# Land Use Planning for Enhanced Resilience of Landscapes (LAUREL)

## An Analysis of Land Use Changes and Land Degradation in Mozambique

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## Authors:

Clovis Grinand[1], Agnès Bégué[2], Frédérique Montfort[1], Louise Leroux[3], Telina Randrianarivo[4]

1. NITIDAE, 500 rue Jean-François Breton, 34093, Montpellier, France
2. UMR TETIS, CIRAD, 500 rue Jean-François Breton, 34093, Montpellier, France
3. UPR AIDA, CIRAD, CSE Fann Residence, Dakar, Sénégal
4. NITIDAE, Lot VE 26L Ambanidia, 101 Antananarivo, Madagascar



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## Executive Summary

The Land Use Planning for Enhanced Resilience of Landscapes (LAUREL) program, led by the World Bank, supports landscape management in Mozambique through improved spatial data on land degradation and through the development of a modeling platform that can analyze and quantify the economic and ecological implications of future land use.

The goal of the former is to develop a sound, consistent and locally relevant estimates of land degradation in Mozambique, following the latest guidance of international UN conventions using state-of-the-art earth observation technology. To achieve these goals we developed an integrated methodology that identifies and quantifies the drivers of land productivity change and estimate land degradation state and trends. The methodology relies on two indicators that provide historical estimates of land degradation: a land use and land cover change (LULCC) analysis and a land productivity trend analysis (NDVI). These analyses were conducted at the national scale, over the 2000-2016 period, with spatial resolutions of 30m and 250m, respectively. Finally, we collected and estimated other land degradation indicators (biodiversity, soil organic carbon, & soil erosion) from global and national datasets to populate additional baseline indicators.

The NDVI trend analysis shows that a large proportion of the country **(77%) is characterized by an overall stable trend**, meaning there is no significant change in terms of vegetation productivity over the period. **Among the significant trends, 19% of the total area have negative NDVI Trends**, **with clear spatial patterns of decreasing trends in Inhambane, Zambezia and Nampula provinces**. On the other hand, **only 3% and of the total area displayed increase trends**, mainly observed along the Zambezia and Sabi rivers and in the Maputo, Niassa and Cabo Delgado provinces.

In the final LULCC map for 2000, 2005, 2010 and 2016 we observed an overall land use pattern of **45.0% (35.8 Mha) of dry forest, 37.0% (29.3 Mha) of grassland and fallow, 13.7% (10.8 Mha) of cropland 2.0% (1.6 Mha) of wetlands, 1.3% (1 Mha) of other categories (rocks, sands, or bare soils), 0.3% (271,000 ha) of Mangroves, and 0.1% (673.1 ha) of urban areas**. These values are broadly in agreement with the National Land Use and Land Cover maps for 2016 currently being finalized by the GoM. The **deforestation over the 2000-2016 period is estimated to have been 207,272 ha per year**.

The result is a nationally consistent database of land degradation and robust information on the underlying causes of degradation in Mozambique. The land degradation assessement methods and results were presented and shared during the development process to national institutions (e.g., DINOTER, DINAB, FNDS/MRV Unit, IIAM, UEM). In addition, a training sesson on land degradation assessment was organised in 2018 at the University Eduardo Mondlane (UEM) with participants from national institutions (including DINOTER, DINAB, FNDS), projects or programs (e.g. BioFund, PNDT, Secosud), civil society (e.g. Micaia Fundation), researchers and students. Two papers were submitted in international peer-review journal to document the methodology and present the results.

The Land Degradation spatial products presented in this report can provide useful information to accompany local interventions (Gilé National Reserve Conservation activities) or be part of larger programs such as REDD+ Zambesia, the National Land Degradation Neutrality Baseline or the Red List Critical Ecosystem Assessment.

## Sumário executivo

O programa LAUREL (Land Use Planning for Enhanced Resilience of Landscapes), liderado pelo Banco Mundial, apoia a gestão da paisagem em Moçambique através de dados espaciais melhorados sobre a degradação da terra e através do desenvolvimento de uma plataforma de modelação que pode analisar e quantificar as implicações económicas e ecológicas do uso futuro da terra.

O objectivo da primeira é desenvolver uma estimativa sólida, consistente e localmente relevante da degradação da terra em Moçambique, seguindo a mais recente orientação das convenções internacionais da ONU, utilizando tecnologia de observação da terra de última geração. Para alcançar estes objectivos, desenvolvemos uma metodologia integrada que identifica e quantifica os impulsionadores da mudança da produtividade da terra e estima o estado e tendências da degradação da terra. A metodologia baseia-se em dois indicadores que fornecem estimativas históricas da degradação da terra: uma análise do uso e cobertura da terra (LULCC) e uma análise das tendências de produtividade da terra (NDVI). Estas análises foram realizadas à escala nacional, ao longo do período 2000-2016, com resoluções espaciais de 30m e 250m, respectivamente. Finalmente, coletamos e estimamos outros indicadores de degradação do solo (biodiversidade, carbono orgânico do solo e erosão do solo) a partir de conjuntos de dados globais e nacionais para preencher indicadores de linha de base adicionais.

A análise de tendências do IVDN mostra que uma grande proporção do país (77%) é caracterizada por uma tendência geral estável, o que significa que não há mudança significativa em termos de produtividade da vegetação durante o período. Entre as tendências significativas, 19% da área total tem tendências NDVI negativas, com padrões espaciais claros de tendências decrescentes nas províncias de Inhambane, Zambézia e Nampula. Por outro lado, apenas 3% e da área total apresentaram tendências de aumento, observadas principalmente ao longo dos rios Zambézia e Sabi e nas províncias de Maputo, Niassa e Cabo Delgado.

No mapa LULCC final para 2000, 2005, 2010 e 2016 observámos um padrão geral de uso da terra de 45.0% (35.8 Mha) de floresta seca, 37.0% (29.3 Mha) de prados e pousios, 13.7% (10.8 Mha) de terras agrícolas 2.0% (1.6 Mha) de zonas húmidas, 1.3% (1 Mha) de outras categorias (rochas, areias, ou solos nus), 0.3% (271.000 ha) de mangais, e 0.1% (673.1 ha) de áreas urbanas. Estes valores estão amplamente de acordo com os mapas Nacionais de Uso e Cobertura do Solo para 2016 que estão actualmente a ser finalizados pelo GdM. Estima-se que o desmatamento no período 2000-2016 tenha sido de 207.272 ha por ano.

O resultado é uma base de dados nacional consistente da degradação da terra e informação robusta sobre as causas subjacentes da degradação em Moçambique. Os métodos e resultados da avaliação da degradação da terra foram apresentados e partilhados durante o processo de desenvolvimento com as instituições nacionais (por exemplo, DINOTER, DINAB, FNDS/MRV Unit, IIAM, UEM). Além disso, uma sessão de formação sobre a avaliação da degradação da terra foi organizada em 2018 na Universidade Eduardo Mondlane (UEM) com participantes de instituições nacionais (incluindo DINOTER, DINAB, FNDS), projectos ou programas (por exemplo, BioFund, PNDT, Secosud), sociedade civil (por exemplo, Micaia Fundation), investigadores e estudantes. Dois artigos foram submetidos em revistas internacionais de revisão por pares para documentar a metodologia e apresentar os resultados.

Os produtos espaciais de Degradação da Terra apresentados neste relatório podem fornecer informações úteis para acompanhar intervenções locais (atividades de Conservação da Reserva Nacional Gilé) ou fazer parte de programas maiores como REDD+ Zambesia, a Linha de Base Nacional de Neutralidade da Degradação da Terra ou a Avaliação Crítica de Ecossistemas da Lista Vermelha.

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# Acronyms

| | |
|---|---|
| ANPP | Above Net Primary Production |
| ARS | Agricultural Research Service |
| CCI | Climate Change Initiative |
| CHG | Climate Hazards Group |
| CHIRPS | Climate Hazards Group InfraRed Precipitation with Station data |
| CRU | Climate Research Unit |
| DEM | Digital Elevation Model |
| DINAB | *Direcção Nacional do Ambiente* (National Directorate of Environment) |
| DINOTER | *Direcção Nacional d'Ordenamento Territorial* (National Directorate of Land Use Planning and Resettlement) |
| DSM | Digital Soil Mapping |
| ESA | European Space Agency |
| FAO | Food and Agriculture Organisation |
| FNDS | National Fund for Sustainable Development |
| FREL | Forest Reference Emissions Level |
| GIS | Geographic Information System |
| GLW | Gridded Livestock of the World |
| GoM | Government of Mozambique |
| IGF | International Foundation for Wildlife Management |
| IIAM | *Instituto de Investigação Agraria de Moçambique* (Mozambique Institute of Agricultural Research) |
| INE | *Instituto Nacional de Estatística* (National Institute of Statistics) |
| IPBES | Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services |
| IPCC | Intergovernmental Panel on Climate Change |
| ISRIC | International Soil Reference Information Centre |
| IUCN | International Union for Conservation of Nature |
| JRC | Joint Research Centre |
| KBA | Key Biodiversity Area |
| LAUREL | Land Use Planning for Enhanced Resilience of Landscapes |
| LDN | Land degradation neutrality |
| LPC | Land Productivity Change |
| LULCC | Land Use and Land Cover Change |
| MODIS | Moderate-Resolution Imaging Spectroradiometer |
| MRV | Measurement, Reporting and Verification |
| NASA | National Aeronautics and Space Administration |
| NDVI | Normalized Difference Vegetation Index |
| NLCS | National Level Classification System |
| OLS | Ordinary-Least Square |
| OSM | OpenStreetMap |
| PNDT | *Plano National do Desenvolvimento Territorial* (National Plan for Territorial Development) |
| REDD+ | Reducing Emissions from Deforestation and forest Degradation |
| RF | Random Forest |
| ROI | Region of Interest |
| SDG | Sustainable Development Goals |
| SOC | Soil Organic Carbon |

| | |
|---|---|
| SRTM | Shuttle Radar Topography Mission |
| TRMM | Tropical Rainfall Measuring Mission |
| UEM | Eduardo Mondlane University |
| UNCBD | United Nations Convention for the Biodiversity |
| UNCCD | United Nation Convention to Combat Desertification |
| UNFCCC | United Nations Framework Convention to Combat Climate Change |
| USLE | Universal Soil Loss Equation |
| WAD | World Atlas of Desertification |
| WB | World Bank |
| WWF | World Wildlife Fund |

# 1 INTRODUCTION

## 1.1 Context

In the last five years, a number of global and regional targets and commitments have been agreed to by national governments to halt and reverse land degradation and restore degraded land. These initiatives push countries to set up ambitious targets to reduce poverty, increase food security and nutrition, and reduce land degradation for the next decades.

Despite these many initiatives, there is still a lack of clear and agreed quantified measurement of land degradation. In addition, many countries currently do not have the capacity to monitor and report on land degradation.

The latest report of UNCCD on land degradation provides some methodological guidance on the choice of land degradation indicators, and how to measure and monitor (UNCCD, 2016). It suggests expressing land degradation as the status of three main indicators: (i) land cover and land cover change, (ii) land productivity, and (iii) carbon stocks above and below ground. These main indicators are justified due to the fact that they can be quantified in a spatially explicit manner using Earth observations and/or ancillary data from national to sub-national databases, and thus provide a practical approach to monitoring and reporting progress. Countries are invited to develop their one other secondary or user-defined land degradation indicators as well.

Land degradation in Mozambique is very important. An assessment by the European Space Agency (ESA) found that ca. 42% of the land in Mozambique are degraded and ca. 19% of the land is now experiencing active degradation (Paganini et al., 2009). A recent report on deforestation in Mozambique estimated that more than 250 000 ha of natural forest were disapearing every year due to human activities (GoM, 2018). This active land degradation can jeopardize the country's agricultural productivity and economic development in the future, and call for actionable informations and anticipation.

In 2017, the World Bank launched a program called "Land Use Planning for Enhanced Resilience of Landscapes (LAUREL)" that aims to support landscape management in Mozambique at national scale through two components: 1) Production of improved spatial data on land degradation; 2) Development of a land modelling platform for simulating, evaluating, and re-orienting as appropriate, land use and land use change processes ("LandSIM" prototype).

**This report presents the work regarding the first component of this projet and carried out by Nitidae and CIRAD**.

## 1.2 Objective

The land degradation baseline component of LAUREL aimed to develop sound, consistent and up-to-date baseline and locally relevant estimates of Land condition in Mozambique. The ultimate goals were to 1) increase our knowledge regarding the location and drivers of the Land condition change (land use / land cover, and land productivity), and 2) produce base layers for the LandSIM prototype.

We selected the 2000-2016 historical period due to the fact that it covers a significant historical time frame (16 years), and corresponds to the period that is expected to be simulated in the future with the LandSIM simulation platform (ranging from 10 to 20 years in the future from 2017).

The overall approach proposed herein is guided by three main principles: i) Cost-effectiveness; ii) Possible replication by local counterpart; iii) Value to other national and sub-national initiatives. Therefore, we based our analysis on free global and national datasets, and open-source data processing tools that can be easily adopted by local counterparts.

## 1.3 Linkages with LANDSIM and other national initiatives

The land degradation component of LAUREL feeds the land simulation prototype (LANDSIM) through two main indicators: the Land Use and Land Cover Change (LULCC), and the Land Productivity Change (LPC) products (Figure 1).

The land use and land cover change map is instrumental to providing LANDSIM with:

- An initial land use/land cover map (2016), as a starting point to estimate future land use change;
- Historical land use/land cover maps (2000…2016), to calibrate/validate various modules of LANDSIM.

The Land Productivity Change product is overlaid with the LULC map in order to produce a Soil Degradation map. This latter is used in LandSIM as a base map for decision rules to account for reduced soil fertility impacting crop yields (moderately degraded soils), and abandonment of land due to infertile soils (severely degraded soils).

Besides, **these products are also valuable for on-going national initiatives that include the REDD+ national strategy, the Land Degradation Neutrality mechanism, and other initiatives (Biodiversity offset program, Restoration program, etc.)** that require to have historical perspectives, and a fine-scale and up-to-date situation on the Land condition. However, LAUREL outputs are not suitable to define REDD+ baseline or any payement based mechanism.

