe. https://doi.org/10.5281/ZENODO.3939050

Callo-Concha, D., Gaiser, T., & Ewert, F. (2020). Co-benefits and trade-offs of agroforestry for climate change mitigation and other sustainability goals in West Africa. Agriculture, Ecosystems & Environment, 295, 106923.

C3S & CDS. (2019). Land cover classification gridded maps from 1992 to present derived from satellite observation. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). https://doi.org/10.24381/cds.006f2c9a

Chakeredza, S., Hove, L., Akinnifesi, F. K., Franzel, S., Ajayi, O. C., & Sileshi, G. (2007). Managing fodder trees as a solution to human–livestock food conflicts and their contribution to income generation for smallholder farmers in southern Africa. Natural Resources Forum, 31(4), 286–296. https://doi.org/10.1111/j.1477-8947.2007.00160.

Center for International Earth Science Information Network (CIESIN). (2018). Gridded Population of the World, Version 4 (GPWv4): Population Count, Revision 11 [Data set]. NASA Socioeconomic Data and Applications Center (SEDAC). https://doi.org/10.7927/H4JW8BX5

Cohen, J. (1960). A coefficient of agreement for nominal scales. Educational and Psychological Measurement, 20(1), 37–46. https://doi.org/10.1177/001316446002000

Copernicus. (2021). Product User Guide and Specification. ICDR Land Cover 2016-2020 (pp. 37–37).

Copernicus Global Land Service (CGLS). (2019). Forest Cover Fraction (FCover) 100m Version 3 Collection 1 [Data set].

De Giusti, G., Kristjanson, P., & Rufino, M. C. (2019). Agroforestry as a climate change mitigation practice in smallholder farming: Evidence from Kenya. Climatic Change, 153(3), 379–394. https://doi.org/10.1007/s10584-019-02390-0

Dietz, T., Börner, J., Förster, J. J., & von Braun, J. (2018). Governance of the bioeconomy: A global comparative study of national bioeconomy strategies. Sustainability, 10(9), 3190.

El-Tantawi, A. M., Bao, A., Chang, C., & Liu, Y. (2019). Monitoring and predicting land use/cover changes in the Aksu-Tarim River Basin, Xinjiang-China (1990–2030). Environmental Monitoring and Assessment, 191(8), 480. https://doi.org/10.1007/s10661-019-7478-0

European Space Agency (ESA). (2017). Land Cover CCI Product User Guide Version 2. Tech. Rep. (pp. 105–105). maps.elie.ucl.ac.be/CCI/viewer/download/ESACCI-LC-Ph2-PUGv2_2.0.pdf

FAO. (2020). WaPOR, FAO's portal to monitor Water Productivity through Open access of Remotely sensed derived data, Version 2.1 [Data set]. Food and Agriculture Organization of the United Nations.

Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: New 1-km spatial resolution climate surfaces for global land areas. International Journal of Climatology, 37(12), 4302–4315. https://doi.org/10.1002/joc.5086

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., ... & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Scientific Data, 2, 150066. https://doi.org/10.1038/sdata.2015.66

Gao, B.-C. (1996). NDWI - A Normalized Difference Water Index for Remote Sensing of Vegetation Liquid Water From Space. Remote Sensing of Environment, 58, 257–266. https://doi.org/10.3109/9781420073553-3

Garrity, D. P., Akinnifesi, F. K., Ajayi, O. C., Weldesemayat, S. G., Mowo, J. G., Kalinganire, A., Larwanou, M., & Bayala, J. (2010). Evergreen Agriculture: A robust approach to sustainable food security in Africa. Food Security, 2(3), 197–214. https://doi.org/10.1007/s12571-010-0070-7

Gilbert, M., Nicolas, G., Cinardi, G., Van Boeckel, T. P., Vanwambeke, S. O., Wint, G. R. W., & Robinson, T. P. (2018). Global distribution data for cattle, buffaloes, horses, sheep, goats, pigs, chickens and ducks in 2010. Scientific Data, 5, 180227–180227. https://doi.org/10.1038/sdata.2018.227