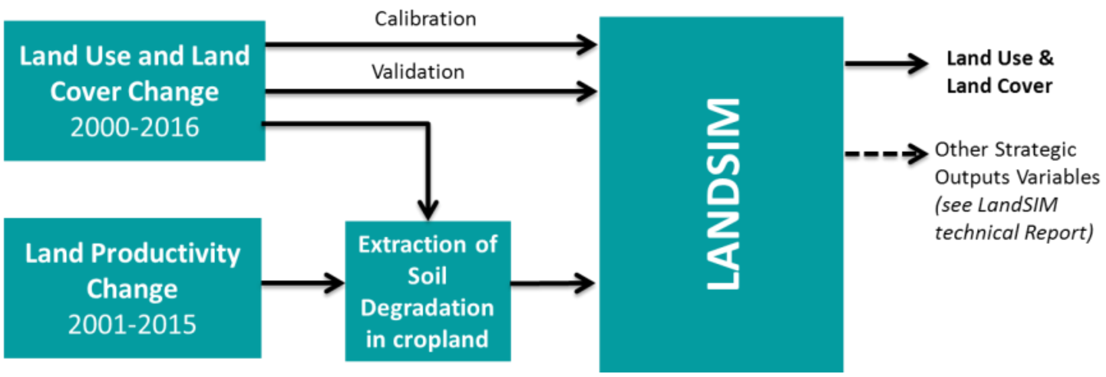



*Figure 1: Illustration of the linkages between Land Degradation and LANDSIM component of LAUREL.*

Part 2 provides a current state of the art on land degradation definition, approachs to measure and monitoring system and the one applied for this study. Part 3 describes the methodology used to identify and quantify the drivers of land productivity change and estimate land degradation state and trends. Part 4, presents the results regarding the location and drivers of the Land condition change observed. Finally, other land degradation indicators (soil organic carbon, soil erosion, & biodiversity,) from global and national datasets are presented in part 5.

# 2 BACKGROUND ON LAND DEGRADATION

This work is based on the best-practice guidance on land degradation assessment (UNCCD, 2016), released at the beginning of LAUREL project. Both policy and science are currently challenged to have agreements, set up rules and methodology to quantify and monitor the progress. The international "science-policy interface" is in constant evolution and we saw new concepts and techniques emerged in the last two years. In this section, we present a short review of the current approaches for land degradation assessment, discuss the limits, and present the approach adopted in this study.

**Definitions of land degradation:**

**According the UNCCD**: "the reduction or loss of the biological or economic productivity and complexity of rainfed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from land uses or from a process or combination of processes, including processes arising from human activities and habitation patterns, such as soil erosion caused by wind and/or water, deterioration of the physical, chemical and biological or economic properties of soil, and long-term loss of natural vegetation" (UNCCD, 2016).

**According the IPBES**: "the many human-caused processes that drive the decline or loss in biodiversity, ecosystem functions or ecosystem services in any terrestrial and associated aquatic ecosystems" (IPBES, 2018).

## 2.1 International context

In the last five years, a number of global and regional targets and commitments have been agreed to by national governments to halt and reverse land degradation and restore degraded land. These include the Aichi Targets of the United Nations Convention on Biological Diversity (UNCBD), the REDD+ (Reducing Emissions from Deforestation and forest Degradation) mechanism of the United Nations Framework Convention on Climate Change (UNFCCC), the Land degradation neutrality (LDN) initiative of the United Nations Convention to Combat Desertification (UNCCD), the Bonn challenge, and the Sustainable Development Goals (SDG), in particular the SDG target 15.3 dedicated to the restoration of degraded land and soil.

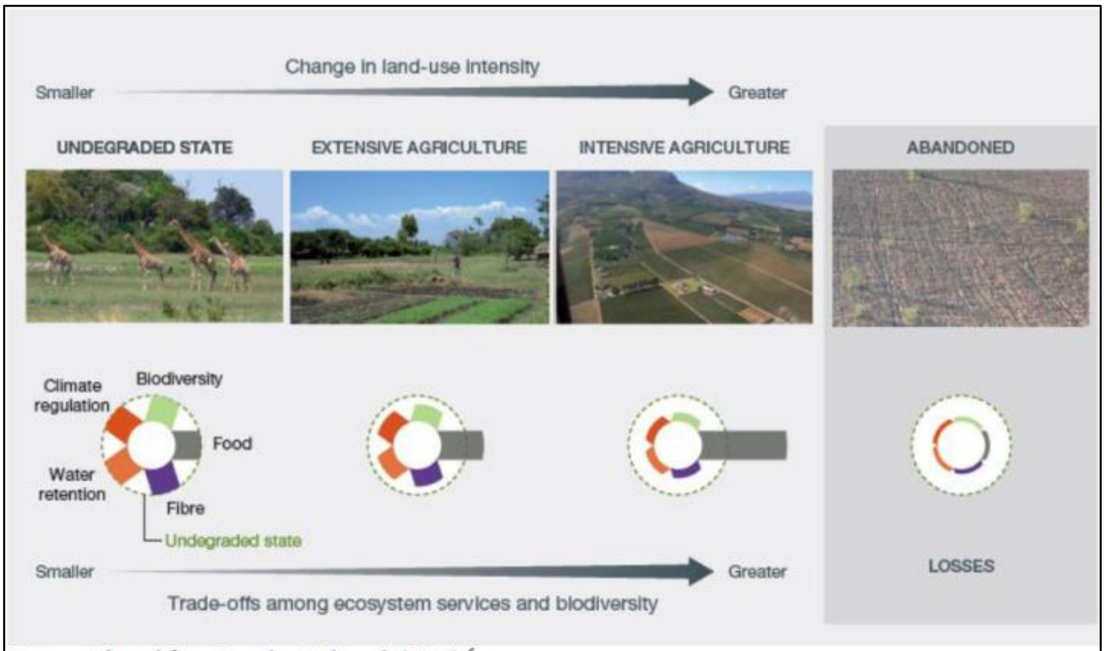
## 2.2 Land degradation versus Land condition

It is clear that unsustainable human activities put land at risk and at the same time threaten the ecosystem services on which all humanity depends. There is enormous pressure on global land resources due to rising food demand, a global shift in dietary habits, biofuel production, urbanization, and other competing demands (mining, and other extraction activities).

Geist and Lambin (2004) analyzed more than 130 case studies about the underlying mechanisms of land degradation processes, and showed that: (1) land degradation is a complex process with biophysical and socio-economic drivers, and (2) there is no unique analytical framework for addressing land degradation at global scale. Since there remains a lack of clear and agreed definitions and a lack of quantified measurement, the differences in definitions, indicators, and even the perception of the land degradation may explain why the estimates on the extent and severity of land degradation vary significantly.

According the UNCCD, the land degradation is mainly defined by the reduction of biological productivity, while for IPBES the land degradation is centered on the loss of biodiversity. A simple and consensual definition of the land degradation is the decline or loss in ecosystem functions and services of a given territory that cannot fully recover unaided within decadal time scales. The time span is here very important to decouple changes on the long run from the impact of short-term fluctuations driven by seasonal pulse or single events (Cherlet et al., 2018). However, this definition also has application limits as it can happen that some ecosystem functions and services are negatively affected while others have been increased. The example given by Van der Esch et al. (2017) illustrates perfectly the difficulty in valuing and balancing the ecosystems trade-offs (Figure 2): transforming natural ecosystems into human-oriented production ecosystems, for instance agriculture, often creates benefits to society but simultaneously can result in losses of biodiversity and other ecosystem services.

There is even a large degree of uncertainty of in land degradation status. In the 3$^{rd}$ edition of the World Atlas of Desertification (WAD), indications of decreasing productivity can be observed globally, with up to 22 million km$^2$ affected (i.e., approximately 20 % of the Earth's vegetated land surface) with persistent declining trends or stress on land productivity (Cherlet et al. 2018). If this trend continues, 95% of the Earth's land areas could become degraded by 2050. According to IPBES (2018), less than one quarter of the Earth's land surface remains free from substantial human impacts (established but incomplete), and currently, degradation of the Earth's land surface through human activities is negatively impacting the well-being of at least 3.2 billion people. However, Gibbs and Salmon (2015) compared the results of four approaches that have been used to assess degraded lands at the global scale: expert opinion, satellite observation, biophysical models, and taking inventory of abandoned agricultural lands. They showed that global estimates of total degraded area vary from less than 1 billion ha to over 6 billion ha (66% of the world land), with equally wide disagreement in their spatial distribution.




*Source*: Adapted from Van der Esch et al. (2017).[6]

*Figure 2 : Human transformation of natural ecosystems and trade-offs among ecosystem services and biodiversity.*

Because degradation is a question of point of view, it is more suitable to refer to Land condition, which is a neutral term, with no negative judgement contrary to the term “degradation”. In the “Scenarios for the UNCCD Global Land Outlook” report, Van der Esch et al. (2017) define Land condition as the potential of land to provide people with various types of services, without prioritizing any of them. They express it in quantifiable indicators, and assess how these indicators have changed over time and are expected to change up to 2050.

## 2.3 The UNCCD approach

The latest report of UNCDD on land degradation provides some methodological guidance on the choice of land degradation indicators and how to measure and monitor (UNCCD, 2016). It suggests expressing land degradation as the status of three main indicators: (i) land productivity dynamic, (ii) land cover and land cover change, and (iii) carbon stocks above/below ground (Figure 3). These indicators can be quantified in a spatially explicit manner using Earth observations and/or ancillary data from national to sub-national databases.

Once calculated, the three indicators are combined into a measurement of the proportion of land that is degraded, which is required in order to fully implement the SDG Indicator 15.3.1. For that, the *One Out, All Out* principle is applied: If one of the indicators is negative (or stable when degraded in the baseline or previous monitoring year) for a particular land unit, then it would be considered as degraded.

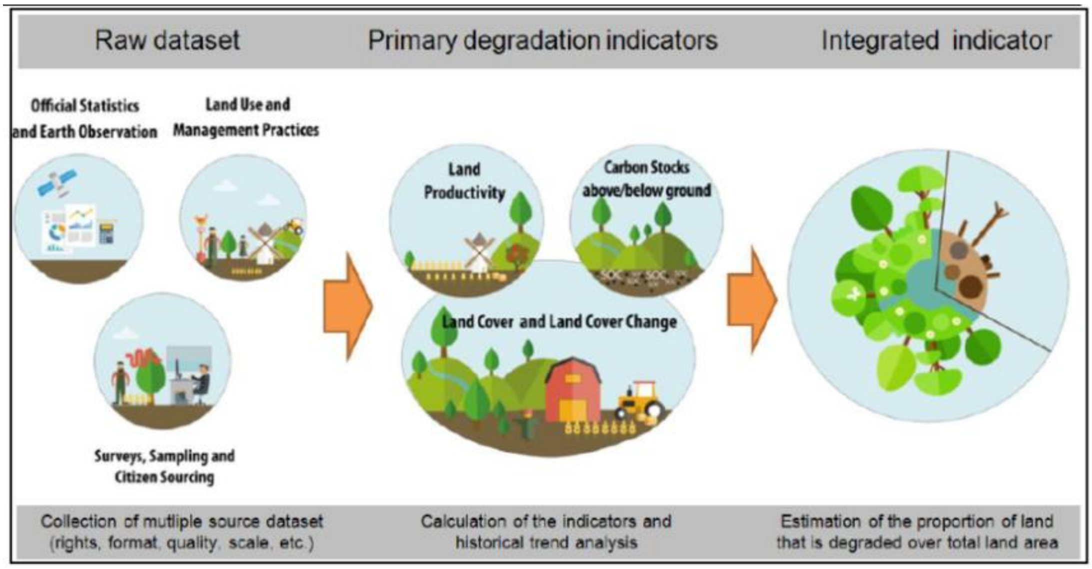



*Figure 3 : Illustration of the general approach to calculate the SDG indicator 15.3.1 (adapted from UNCCD, 2016).*

Land productivity status and trends: For the purposes of reporting on SDG Indicator 15.3.1, it is not necessary to quantify the magnitude of change in productivity in biomass units of Above Net Primary Production (ANPP), but only to know whether productivity is increasing (positive), decreasing (negative), or stable for the land unit at a particular time. The relative change in a unitless index, such as the NDVI, is often sufficient to determine land productivity trends.

The recently proposed method for assessing land productivity trends was developed by the European Commission's Joint Research Centre (JRC) to measure land degradation at global scales (Ivits & Cherlet, 2016). NDVI is interpreted in terms of three main metrics, calculated at the pixel scale (Figure 4):

- **Trajectory (or Trend),** which represents the trajectory of productivity over time;
- **State**, which compares the current productivity level in a given area to historical observations of productivity in that same area;
- **Performance,** which measures local productivity relative to other similar vegetation types in similar land cover types and bioclimatic regions.

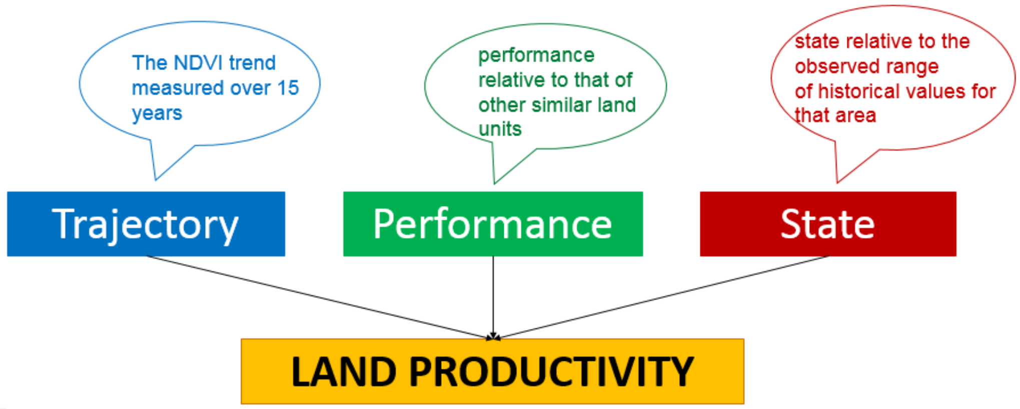



*Figure 4 : Trajectory, Performance and State in Productivity.*

Pixels showing degradation are those with:

- A significant negative trend in any combination of degradation metrics, or
- A trend that is not significantly negative with
  - Degradation indicated in the productivity State analysis, and
  - Degradation indicated in the productivity Performance analysis

Land cover change: The land refers to the observed physical cover of the Earth's surface, which describes the distribution of vegetation types, water bodies and human-made infrastructure. It also reflects the use of land resources (i.e., soil, water and biodiversity) for agriculture, forestry, human settlements and other purposes. To avoid ambiguity, one should always:

- Adopt or formulate a land cover map legend with classes that are unambiguous, exhaustive and complete;
- Generate a land cover class transition matrix that identifies land cover changes that could potentially be classified as degradation.

Soil carbon change: quantity of organic carbon stored in on hectare. The change in time is related to land use or land cover changes. Depending of the LUCC, the soil can act as a sink or source of carbon. In land degradation assessment, the soil carbon is used as a proxy of soil fertility and more broadly representing "soil health" providing numerous ecosystem services to humans (food provision, erosion control, water retention, climate change mitigation, water purification, etc.)

## 2.4 The WAD approach

Considering the drivers and multiple factors underlying land degradation, the WAD builds on a systematic framework that provides a "convergence of evidence" regarding human-environment interactions: when multiple sources of evidence are in agreement, strong conclusions can be drawn even when none of the individual sources of evidence is significant on its own (Cherlet et al., 2018). Convergence maps are compiled by combining global datasets on key processes, using a reference period of 15-20 years. Combinations are made without prior assumptions in the absence of exact knowledge of land change processes at variable locations. Patterns indicate areas where substantial stress on land resource is to be expected. The convergence approach is based on 13 consistent and geographically continuous datasets on socio-economic and biophysical issues (Table 1). As land degradation in itself is a process, dynamic datasets are ideally to be used, but only a limited number currently provide consistent and harmonized global coverage.

*Table 1. Geographical datasets used in the WAD approach.*

| Dynamic data layers | State data layers |
| --- | --- |
| • Population change (2000-2015)<br>• Built-up area change (2000-2014)<br>• Land biomass productivity dynamics (1999-2013)<br>• Tree loss (2000-2014) | • Population density in 2015<br>• Gross national income per capita in 2015<br>• Area equipped for irrigation (2005)<br>• Nitrogen balance on landscape level (2000)<br>• Livestock density (2006)<br>• Fire occurrence (during period 2000 to 2013)<br>• High water stress (2010)<br>• Aridity (aridity index 1981 to 2000)<br>• Climate and vegetation trend anomalies (1982 to 2011) |

Convergence of evidence is often undertaken in two steps:

- A global land cover/use stratification is compiled for 2007-2010 and partitioned into classes representing a range of stakeholder interests, such as cropland or rangeland perspectives;
- For each class, zonal or class statistics are calculated for each dataset or potential issue. The issues are reclassified as being above or below a statistically derived threshold, taking into account their expected effect in terms of land degradation (positive or negative). The resulting layers have values of 0 (no stress) and 1 (potential stress), and are summed together to provide the number of co-existing issues at any geographical position.

The method is flexible and can be applied at all scales.

## 2.5 The LAUREL approach

A simple approach based on NDVI trend was preferred to an approach based on the distance from a reference condition of non-degradation (as the Performance and State indicators in the UNCCD approach), because it is very difficult to find non-degraded conditions representative of each agro-climatic zone. Also, the trend approach was considered wiser than the “Convergence of evidence” or any approach based on the calculation of a environmental risk index that relies on a subjective weighing of the factors, and which result is very sensitive to the scale and accuracy of the input layers, especially at sub-national scale

WAD's key message is that land degradation is a multifaceted global phenomenon with distinct variations between regions and across key land cover/land use systems, and which cannot be captured by one or a limited set of indicators (UNCCD, 2017). In total agreement with this message, we based our analysis on a set of land and environmental indicators. We first expressed Land condition as the status and trend of selected primary indicators with a focus on land cover change, climate variability and land productivity trends, over a selected historical period that ranges from 2000 to 2016. Then we combined these indicators with of other secondary environmental and socio-economic variables.

Our approach is developed around a central indicator which is the land productivity trend estimated from NDVI time series over 15 years. This choice is dictated by different reasons: 1. NDVI is computed from measured physical quantities (electromagnetic radiation), and is not prone to any subjectivity or manipulation; 2. NDVI integrated over time is a good proxy of the above net primary production (ANPP); 3. The ANPP is a synthetic indicator of the Land condition prone to reflect changes in the environment: inter-annual changes such as rainfall amount, land cover/land use changes, loss of soil fertility, etc. However, a single value of NDVI does not permit to understand the drivers of the Land condition changes, and thus additional biophysical and socio-economic indicators are necessary to interpret these trends in terms of land degradation. It is the reason why we develop a model that analyze these NDVI trends in terms of various biophysical and socio-economic drivers, and provide additional maps of drivers.

The general Laurel approach comprises 4 main steps (data collection and preparation; processing indicators; ground control & validation; reporting and publication):

- **Data collection and pre-processing**: This step involved the identification and downloading global and national datasets. This raw dataset was analysed in term of quality, tested and pre-processed.
- **Data processing**: This step involved the processing of the land degradation indicators: land productivity trends; land use and cover changes; climate variability. A land degradation model was developped to further analyses the drivers of change.
- **Ground control**: The land degradation maps were evaluated using ground observations/surveys conducted on hot-spots, either dark-spots (degradation) or bright-spots (improvement), in different agro-climatic regions.
- **Reporting and publication**: Various statistics were derived from these maps and interpreted. We further work on preparing these study in for scientific peer-review publicationsin partnership with local institutions (see abstract in annexe)

# 3 METHODOLOGY

It is generally accepted that long-term variations in vegetation cover reflect land productivity. The frequency of vegetation observed over long periods is indeed a good indicator of ecological conditions or changing production conditions - soil fertility, water availability, and land use. It is therefore a measure of the response of ecosystems to the external impacts, whether they are induced by the human activity or natural variability, and provides information on land condition. The reduction or loss of productivity, biological and/or economic, is a common denominator of the various definitions of land degradation (Escadafal and Bégni, 2016). Land productivity is therefore an essential piece of information for degradation monitoring.

Remote sensing data have been recognized for several decades as a powerful tool to map vegetation cover. In particular, the Normalized Difference Vegetation Index (NDVI) is an index of plant greenness or potential photosynthetic activity. Because NDVI has shown consistent correlation with vegetation biomass and dynamics in various ecosystems worldwide (e.g. Myneni et al. 199512), NDVI trends integrated over a time period can be used as a proxy to monitor changes in vegetation productivity.

While remote sensing data, such as the NDVI temporal trends, can provide important insights in past and present states of land condition, it is not sufficient for a degradation diagnosis, nor a subsequent comprehensive assessment of exposure to future degradation (Weinzier et al., 201618). NDVI temporal trends must be analyzed in more detail in relation to available local data on observed land changes and their potential causes. Areas where the dynamics of vegetation productivity decline are most often areas of multiple stressors that threaten sustainable land use. These stressors may be natural, such as drought, or due to human action, such as deforestation or impoverishment of cropland due to overexploitation of the resources. These areas should receive additional attention in the diagnosis and mapping of ongoing land degradation.

To develop the land degradation indicator we proposed a methodology based on two steps: 1. Data collection and pre-processing; 2. Data processing composed of three steps i) Land Use and Land Cover Change analysis; ii) NDVI time-series analysis, iii) Analysis of the climate and human drivers of NDVI trends. The detailed methodology is presented in Figure 5. The analysis was conducted at the national scale, over the 2000-2016 period, with a spatial resolution between 30 m and 250 m.

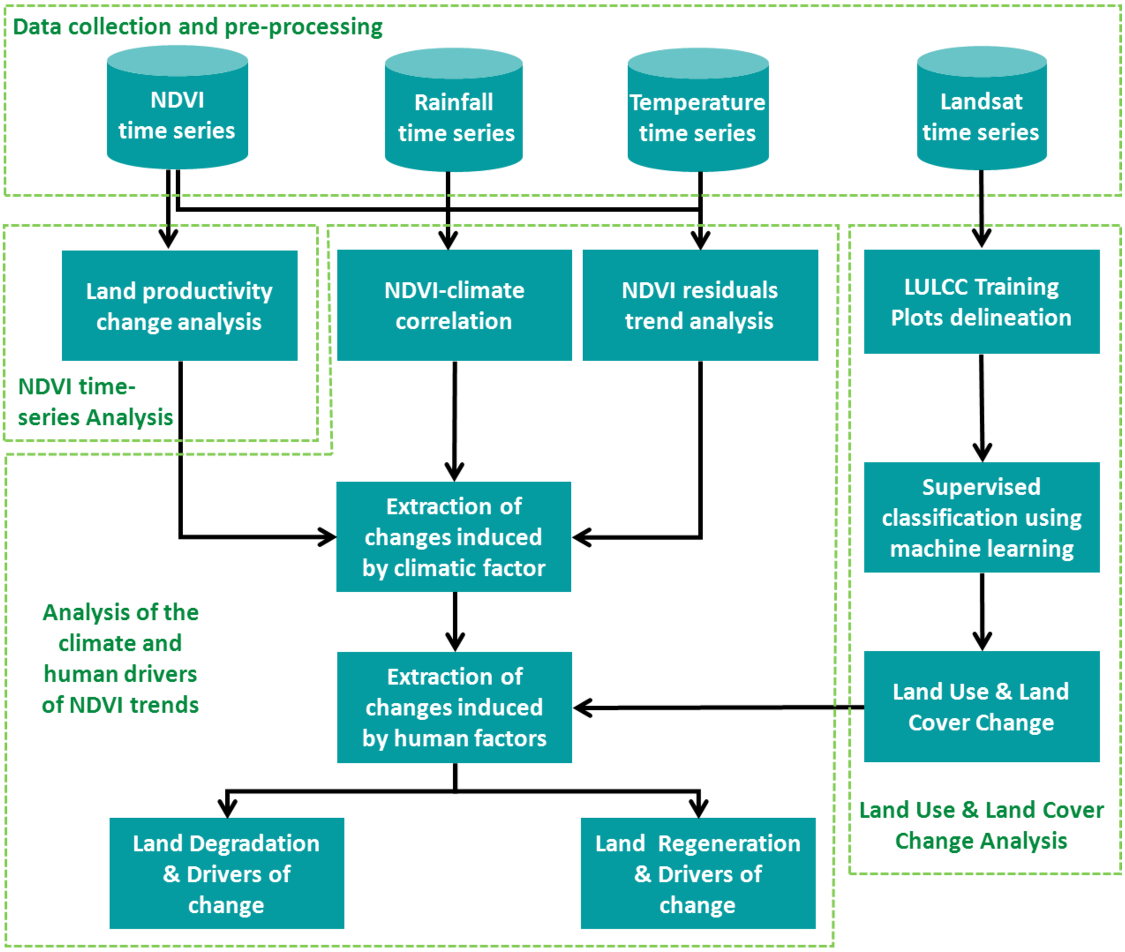



*Figure 5 : The general Land degradation baseline workflow*

## 3.1. Data collection and pre-processing

### 3.1.1 Modis NDVI times series

To analyze the NDVI trends as a proxy for vegetation productivity change, we used the 16-day MODIS NDVI product (MOD13Q1 Collection 6) available at 250 m spatial resolution (Didan et al., 2015). MODIS products were selected because they provide a regular and long term record of vegetation conditions that can be used to detect change and analyze dynamics, and are considered as the most accuracte NDVI record available (Higginbottom and Symeonakis, 2014). MODIS NDVI time series were downloaded using the NASA'S Application for Extraction and Exploring Analysis Ready Samples (AppEEARS). The images time series cover the 2001-2016 period and the entire country. The MODIS image were corrected for molecular scattering, ozone absorption and aerosol (Didan et al., 2015). However, residual noise may persist and disturb the NDVI signal. To reduce this noise, the image time series was pre-processed using a Savitzky-Golay filter (polynomial 3 and windows 4) in order to smooth the data outliers without distorting the signal tendency (Chen et al., 2004). These parameters were iteratively adjusted to minimize the smoothing impact on observations that are known to be accurate, while also sufficiently smoothing outlier values responding to factors other than productivity changes. Then, for each pixel, the annual integrated NDVI was calculated by summing the bi-monthly NDVI values over the year.

### 3.1.2 Rainfall data

Because in Mozambique the rain gauge network is sparse, with few gaps in the temporal records (Toté et al., 2015), we used rainfall estimation from satellite imagery. Rainfall data were obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) rainfall estimates (Funk et al., 2015). After several tests and comparison, CHIRPS products were chosen because they are considered among the most accurate global gridded precipitation products (Beck et al., 2017; Burrell et al., 2018). CHIRPS is a high resolution (0.05°) monthly precipitation dataset, starting in 1981 to near-present, which incorporates satellite imagery with in-situ station data to create gridded rainfall time series (Funk et al., 2015). CHIRPS data were downloaded from 2001 to 2016 using the “heavyRain” R package, and cumulated over the year. The data were resampled using the neighbor resampling method at 250 m to allow the comparison with MODIS NDVI data.

### 3.1.3 Air temperature data

Air temperature data were included is the analysis because temperature is an important factor of vegetation growth (Churkina and Running, 1998), that could explain a part of the vegetation productivity change (Burrell et al., 2019). Temperature data used were the Climate Research Unit Time-series v. 4.01 (CRU TS 4.03) dataset, a global monthly gridded time-series dataset, that covers the 1901-2018 period, and all land areas at 0.5° resolution (Harris et al., 2014). CRU data are based on weather stations measurements. Average maximum temperature was calculated per year for the 2001-2016 period and were resampled using the neighbor resampling method to the MODIS NDVI data spatial resolution of 250 m.