Gismondi, M. (2013). MOLUSCE – An Open Source Land Use Change Analyst - FOSS4G 2013 Nottingham. Presentation. http://2013.foss4g.org/conf/programme/presentations/107/

Golicz, K., Piepho, H.-P., Minarsch, E.-M. L., Niether, W., Große-Stoltenberg, A., Oldeland, J., Breuer, L., Gattinger, A., & Jacobs, S. (2023). Highlighting the potential of multilevel statistical models for analysis of individual agroforestry systems. Agroforestry Systems, 97(8), 1481–1489. https://doi.org/10.1007/s10457-023-00871-x

Gordon, A., & Newman, S. M. (2018). Temperate agroforestry systems, 2nd Edition (CAB Intern, p. 325).

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. Remote Sensing of Environment, 202, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Hansen, M. C.. High-resolution global maps of 21st-century forest cover change. Science, 342, 850–853. https://doi.org/10.1126/science.1244693

Hardisky, M. A., Daiber, F. C., Roman, C. T., & Klemas, V. (1984). Remote Sensing of Biomass and Annual Net Aerial Primary Productivity of a Salt Marsh. Remote Sensing of Environment, 16(2), 91–106. https://doi.org/10.1016/0034-4257(84)90055-5

Hengl, T., de Jesus, J. M., Heuvelink, G. B., Gonzalez, M. R., Kilibarda, M., Blagotic, A., ... & Kempen, B. (2017). SoilGrids250m: Global gridded soil information based on machine learning. PLOS ONE, 12(2), e0169748. https://doi.org/10.1371/journal.pone.0169748

Huntington, J., McGwire, K., Morton, C., Snyder, K., Peterson, S., Erickson, T., Niswonger, R., Carroll, R., Smith, G., & Allen, R. (2016). Assessing the role of climate and resource management on groundwater dependent ecosystem changes in arid environments with the Landsat archive. Remote Sensing of Environment, 185, 186–197. https://doi.org/10.1016/J.RSE.2016.07.004

IPCC, 2019. Climate Change and Land: An IPCC Special Report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems.

Jemal, O. M., Callo-Concha, D., & van Noordwijk, M. (2021). Coffee Agroforestry and the Food and Nutrition Security of Small Farmers of South-Western Ethiopia. Frontiers in Sustainable Food Systems, 5. https://doi.org/10.3389/fsufs.2021.608868

Kusters, K., Pérez, M. R., Foresta, H. D., Dietz, T., Ros-Tonen, M., Belcher, B., Manalu, P., Nawir, A., & Wollenberg, E. (2008). Will Agroforests Vanish? The Case of Damar Agroforests in Indonesia | Human Ecology. https://link.springer.com/article/10.1007/s10745-008-9168-3

Kuyah, S., Öborn, I., Jonsson, M., Dahlin, A. S., Barrios, E., Muthuri, C., Malmer, A., Nyaga, J., Magaju, C., Namirembe, S., Nyberg, Y., & Sinclair, F. L. (2016). Trees in agricultural landscapes enhance provision of ecosystem services in Sub-Saharan Africa. International Journal of Biodiversity Science, Ecosystem Services and Management, 12(4), 255–273. https://doi.org/10.1080/21513732.2016.1214178

Kuyah, S., Whitney, C. W., Jonsson, M., Sileshi, G. W., Öborn, I., Muthuri, C. W., & Luedeling, E. (2019). Agroforestry delivers a win-win solution for ecosystem services in sub-Saharan Africa. A meta-analysis. Agronomy for Sustainable Development, 39(5), 47. https://doi.org/10.1007/s13593-019-0589-8

Lehner, B., & Döll, P. (2004). Development and validation of a global database of lakes, reservoirs and wetlands. Journal of Hydrology, 296(1–4), 1–22. https://doi.org/10.1016/j.jhydrol.2004.03.028

Lesiv, M., Schepaschenko, D., Buchhorn, M., See, L., Dürauer, M., Georgieva, I., Jung, M., Hofhansl, F., Schulze, K., Bilous, A., Blyshchyk, V., Mukhortova, L., Brenes, C. L. M., Krivobokov, L., Ntie, S., Tsogt, K., Pietsch, S. A., Tikhonova, E., Kim, M., … Fritz, S. (2022). Global forest management data for 2015 at a 100 m resolution. Scientific Data, 9(1), 1–14. https://doi.org/10.1038/s41597-022-01332-3