### 3.1.4 Landsat data

The land use and land cover change analysis relies on Landsat imagery as it is the only consistent source of high resolution satellite data available for the period of interest. Our objective was to produce annual (or biannual) cloud-free Landsat composite in order to perform visual observations on land cover changes, and run a supervised classification (see data processing). We used and adapted a Google Earth Engine script that enabled us to 1. access to the full Landsat archive; 2. select suitable images according to the acquisition period; 3. run pre-processing steps including cloud and shadow removal; 4. calculate a cloud-free composite image for the four reference dates. After several tests, we chose images acquired during the transition and dry seasons (April to November) and for 4 time periods (2000/2001, 2005/2006, 2010/2011, 2015/2016). Composite images were produced by calculating the median values of reflectance through the two years time series. The final pre-processed dataset is composed of 4 Landsat and cloud free composite available over the entire country at 30 m resolution.

### 3.1.5 Other geospatial data

In order to perform the statistical analysis of the drivers, we further collected and derived potential explanatory variables based on a literature analysis regarding the main drivers of vegetation productivity change, and the availability of data at national scale. The data were grouped in 5 categories (climatic, natural constraints, accessibility, demography, land use, and land use management) and are presented in Table 2.

*Table 2. List of the geospatial data used for the drivers analysis.*

| Type | Variables name | Description | Data source | Spatial Résolution |
|---|---|---|---|---|
| **Climatic** | | | | |
| | Rainfall | Mean annual rainfall (mm/year) | WorlClim | 1 km |
| | | Annual rainfall trends | TRMM3B43 | 25 km |
| | Temperature | Mean annual temperature (°C) | WorldClim | 1 km |
| **Naturals constraints** | | | | |
| | Altitude | Altitude (m) | SRTM | 30 m |
| | Soil | Soil type | FAO | vector |
| | Soil organic carbone | Soil organic carbon stock (tC/ha) | SoilGrid | 250 m |
| | Soil erosion | Erosion hazard (t.ha/yr) | LAUREL data | 250 m |
| **Accessibility and socio-economic factors** | | | | |
| | Distance city | Euclidean distance from city (m) | INE | vector |
| | Distance villages | Euclidean distance from villages (m) | INE | vector |
| | Distance road | Euclidean distance from roads (m) | OSM, WB | vector |
| | Distance rivers | Euclidean distance from rivers (m) | FAO, WB | vector |
| | Distance edge | Euclidean distance from forest edge (ms) | LAUREL data | vector |
| **Demography and population factors** | | | | |
| | | Population density in 2015 | Worldpop - AfriPop | 100 m |
| | | Population density difference between 2010 and 2015 | Worldpop - AfriPop | 100 m |
| **Land use and land management** | | | | |
| | Land cover | Land cover in 2000 | LAUREL data | 30 m |
| | Cropland loss | Cropland loss between 2001 and 2015 | CCI – ESA | 300 m |
| | Grassland loss | Grassland loss between 2001 and 2015 | CCI – ESA | 300 m |
| | Urbanization | Urban expansion between 2001 and 2015 | CCI – ESA | 300 m |
| | Irrigated area | Irrigated area | NASA | 1 km |
| | Livestock density | Cattle and goats density (head per km²) | GLW v2.0 | 5 km |
| | Fire | Fire frequency between 2001 and 2016 | MODIS burnt areas | 500 m |
| | Protected areas | Protected area categories | WB | vector |
| | Deforestation | % deforestation pixel MODIS – 2000 - 2016 | Laurel data | 250 m |

### 3.1.6 Ground observations

Ground surveys were conducted in order to validate patterns of land use and vegetation changes, and understand the underlying drivers. They were conducted in four provinces (Gaza, Inhambane, Manica, and Zambezia) from April and November 2018. Observations recorded included current and past land use and land cover, vegetation characteristics, natural external pressures, impact of human activities (cultivation, grazing, fire, logging…). These informations were complemented by visual interpretation of Very High Resolution Satellite images.

The field visits were conducted in 4 areas, with constrated landscape features and dynamics in order to capture different land use and vegetation dynamics (Figure 6):

1) **The Gilé National Reserve** (GNR), located in Zambezia Province, composed mainly of Miombo Forest. Currently, the periphery and the buffer zone of the RNG are subject to strong and growing anthropogenic pressures, due mainly to a significant demographic growth, and to slash-and-burn agriculture practices;
2) **The mountain region of Gurué and the Mount Namuli**, located in the northwest of the Zambezia province. The valley is dominated mainly by commercial tea and eucalyptus plantations, and the Mount Namuli's slopes are covered by a mosaic of forests, grasslands, and agricultural land;
3) **The Chimanimani National Reserve** in Manica Province, a mountainous region. The mountains are interspaced with several rocky or grassland plateau as well as deep gorges with evergreen forests;
4) **The semi-arid lowland region of Gaza and Inhambane** provinces in the southern part of the country dominated by cropland and grassland.

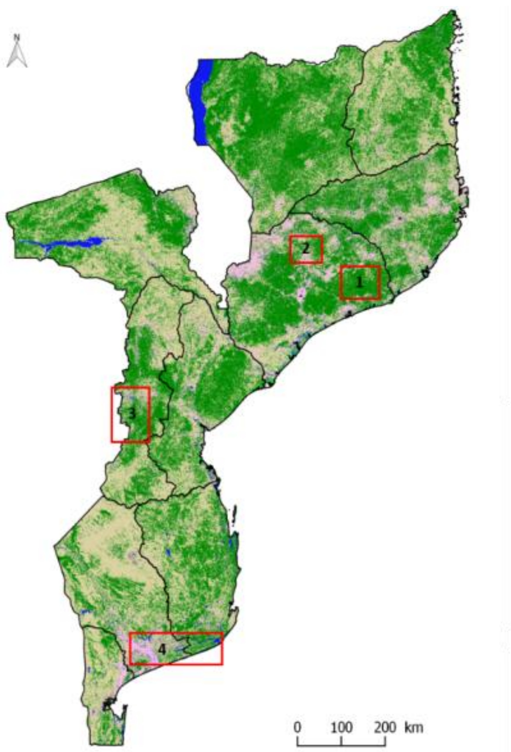



*Figure 6. Location of the 2018 field visits (red squares).*

The field trips consisted in visiting the “red” and “green” areas obtained in the LPC maps, observing the landscape and collecting information about the past and current LULC or pressure (natural or not), in order to identify the main factors of the observed vegetation changes. Illustration maps and ground photos for two study areas (Gilé and Gurué) are presented in Figure 7.

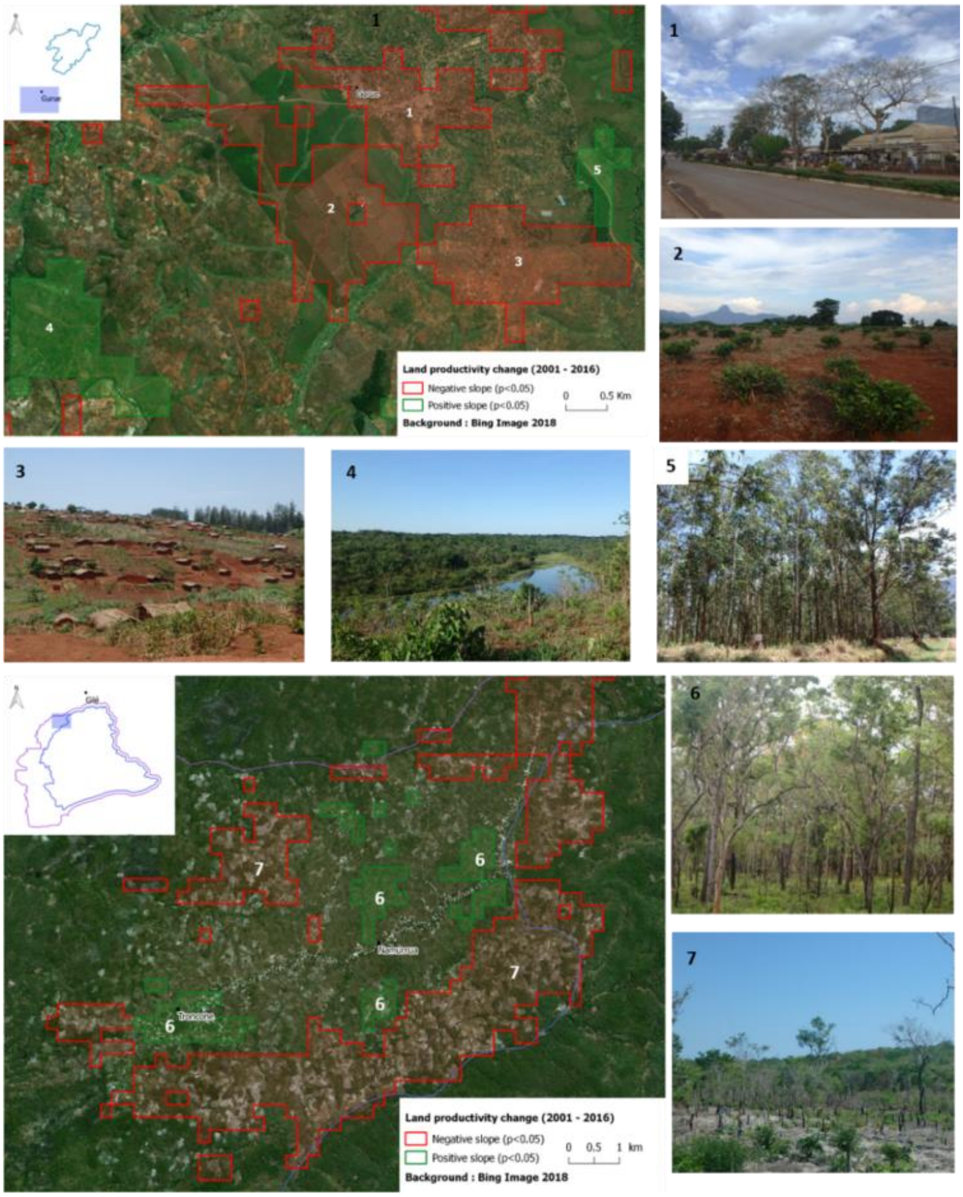



*Figure 7 : Areas of significant vegetation productivity change in Gurué and Gilé provinces. The red and green large pixels indicate areas of decreasing and increasing land productivity, respectively, as assessed using MODIS time series. The numbered ground photos illustrate the LULC of green and red areas samples:*

*- Gurué Région: **picture 1**: Urban densification in Gurué city (red); **picture 2**: Old tea plantation still under exploitation, but degraded (red); **picture 3**: Settlement on an old tea plantation (red); picture **picture 4**: Post-agriculture forest regeneration (green); **picture 5**: Eucalyptus plantation (green).*

*- Gilé Region: **picture 6**: Forest regeneration, 15-20 years old, after slash and burn agriculture and human settlement (green); **picture 7**: Recent deforestation (red).*

## 3.2 Data processing

### 3.2.1 LULCC Analysis

#### *Training plots delineation*

The process of collecting training polygons for a successful model calibration has been fully described in a previous study (Grinand et al, 2013; Rakotomalala et al, 2015). Polygons that represent land uses (LU) in 2016, as well as land cover changes (LCC) between 2000-2005, 2005-2010 and 2010-2016 periods, were delineated. Landsat composites were loaded into a GIS (QGis) and, by iteratively switching on and off the images, land cover changes were visually interpreted and delineated. We used Google Earth very-high resolution images (Open Layer plugin and GEarthView in Google Earth) to ascertain or “ground control” the land uses and get higher degrees of confidence in the land categories. Multiple plots were delineated in clusters over the landscape to better capture the boundaries between two categories throughout the landscape. This work was performed by two operators. Tasks were organized by Province. Finally, 22 4000 plots were collected (Table 3).

**The typology used is the higher level (level 1) of the national land cover classification system** (NLCS) that corresponds to the IPCC land representation categories, to say, the 6 land cover categories: forest, cropland, grassland, wetland, other land (rocks, etc.), settlements. We visually delineated training plots (Region of Interest-ROI) over both Landsat mosaic and Google Earth Images to ascertain land use definition especially forest definition (>30% of canopy cover). We further discriminated mangroves from the other types of forest (mainly open semi-deciduous forest, Miombo forest) since those forests have a very specific spectral signature. Besides, we identified and used 3 land cover change categories: deforestation between 2000 and 2005, 2005 and 2010, and 2010 and 2016.

*Table 3. Number, mean and total area of the training plots used for the classification, by province.*

| Province | Number of training plots | Average size of the training plot (hectares) | Total area of the training plots (hectares) |
|---|---:|---:|---:|
| **Cabo Delgado** | 2 369 | 3.64 | 8 621 |
| **Gaza** | 1 742 | 3.02 | 5 254 |
| **Inhambane** | 1 748 | 2.94 | 5 140 |
| **Manica** | 2 807 | 3.41 | 9 558 |
| **Maputo** | 1 590 | 3.81 | 6 060 |
| **Nampula** | 2 625 | 2.42 | 6 353 |
| **Niassa** | 2 493 | 4.89 | 12 192 |
| **Sofala** | 2 560 | 3.17 | 8 124 |
| **Tete** | 1 647 | 3.84 | 6 330 |
| **Zambezia** | 2 819 | 3.33 | 9 384 |
| **MOZAMBIQUE** | **22 400** | **3.45** | **77 015** |

### *Processing and post-processing*

The supervised classification was performed using the Random Forest (RF) machine learning classifier in the R software (Breiman, 2001). As oftenly used in the litterature, we used the default parameters values. Random Forest produces a bootstrap of small decision trees, the final predicted value is obtained by using a majority vote of every single tree predictions. This non-linear algorithm is recognized to prevent for over-fitting of the model.

The model was built using the training plots database (shapefile) intersected with the Landsat composite time series (4 dates with the 9 Landsat bands). A 30 m Digital Elevation Model (DEM) from SRTM was added to the variables stack, in order to account for biophysical and environmental constraints (e.g. mangrove in the littoral). The iterative process described above was performed by province in order to ease the training plots delineation and production of interim maps process. The final RF model was calibrated using the full dataset (2.4 billions of pixels with 37 variables) over the entire country in order to account for the full signature of the class and avoid boundary effects.

Once calibrated, we analysed the confusion matrix provided by the algorithm (Out-of-the-bag errors) to evaluate the omission and commission errors. The model was then applied to the full landsat times series (4 dates) composite stack to produce the raw LULCC map.

The raw LULCC map was further processed. These “post-processing” steps are described below:

- Reclassification of LULCC to get the LULC in 2000;
- Sieving of all categories at 1 ha in LULC 2000;
- Sieving of deforestation categories at 0.36 ha in order to account for the 1 pixel geometric accuracy and remove the noise, inherent to such process;
- Intersection of LULC 2000 with deforestation categories;
- Extraction of individual dates: LULC 2000, LULC 2005, LULC 2010, LULC 2016.

### 3.2.2 NDVI time series analysis

The vegetation productivity changes were analyzed using a statistical trend analysis based on an Ordinary-Least Square (OLS) regression over a 16-year period (2001-2016), applied to each pixel of the annual NDVI time series. OLS is applied to quantify change in the dependent variable (NDVI value) against an independent variable (time). The significance of the slope coefficient was determined using the p-value at a 95% confidence level ($p\text{-value}<0.05$). Three classes of significancy ($0.01<\text{value}<0.05$, $0.001<p\text{-value}<0.01$, $p\text{-value}<0.001$) were defined. The direction of change (increase or decrease in productivity) was determined using the sign of the slope coefficient. Each pixel was then classified regarding these two parameters. Finally, the resulting map has seven classes: three classes for significant increase, three classes for significant decrease, and one class for non significant trend at a 95% confidence level (p-value>0.05).

### 3.2.3 Mapping drivers of Land Productivity Changes

To understand the main drivers of the land productivity change, a two-step framework was applied: first the climate effect was extracted using rainfall and temperature datasets, and then the human activities effects were extracted using LULCC dataset and ground knowledge.

#### *Climate*

This step aims to separate the vegetation changes induced by the rainfall or temperature trends, from the vegetation changes due to other factors, following the methodology proposed by Leroux et al. (2017). In order to separate the relative role of rainfall/temperature changes or other causes, this study proposed a classification scheme based on the NDVI-climate data correlation and the NDVI residuals trends analysis over the 2001-2016 period.

*NDVI-climate data correlation:* The Pearson correlation coefficient between annual cumulated NDVI value and, annual cumulated Rainfall value and annual average maximum temperature value, was calculated for each pixel. The correlation was considered statistically significant at the 95% level (p-value<0.05), corresponding to r = 0.4973 or r = -0.4973, according to the Bravais-Pearson table. Pixels with a significant correlation are largely characterized by a negative correlation between temperature and NDVI, and a positive correlation between NDVI and rainfall. For the next step, we only considered the positive NDVI-rainfall and negative NDVI-temperature correlations.

*NDVI residuals trends analysis:* To distinguish climate-induced changes from the effects induced by other factors, such as the human factors, the climatic component is removed from the NDVI trends, using a robust and widely accepted method currently known as RESTREND (Evans and Geerken, 2004; Wessels et al., 2007). This procedure consists of: 1. Fitting a linear model between the annual cumulated NDVI value and the annual cumulated rainfall value or annual average maximum temperature per pixel; 2. Performing a new trend analysis on the model residuals. Trends in the residuals could be interpreted as the part of the vegetation productivity that is not explained by the rainfall or temperature inter-annual variability.

*Mapping rainfall effect:* In order to assign relative effect of rainfall or temperature and other factors to NDVI change, we used a classification scheme close to the one proposed by Leroux et al. (2017). This classification scheme is based on 6 decision rules depending on the slope of the NDVI trend and its significance (p-value < 0.05), the coefficient of correlation between NDVI and Rainfall/temperature, the slope and the significance of the Residuals trends (p-value < 0.05) (Table 4). As a result, pixels are classed into 3 classes of change: 1. Rainfall/Temperature change only; 2.

Rainfall/temperature change and other factors; 3. Other factors. According to Leroux et al. (2017), if the correlation between NDVI and rainfall/temperature is significant, and if the sign of the slopes of the NDVI and NDVI residual trends are identical, the vegetation productivity changes in a larger proportion than if it was due to the climate alone. On the contrary, if the sign of the slopes of the NDVI and NDVI residual trends are opposite, the vegetation productivity change is explained mainly by the climate. If there is no correlation between NDVI and rainfall/temperature, the vegetation productivity is driven by other factors than climate. This analysis is carried out separately for rainfall and temperature data, and results into 6 classes of change: 1. Rainfall change only; 2. Temperature change only; 3. Rainfall change and other factors; 4. Temperature change and other factors; 5. Rainfall and temperature change and other factors; 6. Other factors.

*Table 4. Classification scheme to assign relative effect of rainfall or temperature and other factors to NDVI changes.*

| NDVI trends (p-value < 0.05) | Coefficient of correlation NDVI-Rain | Coefficient of correlation NDVI-temperature | Residuals trends (p-value < 0.05)* | Change Factor |
|---|---|---|---|---|
| **Slope >0** | r > 0.4973 | r< -0.4973 | Slope >0 | Rainfall/temperature change + other |
| | r > 0.4973 | r< -0.4973 | Slope < 0 or n.s | Rainfall/temperature change |
| | r < 0.4973 | r> -0.4973 | | Other |
| **Slope <0** | r > 0.4973 | r< -0.4973 | Slope <0 | Rainfall/temperature change + other |
| | r > 0.4973 | r< -0.4973 | Slope > 0 or n.s. | Rainfall/temperature change |
| | r < 0.4973 | r> -0.4973 | | Other |

*n.s : not significant

### Human activities

This step aims to differentiate the “other factors of change” category from the previous analysis (with no correlation between NDVI and climate data), using the LULCC map to represent the potential factors of change due to human activities. A classification scheme based on decision rules depending on the slope of the NDVI trend and its significance (p-value < 0.05), and the LULCC category was proposed (Table 5). Each potential change factor represents the main potential factor for productivity change related to each LULC category. These potential factors come from expert opinion, review of literature and in-situ observation (see section 3 “Ground control”) regarding the current and past LULC, vegetation characteristics, natural and anthropic pressures.

*Table 5: Classification scheme for human induced factors.*

| NDVI trends | LULCC | Change Factor |
|---|---|---|
| **Slope >0 Positive** | Forest 2016 | Native Forest Growth or Plantations |
| | Cropland 2000 – 2016 | Agricultural Productivity Increase or Fallow regrowth |
| | Grassland 2000 – 2016 | Grassland Productivity increase |
| | Mangrove 2000 - 2016 | Mangrove Productivity increase or Regrowth |
| | Urban area 2016 | Urban greening |
| | Other land use | Others (undifferentiated multiple factors) |
| **Slope <0 Negative** | Forest 2000 & defor.> 10% | Deforestation |
| | Forest 2000 – 2016 | Forest degradation |
| | Cropland 2000 – 2016 | Agricultural Productivity Decline |
| | Grassland 2000 – 2016 | Grassland Productivity Decline |
| | Mangrove 2000 - 2016 | Mangrove degradation or deforestation |
| | Urban area 2016 | Urban expansion or densification |
| | Other land use | Others (undifferentiated multiple factors) |

### 3.2.4 Statistical analysis using Random Forest

To complement the above analysis of the underlying factors of NDVI trends, we tested a multivariate and stastiscal analysis. Random forest algorithm was used to statistically classify and identify the main important factors at national scale. To accomplish this, the variables presented in the Table 2 were used as explanatory variables in RF, while NDVI trend classes (negative, positive or not significant) were treated as the variables to be explained.

# 4 RESULTS

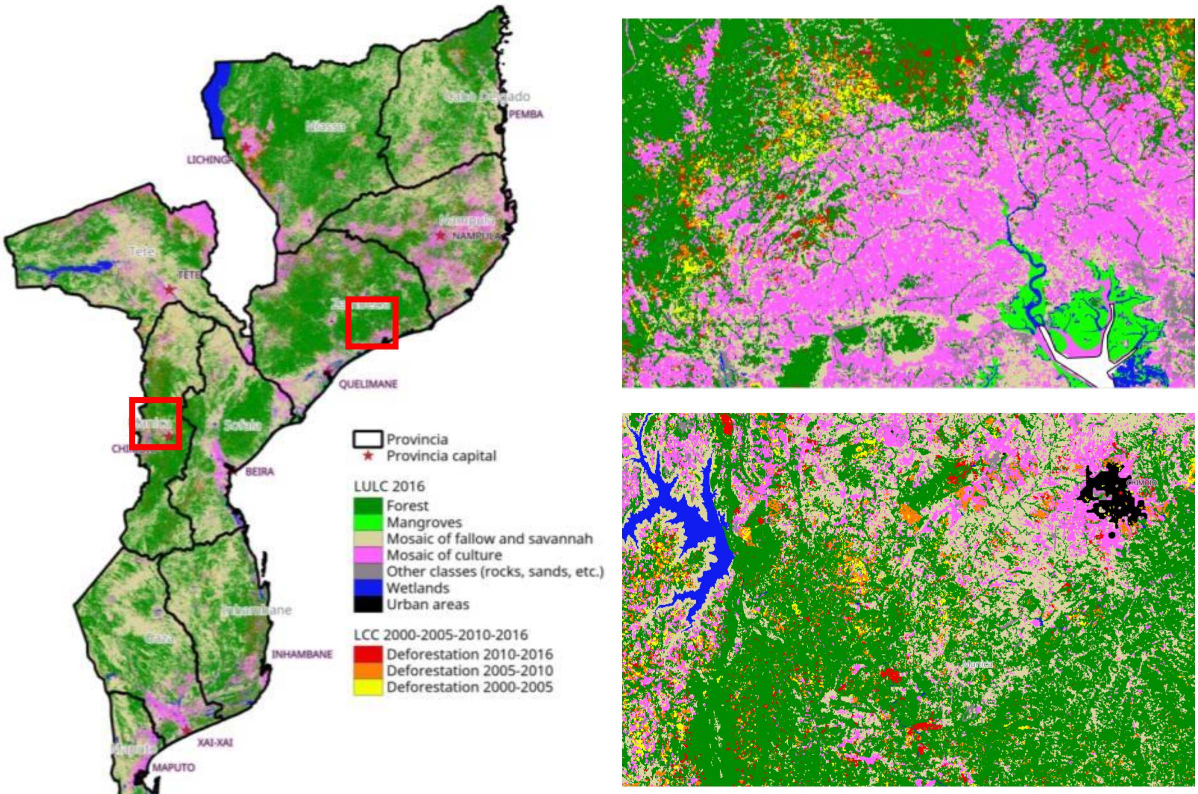
## 4.1 LU&LCC map and statistics

The final LULCC map for 2000-2016 is presented in Figure 8. We observed an overall pattern of 45% (35.8 Mha) of dry forest, 0.3% (0.271 Mha) of mangroves, 37% (29.3 Mha) of grassland and fallow, 13.7% (10.8 Mha) of cropland, 2% (1.63 Mha) of wetland, 1.3% (1 Mha) of other categories (rocks, sands, bare soils) and 0.1% (0.67 Mha) of urban areas (see

Table *6* and Table 7 for results per province). These values are broadly in agreement with the 2016 national Land Use and Land Cover map currently being finalized.

The annual deforestation for the 2000-2016 period was 207 272 ha per year (Table 8). This value is slightly lower than the Forest Reference Emissions Level (FREL) values for the 2000-2016 period (269 000 +/- 12 000 ha yr$^{-1}$), but could be considered conservative.

*Pebane region*




*Chimoio region*

*Figure 8 : Final Mozambique LULCC 2000-2016 map, with zooms in Pebane (top) and Chimoio (bottom) regions.*

*Table 6: Mozambique LULC area statistics for 2016.*

| Province | Forest | Grassland | Cropland | Other land | Wetland | Urban areas |
|---|---|---|---|---|---|---|
| **Cabo Delgado** | 2 926 934 | 3 933 151 | 739 500 | 70 912 | 40 617 | 11 193 |
| **Gaza** | 2 845 284 | 3 574 690 | 931 528 | 142 037 | 108 007 | 2 807 |
| **Inhambane** | 2 777 743 | 3 271 923 | 569 857 | 92 914 | 164 153 | 1 703 |
| **Manica** | 2 499 358 | 2 912 514 | 804 033 | 38 179 | 19 291 | 3 004 |
| **Maputo** | 467 161 | 1 557 183 | 248 558 | 13 738 | 49 814 | 27 380 |
| **Nampula** | 3 458 305 | 1 444 821 | 2 542 157 | 259 790 | 42 587 | 10 735 |
| **Niassa** | 7 201 799 | 3 584 979 | 1 077 650 | 277 940 | 702 486 | 1 858 |
| **Sofala** | 2 996 370 | 2 554 350 | 1 012 334 | 96 888 | 74 353 | 3 743 |
| **Tete** | 3 884 902 | 3 567 188 | 2 382 564 | 27 986 | 288 700 | 2 417 |
| **Zambezia** | 5 368 239 | 1 397 831 | 3 083 217 | 190 894 | 135 814 | 4 711 |
| **MOZAMBIQUE** | **34 426 095** | **27 798 632** | **13 391 398** | **1 211 280** | **1 625 823** | **69 550** |

*Table 7: Mozambique area statistics of the forest class calculated from the LULCC 2000-2016 map (ha).*

| Province | All forest type (except mangrove) | | | | Mangrove |
|---|---|---|---|---|---|
| | 2000 | 2005 | 2010 | 2016 | 2016 |
| **Cabo Delgado** | 3 752 290 | 3 651 826 | 3 554 292 | 3 494 461 | 27 745 |
| **Gaza** | 2 998 345 | 2 934 797 | 2 887 113 | 2 862 194 | 454 |
| **Inhambane** | 3 318 406 | 3 229 709 | 3 137 710 | 3 044 096 | 15 331 |
| **Manica** | 3 561 874 | 3 445 190 | 3 281 111 | 3 141 596 | 0 |
| **Maputo City** | 2 609 | 2 552 | 2 537 | 2 521 | 515 |
| **Maputo Prov.** | 708 742 | 703 350 | 696 640 | 680 465 | 3 692 |
| **Nampula** | 3 127 457 | 2 960 164 | 2 846 760 | 2 625 383 | 42 222 |
| **Niassa** | 8 149 633 | 8 020 012 | 7 875 534 | 7 711 423 | 0 |
| **Sofala** | 3 150 127 | 3 108 333 | 3 027 820 | 2 976 344 | 59 237 |
| **Tete** | 3 622 774 | 3 528 640 | 3 389 847 | 3 275 914 | 0 |
| **Zambezia** | 6 567 546 | 6 381 863 | 6 200 247 | 6 036 267 | 122 040 |
| **MOZAMBIQUE** | **38 959 804** | **37 966 435** | **36 899 611** | **35 850 663** | **271 235** |