Li, P., Jiang, L., & Feng, Z. (2013). Cross-Comparison of Vegetation Indices Derived from Landsat-7 Enhanced Thematic Mapper Plus (ETM+) and Landsat-8 Operational Land Imager (OLI) Sensors. Remote Sensing 2014, Vol. 6, Pages 310-329, 6(1), 310–329. https://doi.org/10.3390/RS6010310

Maia, F. R. (2023). THE ECONOMIC VIABILITY OF AN AGROFORESTRY SYSTEM IN RELATION TO MONOCULTURE. Journal of Interdisciplinary Debates, 4(04), Article 04. https://doi.org/10.51249/jid.v4i04.1744

Mbow, C., Smith, P., Skole, D., Duguma, L., & Bustamante, M. (2014). Achieving mitigation and adaptation to climate change through sustainable agroforestry practices in Africa. Current Opinion in Environmental Sustainability, 6, 8–14. https://doi.org/10.1016/j.cosust.2013.09.002

Mbow, C., Toensmeier, E., Brandt, M., Skole, D., Dieng, M., Garrity, D., & Poulter, B. (2020). Agroforestry as a solution for multiple climate change challenges in Africa. In D. Deryng (Ed.), Climate change and agriculture (Third Edit, pp. 1–35). Burleigh Dodds Science Publishing. https://doi.org/10.1016/B978-0-12-821575-3.00031-1

Millenium Ecosystem Assessment. (2005). Millennium Ecosystem Assessment. https://www.millenniumassessment.org/en/index.html

Mirzabaev, A. Rothenberger, P., Diouf, A.A., Baumüller, H., Mbow, C. and von Braun, J. (2025) Database on the costs and benefits of agroforestry in Africa. Bonndata. https://doi.org/10.60507/FK2/KJR2HW.

Mirzabaev, A., Sacande, M., Motlagh, F., Shyrokaya, A., & Martucci, A. (2021). Economic efficiency and targeting of the African Great Green Wall. Nature Sustainability, 5, 17–25. https://doi.org/10.1038/s41893-021-00801-8

Mwase, W., Sefasi, A., Njoloma, J., Nyoka, B. I., Manduwa, D., & Nyaika, J. (2015). Factors Affecting Adoption of Agroforestry and Evergreen Agriculture in Southern Africa. Environment and Natural Resources Research, 5(2). https://doi.org/10.5539/ENRR.V5N2P148

Nagelkirk, R. L., & Dahlin, K. M. (2020). Woody cover fractions in African Savannas from landsat and high-resolution imagery. Remote Sensing, 12(5), 813. https://doi.org/10.3390/rs12050813

Nair, P. K. R. (1985). Classification of agroforestry systems. Agroforestry Systems, 3(2), 97–128. https://doi.org/10.1007/BF00122638

Nair, P. K. R. (1993). An Introduction to Agroforestry. In Outlook on Agriculture (Vol. 23, Issue 4). Kluwer Academic Publishers. https://doi.org/10.1177/003072709402300413

Nair, P. K. R., Kumar, B. M., & Nair, V. D. (2021). An Introduction to Agroforestry. An Introduction to Agroforestry. https://doi.org/10.1007/978-3-030-75358-0

Ngaba, M. J. Y., Mgelwa, A. S., Gurmesa, G. A., Uwiragiye, Y., Zhu, F., Qiu, Q., Fang, Y., Hu, B., & Rennenberg, H. (2024). Meta-analysis unveils differential effects of agroforestry on soil properties in different zonobiomes. Plant and Soil, 496(1), 589–607. https://doi.org/10.1007/s11104-023-06385-w

Nguyen, C. T., Chidthaisong, A., Diem, P. K., & Huo, L. (2021). A Modified Bare Soil Index to Identify Bare Land Features during Agricultural Fallow-Period in Southeast Asia Using Landsat 8. Land, 10, 231. https://doi.org/ 10.3390/land10030231