*Table 8: Mozambique area statistics for deforestation calculated from the LULCC 2000-2016 map (ha yr$^{-1}$).*

| Province | Deforestation (Forest loss in hectares/year) | | | |
|---|---|---|---|---|
| | 2000-2005 | 2005-2010 | 2010-2016 | 2000-2016 |
| **Cabo Delgado** | 20 093 | 19 507 | 11 966 | 17 189 |
| **Gaza** | 12 710 | 9 537 | 4 984 | 9 077 |
| **Inhambane** | 17 739 | 18 400 | 18 723 | 18 287 |
| **Manica** | 23 337 | 32 816 | 27 903 | 28 019 |
| **Maputo City** | 11 | 3 | 3 | 6 |
| **Maputo Prov.** | 1 078 | 1 342 | 3 235 | 1 885 |
| **Nampula** | 33 459 | 22 681 | 44 275 | 33 472 |

| | | | | |
|---|---|---|---|---|
| **Niassa** | 25 924 | 28 896 | 32 822 | 29 214 |
| **Sofala** | 8 359 | 16 103 | 10 295 | 11 586 |
| **Tete** | 18 827 | 27 759 | 22 787 | 23 124 |
| **Zambezia** | 37 137 | 36 323 | 32 796 | 35 419 |
| **MOZAMBIQUE** | **198 674** | **213 365** | **209 789** | **207 276** |

## 4.2 NDVI trends between 2001 and 2016

The annual vegetation productivity trends statistics for the 2001-2016 period at national level are presented in Figure 9 and Table 9. The NDVI trend analysis shows that a large proportion of the country (77%) is characterized by an overall stable trend, meaning there is no significant land productivity change over the period. **Among the significant trends, 19% of the total area display negative NDVI trends, with clear spatial patterns of decreasing trends in Inhambane, Zambezia and Nampula provinces**. On the other hand, **only 3% of the total area display positive NDVI trends**, mainly observed along the Zambezia and Sabi rivers, and in the Maputo, Niassa and Cabo Delgado provinces.

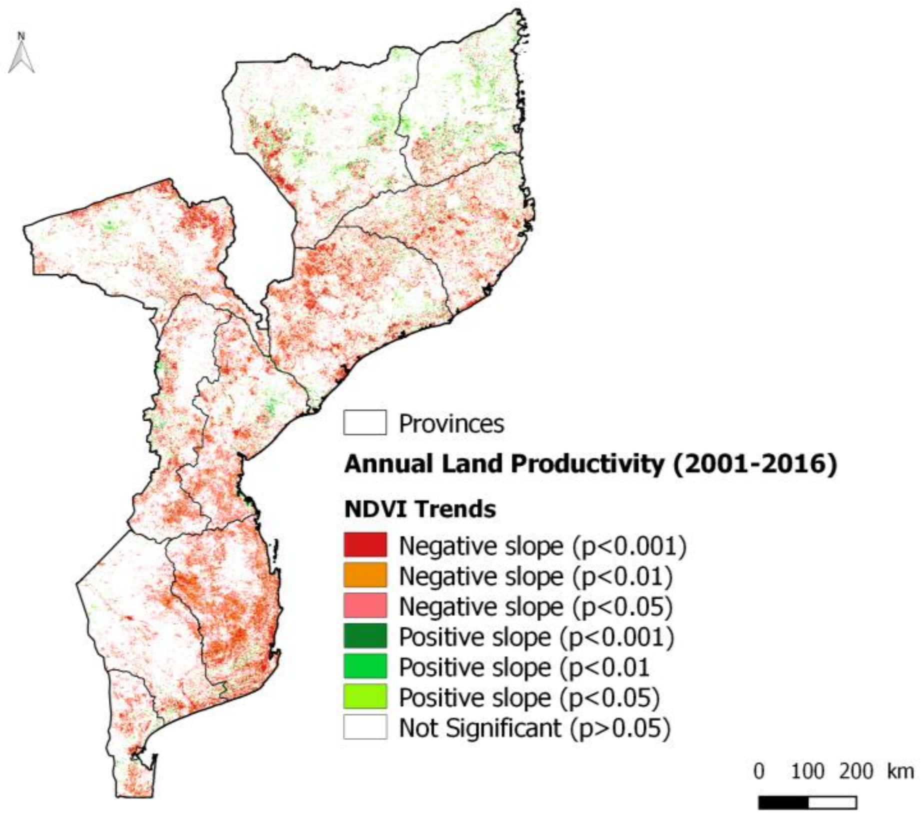



*Figure 9. Annual land productivity trend maps of Mozambique calculated for the 2001-2016 period: a) NDVI trend without climate correction, b) NDVI trend with rainfall correction, c) NDVI trend with temperature correction.*

*Table 9. Distribution of annual land productivity trend of Mozambique calculated for the 2001-2016 period with and without climate correction.*

| Annual | NDVI trends | | Restrends Rainfall (CHIRPS data) | | Restrends Temperature (CRU data) | |
|---|---|---|---|---|---|---|
| Trends classes | Area (ha) | % | Area (ha) | % | Area (ha) | % |
| Decrease (p<0.05) | 15 266 681 | 19.38 | 13 100 414 | 16.63 | 13 308 811 | 16.89 |
| Increase (p<0.05) | 2 706 431 | 3.44 | 3 038 069 | 3.86 | 2 437 929 | 3.09 |
| Stable | 60 725 361 | 77.08 | 62 550 150 | 78.39 | 62 919 403 | 79.86 |

At provincial level, although all the provinces display mostly non-significant land productivity changes between 2001 and 2016, the results differ greatly from one province to another (Figure 10).

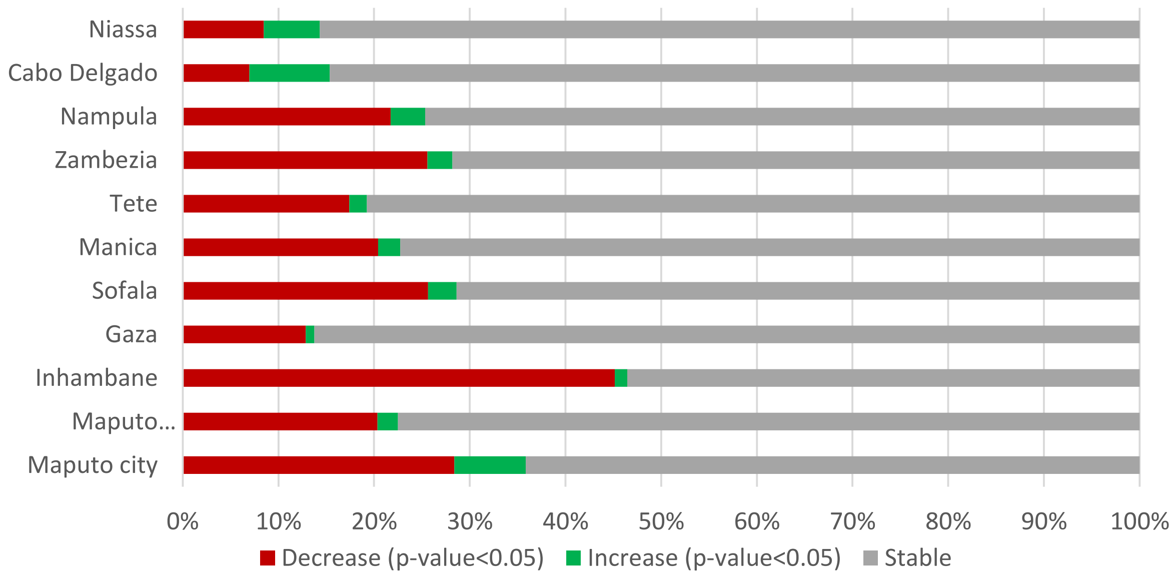



*Figure 10. Distribution by province of the land productivity trend classes (NDVI trends).*

## 4.3 Analysis of climate variability effect on NDVI trend

### 4.3.1 NDVI and climate

A large part of the country did not exhibit significant NDVI-rainfall and NDVI-temperature relationships during the 2001-2016 period (84 % and 80 % of the total area, respectively; see Figure 11 and Table 10). Areas with significant correlation are largely characterized by a positive correlation between NDVI and rainfall (18% of the total area) and a negative correlation between NDVI and temperature (14 % of the total area). Significant NDVI and climatic variables relationships are spatially heterogeneous and more importantly distributed in the semi-arid region of the southern provinces. This result is in agreement with the observations of Ichii et al. (2002) on dryland vegetation.

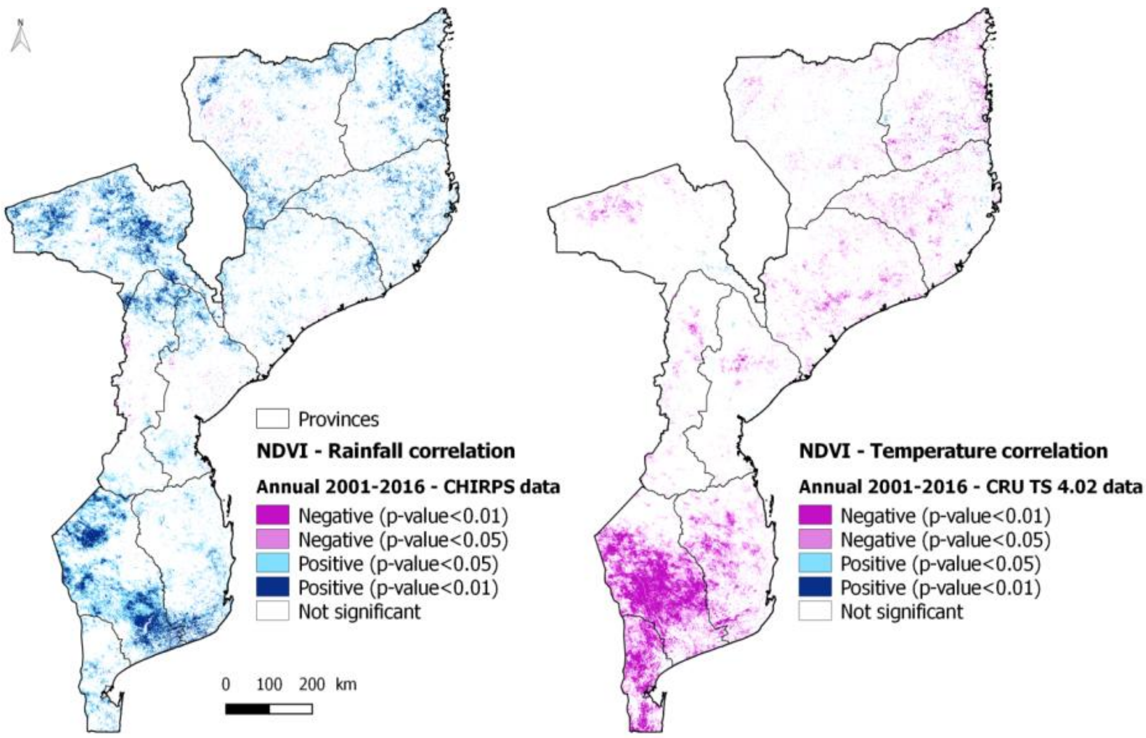



*Figure 11. NDVI-rainfall and NDVI-temperature relationship during the 2001-2016 period (Pearson-coefficient, statistically significant at the 95% level or r= 0.4973 or r=-0.4973).*

*Table 10. Area statistics of the NDVI-rainfall and NDVI-temperature correlations for the 2001-2016 period.*

| | NDVI-Temperature correlation | | NDVI-Rainfall correlation | |
|---|---|---|---|---|
| | Area (ha) | % total area | Area (ha) | % total area |
| Negative (p<0.05) | 11 360 573 | 14.42 | 289 418 | 0.37 |
| Positive (p<0.05) | 34 186 | 0.04 | 14 555 363 | 18.48 |
| No correlation | 66 468 162 | 84.37 | 63 347 776 | 80.41 |

### 4.3.2 NDVI residual trends analysis

As previously explained, the RESTREND method removes the influence of the climate variability on the NDVI trends, in order to help identifing the human factors contributing to the land productivity increase or decrease (Evans and Geerken, 2004). A large proportion of the country (79 %) is characterized by an overall stable NDVI residual trend over the 2001-2016 period, meaning that a significant part of the dynamic is not explained by the rainfall and temperature inter-annual variability alone (Table 9). Among the significant trends, 16.6 % and 16.9 % of the total area have negative NDVI, while 3.9 % and 3.1 % of the total area have positive trends, with rainfall and temperature correction, respectively

### 4.3.3 Mapping the rainfall effect

**The classification scheme, presented in Table 4, allows us to assess the respective role of the climate variability and others factors in the NDVI trends**. Results presented in Table 11 show that the climate variability alone (rainfall or temperature) is responsible for 1.14% of the increase trend and 12.63% of the decrease trend over the 2001-2016 period. **Temperature effect is more pronounced on vegetation dynamics (especially decrease trends) than rainfall effect. Climatic variability combined with other factors explained 4.21 % of the increase trend and 16.67 % of the decrease trend**. The spatial distribution of the factors shows that the climatic variability (mainly temperature) is one of **the main factor of NDVI change in the southern provinces** (Figure 12). However, a significant part of the land productivity dynamics is not explained by climate variability (93.9 % of the increase trend and 69.8 % of the decrease trend).

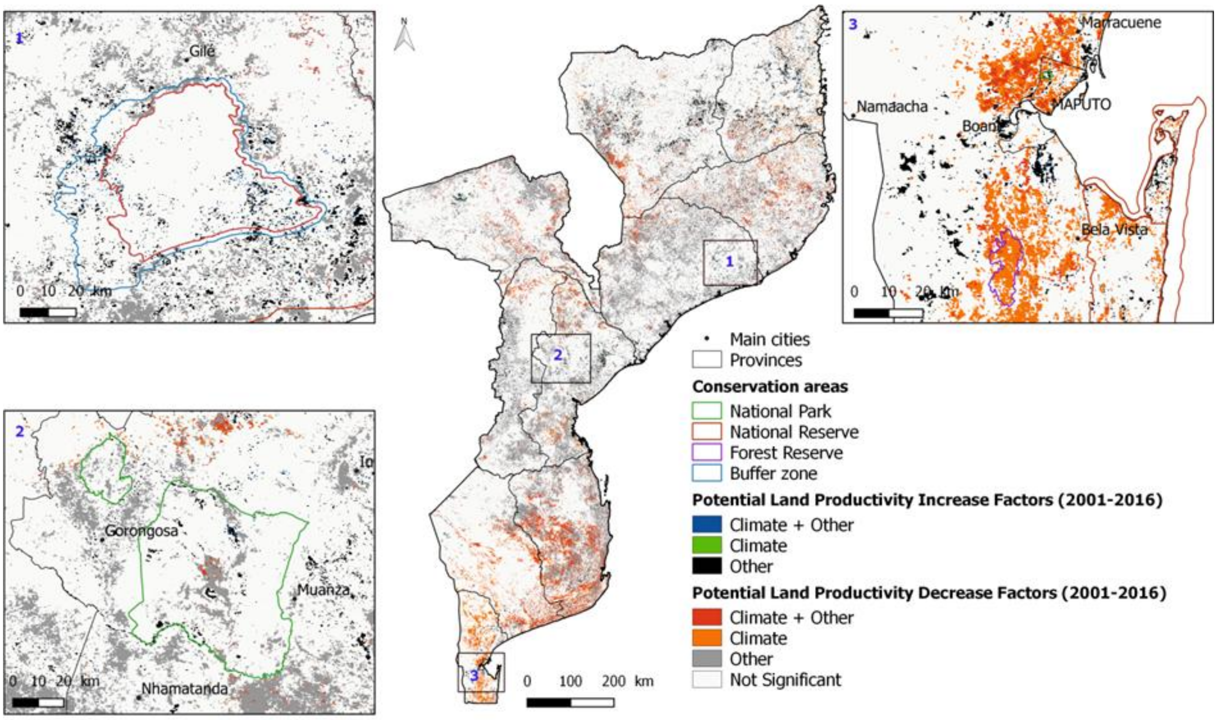



*Figure 12 : Spatial distribution of the climate drivers of the NDVI trends.*

*Table 11. Spatial distribution of the climate drivers of the NDVI trends.*

| NDVI trends | Change factor | Area (ha) | % increase /decrease |
|---|---|---|---|
| Increase | Rainfall change + other | 67374 | 2.49 |
| | Temperature change + other | 45353 | 1.68 |
| | Rainfall & Temperature change + other | 1162 | 0.04 |
| | Temperature change | 14559 | 0.54 |
| | Rainfall change | 16 607 | 0.61 |
| | Other | 2 542 722 | 93.95 |
| Decrease | Rainfall change + other | 1 157 213 | 7.58 |
| | Temperature change + other | 906 005 | 5.93 |
| | Rainfall & Temperature change + other | 482 020 | 3.25 |
| | Rainfall & Temperature change | 13 909 | 0.09 |
| | Temperature change | 1 205 712 | 7.90 |
| | Rainfall change | 708 495 | 4.64 |
| | Other | 10 656 406 | 69.80 |
| Not significant | | 60 725 361 | |

## 4.4 Analysis of the human drivers of NDVI trends

### 4.4.1 At national level

Since a large part of the NDVI trends cannot be explained by climate changes, it is important to go more deeply in the interpretation of the potential others factors related to human activities. The classification trees presented in Table 5, based on the slope of the NDVI trend and the LULC category, are used to assess the contribution of the other factors to NDVI change according to in-situ observation and expert knowledge. **Land cover classes that display an increase or decrease NDVI trends between 2001 and 2016 are mainly forest, cropland and grassland** (Figure 13, Figure 14, Table 12).

For the positive trends, according to the LULC categories:

- N**ative forest growth or commercial plantations account for 45% of the total NDVI increase trends** and mainly occurred in the northern part of the country;
- **Grassland experienced an increase in vegetation productivity due possibly to management or bush encroachment, accounting for 23% of the total NDVI increase trends**;
- Agricultural productivity increase or fallow regrowth in cropland (linked to the slash and burn agriculture practice) accounts for 16% of the total NDVI increase trends.

For the negative trends, according to the LULC categories:

- Forest degradation (burning, illegal logging, charcoal production or mining) and deforestation represents a large part of the NDVI decrease trends (21% and 17% of the decreased trend, respectively). The areas characterized by a decrease trend due potentially to deforestation are mainly localized in the Zambezia and Nampula provinces;

- The grassland productivity decline, potentially due to natural pressure or overgrazing, is mainly found in the southern provinces, and accounts for 20% of the NDVI decrease trend;
- The cropland productivity decline, possibly due to erosion, fertility depletion, or salinity, accounts for 8% of the NDVI decrease trend.

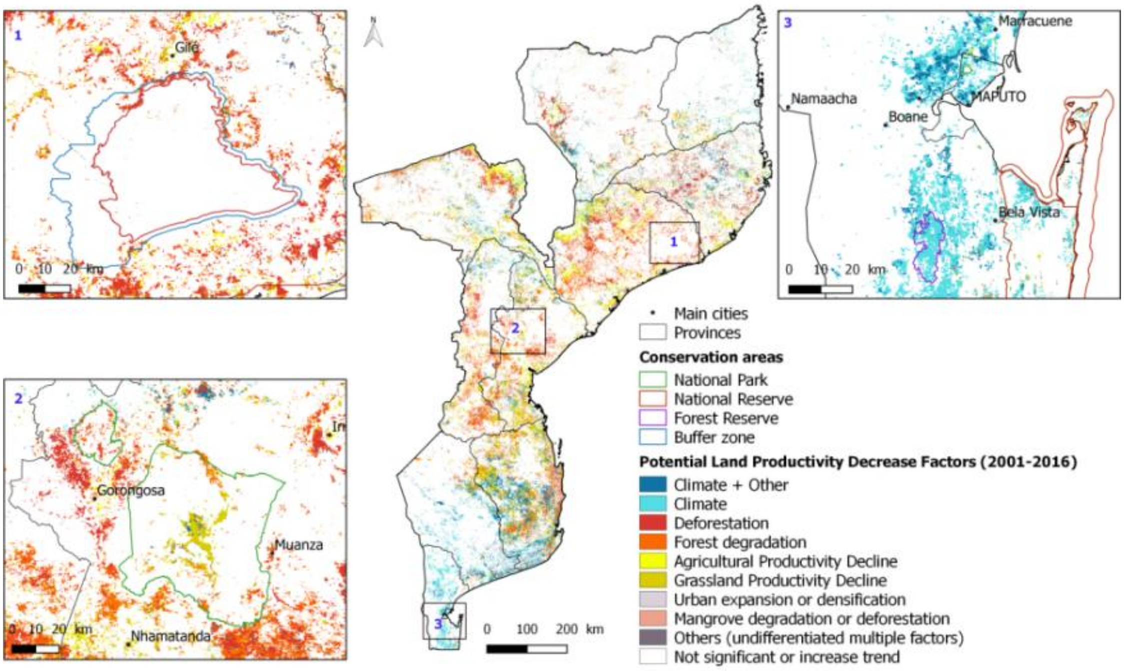



*Figure 13. Spatial distribution of the main drivers of the biomass production decrease.*

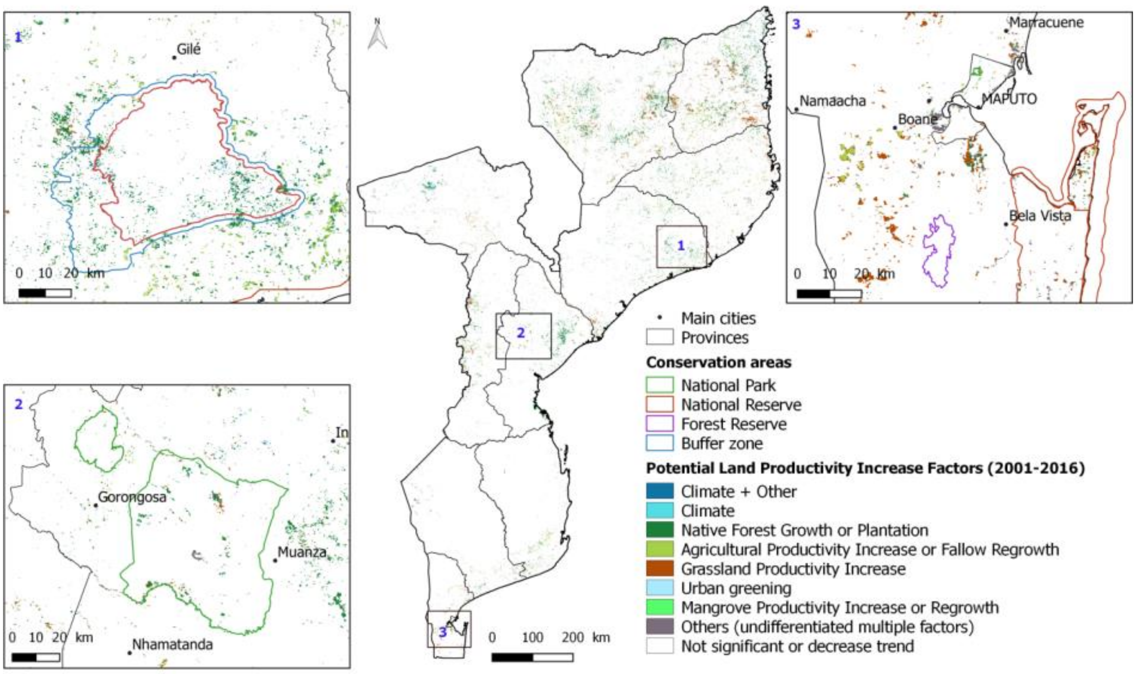


*Figure 14. Spatial distribution of the main drivers of the biomass production increase.*

*Table 12. Distribution of the main drivers of the biomass production change.*

| Land productivity | Potential factors | hectares | % increase or decrease |
|---|---|---|---|
| **Increase** | Native Forest Growth or plantation | 1 211328 | 44.8 |
| | Grassland Productivity Increase | 621 403 | 23.0 |
| | Agriculture Productivity Increase or Fallow regrowth | 423 944 | 15.7 |
| | Climate change + Other | 115 132 | 4.2 |
| | Mangrove Productivity Increase or Regrowth | 35 752 | 1.3 |
| | Climate change | 30 787 | 1.1 |
| | Urban greening | 1 876 | 0.1 |
| | Others (undifferentiated multiple factors) | 254 291 | 9.4 |
| **Decrease** | Forest degradation | 3 197 355 | 21.0 |
| | Grassland Productivity Decline | 3 055 765 | 20.0 |
| | Deforestation | 2 557 396 | 16.8 |
| | Climate change + Other | 2 555 090 | 16.7 |
| | Climate change | 2 064 190 | 13.5 |
| | Agricultural Productivity Decline | 1 294 960 | 8.5 |
| | Urban expansion or densification | 16 885 | 0,1 |
| | Mangrove degradation or deforestation | 47 927 | 0,3 |
| | Others (undifferentiated multiple factors) | 522 493 | 3.4 |

### 4.4.2 At provincial level

Distributions by province of land productivity change drivers are presented in Figure 15 and 16. Niassa and Cabo Delgado provinces are characterized by an increase trend that can be explained by forest regeneration/plantation and grassland management/bush encroachment. These two provinces contain the largest area of national parks and reserves in Mozambique, and are characterized by low human population densities. This situation, together with favorable climatic conditions, could explain the increase in vegetation productivity.

Zambezia and Nampula provinces are characterized by decreasing trends. These two provinces have the country's highest population density, after Maputo province, and the country's highest deforestation rates between 2003 and 2013 (GoM, 2018). Zambezia and Nampula provinces have also extended cropland (mostly small-scale farms), but a large part of this cropland is characterized by a decrease in productivity. This decline could be linked to soil erosion, salinity problems and soil fertility depletion due to agriculture practices. This can affect greatly the agriculture productivity and, consequently, the national economy and food security.