Nkonya, E., Johnson, T., Kwon, H. Y., & Kato, E. (2016). Economics of land degradation in sub-Saharan Africa. In E. Nkonya, A. Mirzabaev, & J. von Braun (Eds.), Economics of land degradation and improvement–a global assessment for sustainable development (pp. 215–259). Springer. https://doi.org/10.1007/978-3-319-19168-3_9

Oguntuase, A. M., & Adu, M. O. (2021). Agroforestry development in Africa: The role of extension services and research institutions. International Journal of Agricultural Extension, 9(1), 1–10.

Oktoyoki, H., Pratama, B., Putra, Y. P., Novrian, W., Douni, J. B., & Ansiska, P. (2024). Financial Feasibility Study and Development of Technical Specifications for Coffee Agroforestry for Community Forest Farmers with Revolving Fund Support for Productivity Optimization. JENDELA PENGETAHUAN, 17(2), Article 2. https://doi.org/10.30598/jp17iss2pp239-251

Olsson, L., Barbosa, H., Bhadwal, S., Cowie, A., Delusca, K., Flores-Renteria, D., Hermans, K., Jobbagy, E., Kurz, W., Li, D., Sonwa, D., Stringer, L.C., 2019. Land Degradation, in: Climate Change and Land:

An IPCC Special Report on Climate Change, Desertification, Land Degradation, Sustainable Land Management, Food Security, and Greenhouse Gas Fluxes in Terrestrial Ecosystems

Rizvi, R. H., Handa, A. K., Sridhar, K. B., Kumar, A., Bhaskar, S., Chaudhari, S. K., Arunachalam, A., Thomas, N., Ashutosh, S., Sapra, R. K., Pujar, G., Singh, R. K., Londhe, S., Nayak, D., Dogra, A., Choudhary, R., Dhyani, S. K., Rizvi, J., Vagen, T.-G., … Dongre, G. (2020). Mapping Agroforestry and Trees Outside Forest—CGIAR, Jointly published by the ICAR, Central Agroforestry Research Institute (CAFRI), Jhansi and World Agroforestry (ICRAF), South Asia Regional Programme, New Delhi. https://www.cgiar.org/research/publication/mapping-agroforestry-and-trees-outside-forest/

Robinson, T. P., Franceschini, G., & Wint, W. (2007). The Food and Agriculture Organization's Gridded Livestock of the World. Veterinaria Italiana, 43(3), 745–751.

Robinson, T. P., William, W., Franceschini, G., & Notenbaert, A. (2014). Mapping the global distribution of livestock. PLOS ONE, 9(5), e96084. https://doi.org/10.1371/journal.pone.0096084

Rouse, W. J., Haas, R. H., Schell, J. A., & Deering, D. W. (1974). Monitoring Vegetation Systems in the Great Plains With ERTS (Patent No. PAPER-A20). https://doi.org/10.1021/jf60203a024

Rubio-Delgado, J., Schnabel, S., Burgess, P. J., & Burbi, S. (2023). Reduced grazing and changes in the area of agroforestry in Europe. Frontiers in Environmental Science, 11. https://doi.org/10.3389/fenvs.2023.1258697

Russell, D., & Franzel, S. (2004). Trees of prosperity: Agroforestry, markets and the African smallholder. In: Nair, P.K.R., Rao, M.R., Buck, L.E. (eds) New Vistas in Agroforestry. Advances in Agroforestry, vol 1. Springer, Dordrecht. https://doi.org/10.1007/978-94-017-2424-1_24

Timite, N., Koua, K. A. N., Kouakou, A. T. M., & Barima, Y. S. S. (2023). Dynamiques spatio-temporelles des parcs agroforestiers dans la zone soudanienne de la Côte d'Ivoire de 1990 à 2020 dans un contexte d'expansion de l'anacarde. International Journal of Biological and Chemical Sciences, 17(2), 484–504. https://dx.doi.org/10.4314/ijbcs.v17i2.16African Journals Online

Sources

Toth, G., Nair, P. K. R., Jacobson, M., Widyaningshi, Y., & Duffy, C. (2019). Malawi's energy needs and agroforestry: Impact of woodlots on fuelwood sales. Energy for Sustainable Development, 49, 106–117. https://doi.org/10.1016/j.esd.2019.01.006

Tschora, H., & Cherubini, F. (2020). Co-benefits and trade-offs of agroforestry for climate change mitigation and other sustainability goals in West Africa. Global Ecology and Conservation, 22, e00919. https://doi.org/10.1016/j.gecco.2020.e00919

Turner, H. C., Lauer, J. A., Tran, B. X., Teerawattananon, Y., & Jit, M. (2019). Adjusting for inflation and currency changes within health economic studies. Value in Health, 22(9), 1026–1032. https://doi.org/10.1016/j.jval.2019.03.021

UNEP-WCMC and IUCN. (2021). Protected Planet: The World Database on Protected Areas (WDPA) [Data set]. UNEP-WCMC. https://www.protectedplanet.net/en/thematic-areas/wdpa

U.S. Geological Survey (USGS). (2000). NASA SRTM Digital Elevation Model (30m) [Data set]. U.S. Geological Survey. https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-shuttle-radar-topography-mission-srtm-1-arc-second-global

van Noordwijk, M., Bizard, V., Wangpakapattanawong, P., Tata, H. L., Villamor, G. B., & Leimona, B. (2014). Tree cover transitions and food security in Southeast Asia. Global Food Security, 3(3), 200–208. https://doi.org/10.1016/j.gfs.2014.10.005

von Braun, J. (2018). Bioeconomy – The global trend and its implications for sustainability and food security. Global Food Security, 19, 81–83. https://doi.org/10.1016/j.gfs.2018.10.003

von Maydell, H. J. (1987). Agroforestry in the Dry Zones of Africa: Past, Present and Future. ICRAF, International Council for Research in Agroforestry. https://books.google.sn/books?id=Gn7GGwAACAAJ

Wilson, N. R., & Norman, L. M. (2018). Analysis of vegetation recovery surrounding a restored wetland using the normalized difference infrared index (NDII) and normalized difference vegetation index (NDVI). International Journal of Remote Sensing, 39(10), 3243–3274. https://doi.org/10.1080/01431161.2018.1437297

World Bank, 2021. World Development Indicators [WWW Document]. URL https://databank.worldbank.org/source/world-development-indicators

Wunder, S., Angelsen, A., & Belcher, B. (2014). Forests, Livelihoods, and Conservation: Broadening the Empirical Base. World Development, 64, S1–S11. https://doi.org/10.1016/j.worlddev.2014.03.007

Young, A. (1983). An environmental database for agroforestry. ICRAF Working Paper, International Centre for Research in Agroforestry (ICRAF), Nairobi, Kenya.

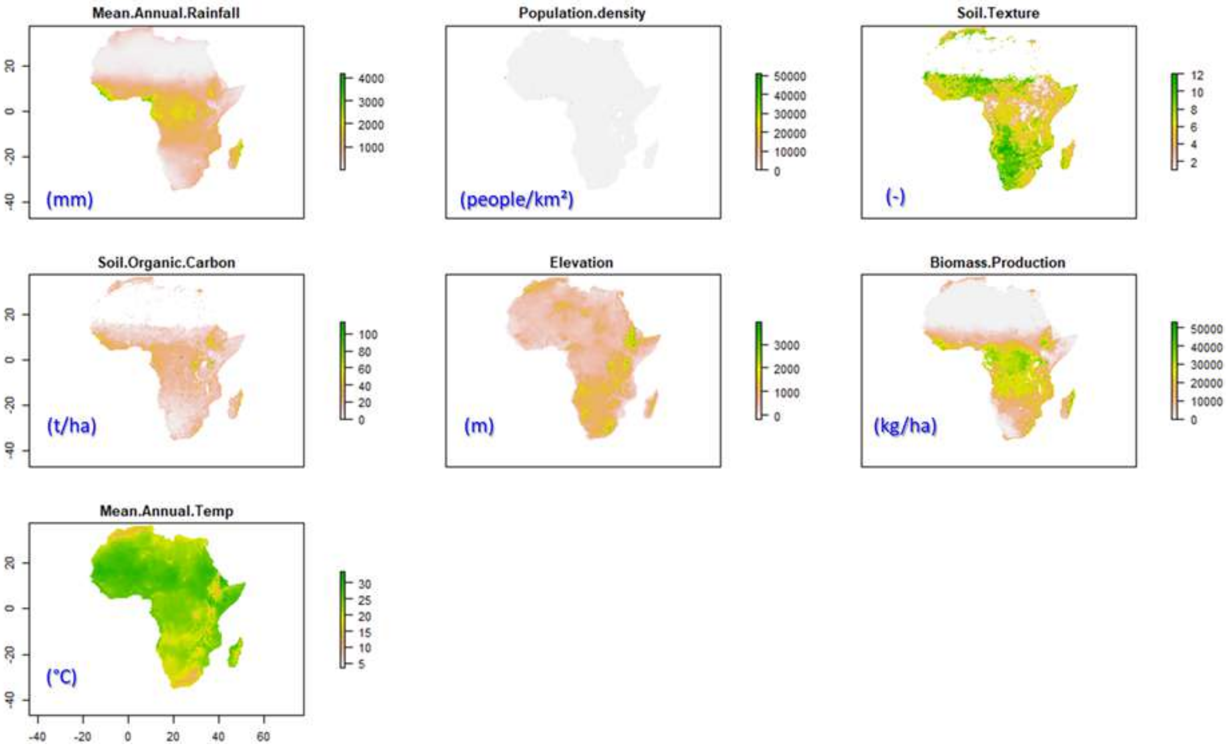
Zhang, W., Fensholt, R., & Brandt, M. (2023). Projected Rainfall-Driven Expansion of Woody Cover in African Drylands. Geophysical Research Letters 50(15): e2023GL103932. https://doi.org/10.1029/2023GL103932

Zomer, R. J., Neufeldt, H., Xu, J., Ahrends, A., Bossio, D. A., Trabucco, A., van Noordwijk, M., & Wang, M. (2016). Global tree cover and biomass carbon on agricultural land: The contribution of agroforestry to global and national carbon budgets. Scientific Reports, 6, 29987. https://doi.org/10.1038/srep29987

Annex

Annex 1: Environmental variables

Figure A1: Environmental variables used for clustering the African continent



Annex 2: Final classification maps and categories

Figure A2: Land use and land cover maps after reclassification using original datasets

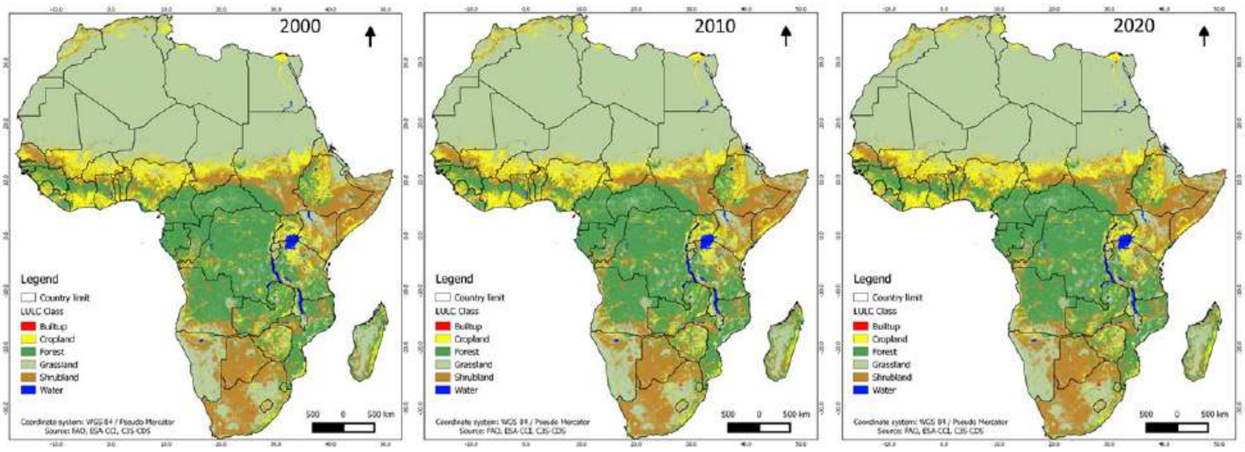
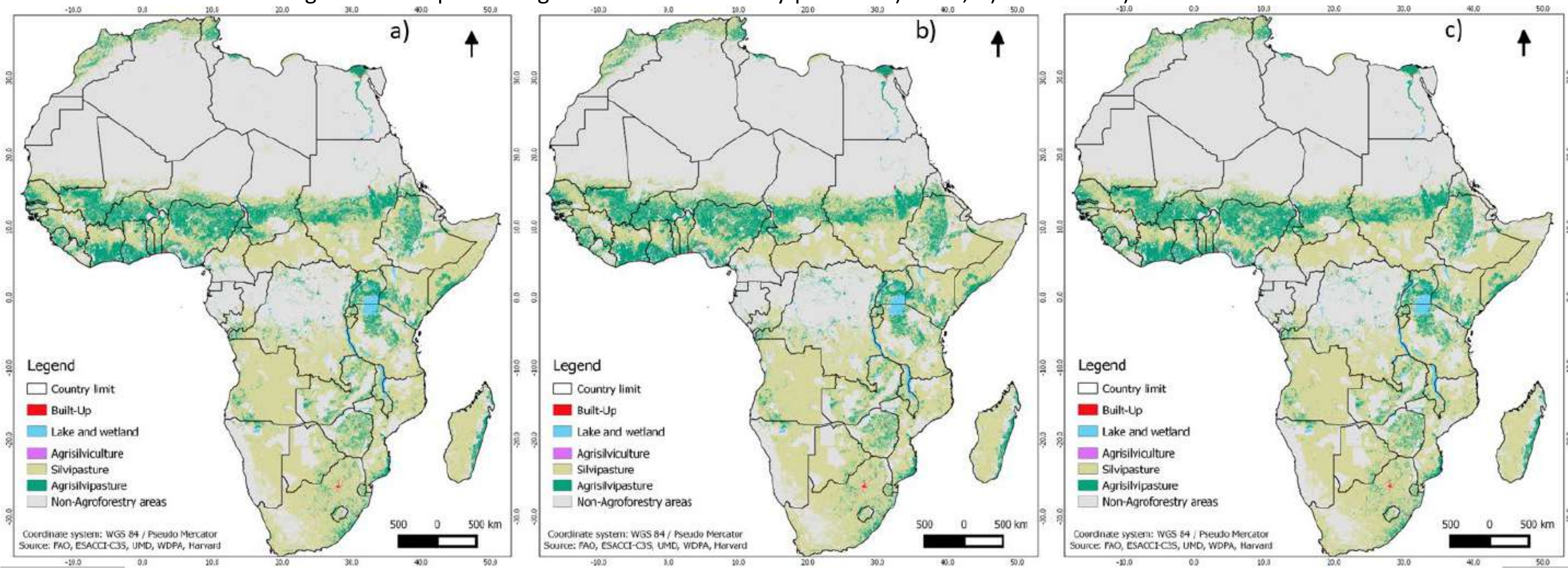


Table A1: Land use and land cover classes after reclassification using original datasets

NB_LAB	Rclass	Rclass_ code	LCCOwnLabel
190	Builtup area	1	Urban areas
10	Cropland	2	Cropland, rainfed
20	Cropland	2	Cropland, irrigated or post-flooding
40	Cropland	2	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (<50%)
50	Forest	3	Tree cover, broadleaved, evergreen, closed to open (>15%)
60	Forest	3	Tree cover, broadleaved, deciduous, closed to open (>15%)
61	Forest	3	Tree cover, broadleaved, deciduous, closed (>40%)
62	Forest	3	Tree cover, broadleaved, deciduous, open (15-40%)
70	Forest	3	Tree cover, needleleaved, evergreen, closed to open (>15%)
71	Forest	3	Tree cover, needleleaved, evergreen, closed (>40%)
72	Forest	3	Tree cover, needleleaved, evergreen, open (15-40%)
80	Forest	3	Tree cover, needleleaved, deciduous, closed to open (>15%)
81	Forest	3	Tree cover, needleleaved, deciduous, closed (>40%)
82	Forest	3	Tree cover, needleleaved, deciduous, open (15-40%)
90	Forest	3	Tree cover, mixed leaf type (broadleaved and needleleaved)
160	Forest	3	Tree cover, flooded, fresh or brakish water
170	Forest	3	Tree cover, flooded, saline water
11	Grassland	4	Herbaceous cover
110	Grassland	4	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)
130	Grassland	4	Grassland
150	Grassland	4	Sparse vegetation (tree, shrub, herbaceous cover) (<15%)
153	Grassland	4	Sparse herbaceous cover (<15%)
180	Grassland	4	Shrub or herbaceous cover, flooded, fresh/saline/brakish water
200	Grassland	4	Bare areas
201	Grassland	4	Consolidated bare areas
202	Grassland	4	Unconsolidated bare areas
30	Shrubland	4	Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)
12	Shrubland	5	Tree or shrub cover
100	Shrubland	5	Mosaic tree and shrub (>50%) / herbaceous cover (<50%)
120	Shrubland	5	Shrubland
121	Shrubland	5	Shrubland evergreen
122	Shrubland	5	Shrubland deciduous
151	Shrubland	5	Sparse tree (<15%)
152	Shrubland	5	Sparse shrub (<15%)
210	Water	6	Water bodies

Annex 3: Agroforestry in 2030, 2040, 2050

Figure A3: Map of changed areas for the study periods a) 2030, b) 2040 and c) 2050



Annex 4: Total economic values of agroforestry and other land uses

Table A2: Total economic values of agroforestry and other land uses and covers in Africa (USD per hectare, values for 2020)

Ecosystem services	Forests	Grassland	Wetlands	Cropland	Agroforestry in pastoral systems	Agroforestry in cropping systems	Agroforestry in mixed systems
Provisioning services	**284**	**49**	**423**	*589**	**192**	**738***	**412***
Food	132	36	25		33		
Water	33		257				
Raw materials	76	12	16		42		
Genetic resources	38		68		25		
Medicinal resources	5	1	46		2		
Ornamental resources			11		90		
Regulating services	**1,838**	**316**	**2,664**	**38**	**216**	**216**	**216**
Air quality regulation	14	23	67				
Climate regulation	1,343	75	109	2	49	49	49
Disturbance moderation							
Regulation of water flows	55			19	33	33	33
Waste treatment	153		2,206	4			
Erosion prevention	221	140	179	2	104	104	104
Nutrient cycling	19	78	103		10	10	10
Pollination	19			9	19	19	19
Biological control	14			2	1	1	1
Habitat services	**24**	**0**	**45**	**0**	**215**	**215**	**215**
Nursery service	8		29				
Genetic diversity	16		16		215	215	215
Cultural services	**6**	**5**	**55**	**1**	**6**	**6**	**6**
Esthetic information							
Recreation	6	5	12	1	6	6	6
Inspiration							
Spiritual experience			41				
Cognitive development			2				
Total	**2,152**	**370**	**3,187**	**628**	**629**	**1069**	**849**

zef

Center for Development Research University of Bonn

Working Paper Series

Authors: Abdoul Aziz Diouf, Alisher Mirzabaev, Cheikh Mbow, Heike Baumüller, Zahra Didarali and Joachim von Braun

Contact: aziz.diouf@cse.sn, a.mirzabaev@cgiar.org, mbow@cse.sn, hbaumueller@uni-bonn.de, zdid@uni-bonn.de, jvonbraun@uni-bonn.de

Photos: Friedericke Schilling

Published by:
Zentrum für Entwicklungsforschung (ZEF)
Center for Development Research
Genscherallee 3
D – 53113 Bonn
Germany

Phone: +49-228-73-1861
Fax: +49-228-73-1869
E-Mail: presse.zef@uni-bonn.de

www.zef.de