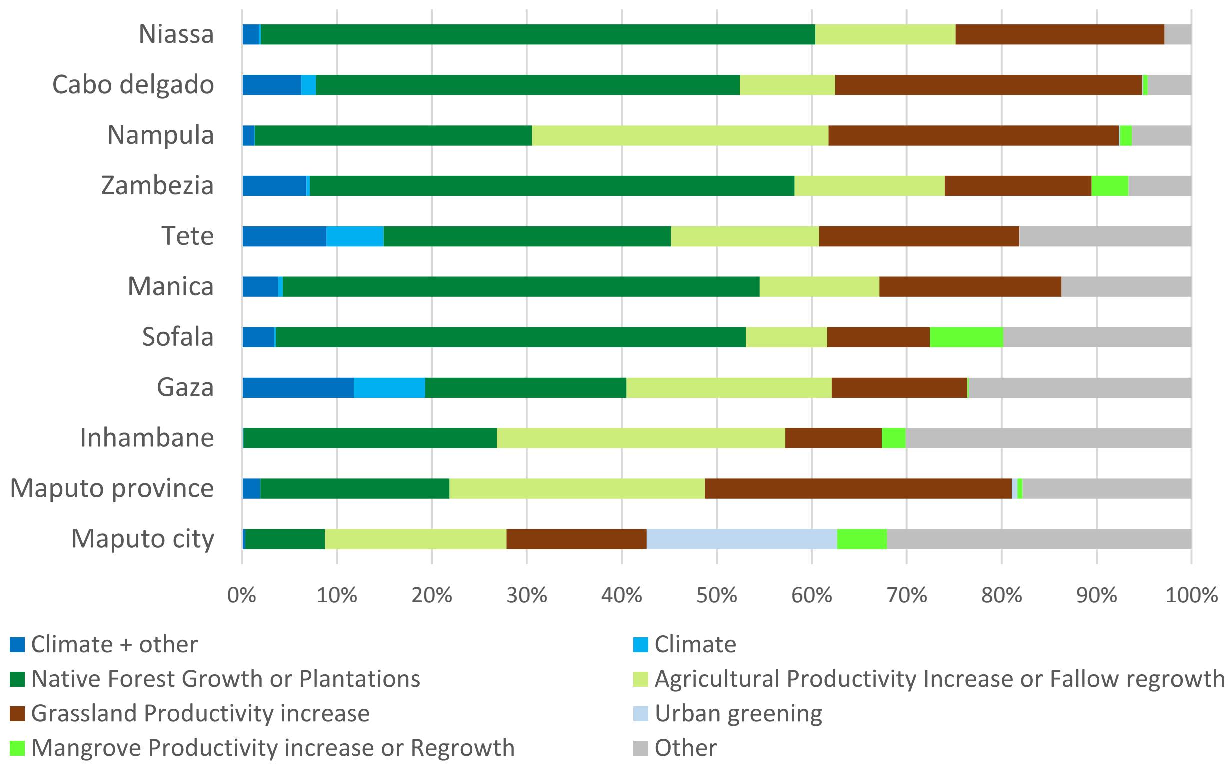



*Figure 15. Distribution by province of land productivity increase drivers.*

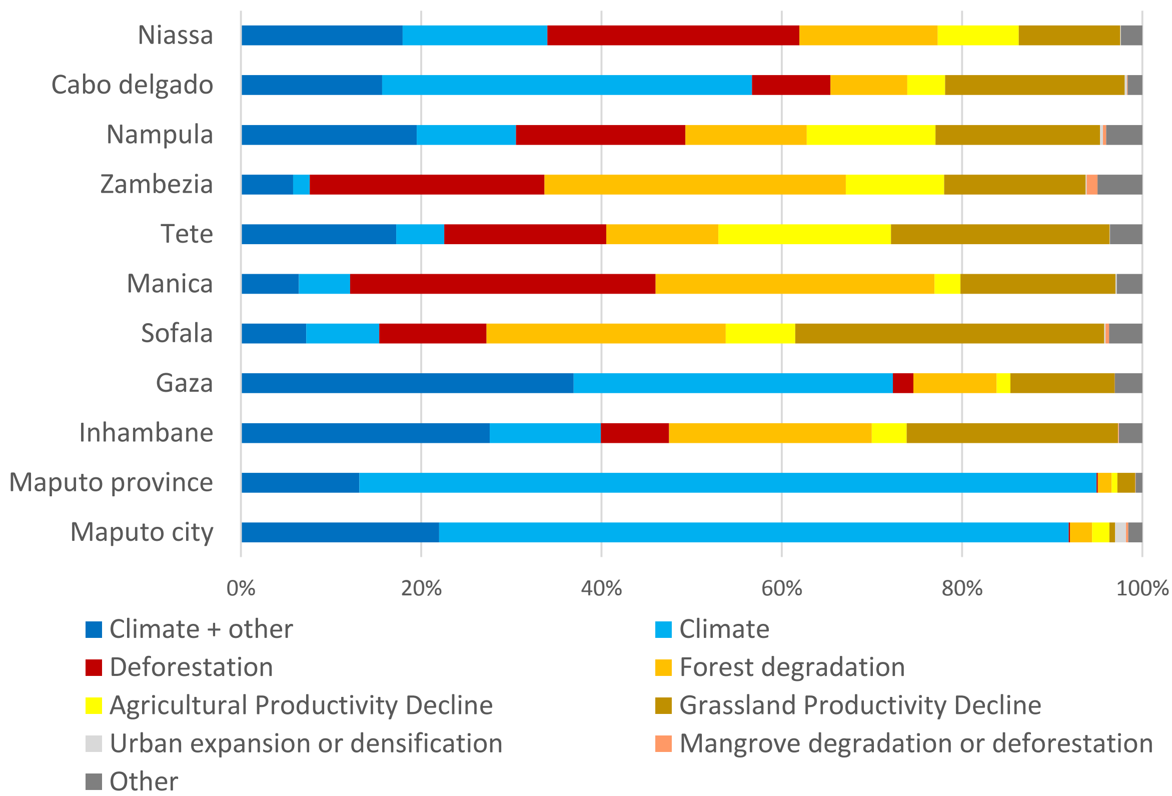



*Figure 16. Distribution by province of land productivity decrease drivers.*

## 4.5 Random forest analysis

A Random Forest algorithm was used to identify the most important drivers of NDVI changes. Figure 17 and 18 show the relative importance of the contribution of the variables to the RF classification model for the negative and positive trends.

**For the negative trends the most important variables identified by the RF model are the deforestation and the rainfall** (mean annual rainfall and rainfall trend over the 2001-2016 period). This result shows the importance of deforestation, estimated at 207 272 ha per year for the 2000-2016 period by the LULCC analysis, in the vegetation productivity decline in Mozambique.
**The most important factors identified by the RF model for the positive trends are linked to the climatic variables and population density**. This suggests that the human activities have a strong impact on increasing vegetation productivity.

This analysis identifies the most important factors of significant trend at national level, but does not provide spatial and quantitative information on the contribution of each factor permitting to identify priority areas of intervention for restoration or conservation of land resources. This confirms the relevance of the approach developed with the classification scheme to isolate the relative role of climate variabilities and human activities to understand the underlying drivers of vegetation changes.

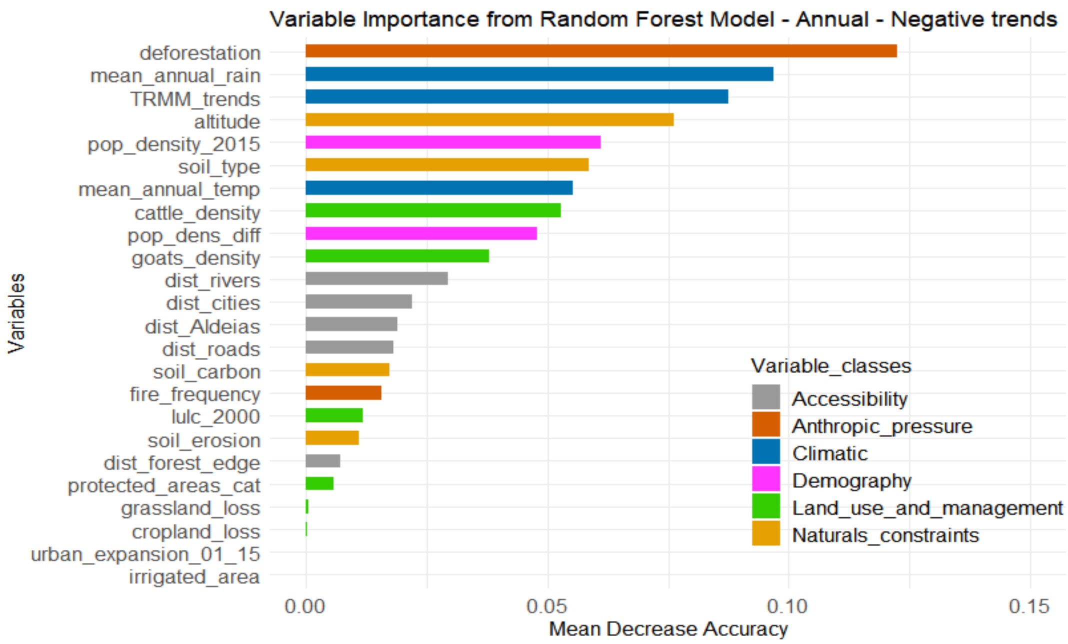



*Figure 17. Variables importance in the Random Forest model according to negative trends classes at national level.*

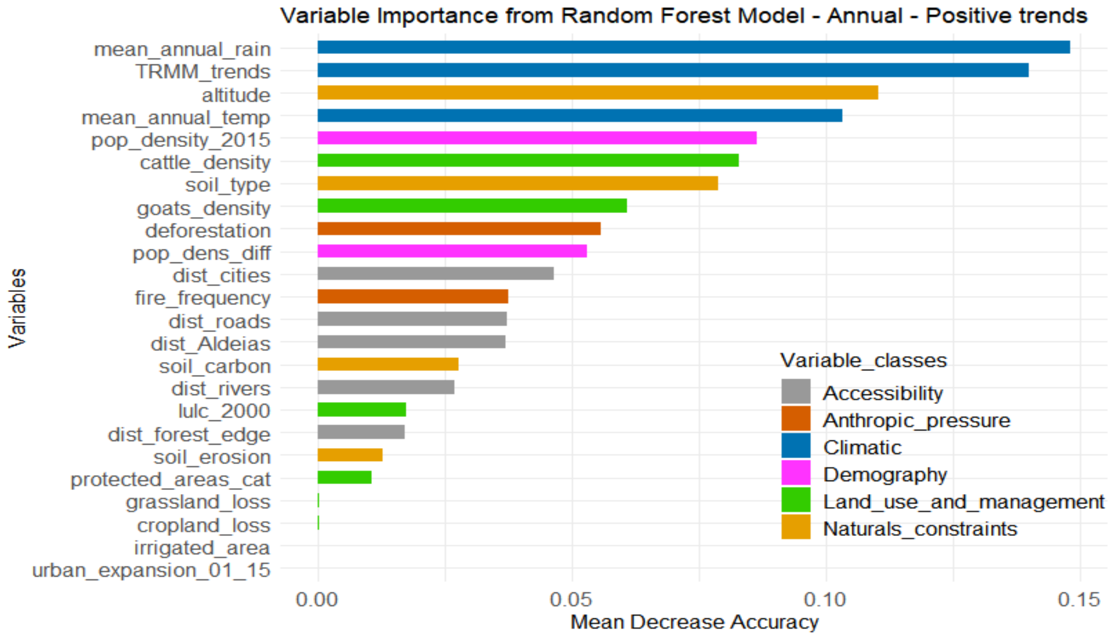



*Figure 18. Variables importance in the Random Forest model according to positive trends classes at national level.*

# 5 OTHER LAND DEGRADATION INDICATORS

## 5.1 Rationale

The two previous indicators (land productivity change and land cover and land cover change) are the most important indicators of land status and trend, based on biophysical evidence (soil and vegetation energy captured or reflected). Thanks to satellite data and archive, we are able to depict fine process of land change over the last 15 years.

However, there are limits: In one hand, Land Use and Land Cover Change map cannot be used solely for land degradation estimate, and in the other hand, Land Productivity Change is inclusive and does identify all forms of productivity change, which can be caused by a wide range of factors (agriculture intensification, village expansion, fallow, mining, soil erosion, plantations, etc.).

Land degradation in the current policy framework is not yet well defined but some recommendations exists, including to work on 3 sub-indicators (land productivity change, land cover and land cover change, and carbon stocks above/below ground), and does require to account for national evidence or agreed form of land degradation. Therefore, we further worked on three other land degradation indicators: **Soil erosion** (identified at the beginning of this assignment, **soil organic carbon** (mandatory in the land degradation global guidance), and **biodiversity** (highly important for Mozambique).

Those indicators are not directly derived from satellite or direct measurements; they are derived from various sources of information (with their own uncertainty) and/or expert knowledge. In addition, those indicators are not related to a particular point in time which limits their use in calibration of validation of the LandSIM prototype. However, we believe they provide useful information in a land degradation status and should be part of the land degradation baseline assessment.

In Table 13, we provide a summary of these three additional indicators. They are further presented in the following sections.

*Table 13. Description of the three additional land degradation indicators.*

| Other Land degradation indicators | Justification | Methods | Pros&cons |
|---|---|---|---|
| Soil organic carbon | SOC is a commonly agreed indicator of many ecosystem services: food production, erosion control, biodiversity and climate change.<br><br>SOC is a mandatory indicator of Land Degradation (SDG's) | SOC is measure on the field (soil survey) and samples are analyzed in soil laboratory. Recent digital soil mapping techniques allow estimating soil properties at pixel level, depicting the gradient over soil properties in the landscape and quantified uncertainties.<br>SOC stocks values are in tonnes of carbon by hectare. | SOC maps as any soil mapping exercise, takes time and are expensive. Digital soil scientist communities recently succeed to produce global and high-resolution soil maps. National initiatives are currently working on developing a national SOC map (legacy soil survey, 2015 National Soil and Forest inventory, DSM techniques) |
| Soil erosion | Soil erosion is considered in many countries as one of the main threat of Land Degradation.  It results from a combination of multiple factors: removal of vegetation layer, intense rainfall, slope gradient and length, and land practices. | Many quantified and spatially explicit soil erosion method exist, the most common approach is the Revised Universal Soil Loss Equation (RUSLE). Initially developed in the USA, it has been used worldwide in many studies. It use a proxy of rain erosivity (rainfall), soil erodibility derived from soil properties (mainly soil texture), topography (mainly slope) and land cover & land use factors, estimated from ground measurement or expert knowledge. | The USLE method allows carrying out a rapid soil erosion assessment and at a low cost. The advantage is to provide a scientifically sound and quantified framework. However, the method does rely heavily on input factors, their own uncertainties, and assumptions (e.g. crop factor value assigned by land cover type) and does not account for temporal dynamics (rainfall). This method allows to express soil erosion in tonnes of soil loss by hectares, but due to those constraints, authors refers also to soil erosion *hazard* or vulnerability. |
| Biodiversity | Biodiversity is an broadly agreed indicator of land degradation and provide many ecosystem services: food production, ecosystem resilience, water provision, etc. | Biodiversity is a wide indicator, including theoretically, both fauna and flora species, richness and diversity. Since most of biodiversity is present in forested ecosystem, most of the biodiversity studies use forest cover and structure (fragmentation, connectivity, patch size, etc.) as a proxy of biodiversity. Other biodiversity study used ground observations and ecological modeling techniques to directly estimate species distributions and richness. | Biodiversity studies based on forest cover and structure provide a mean to rapidly assess this complex indicator. However ecological researches do not have an agreed and quantified measurement and it fail to capture biodiversity gradient due to forest type and species composition.<br>Quantitative and observation-based biodiversity studies enable to estimate agreed biodiversity indicators such as richess of Shannon index. However it requires a large amount of field records, which takes years and is expensive. |

## 5.2 Soil organic carbon

Soil is a key indicator of land degradation as this natural resource - often considered as "non-renewable" at human time scale - provides key ecosystem services such as climate change regulation, food provision, control of erosion and water holding capacity. Hence, soils and especially soil organic carbon (SOC) indicators are currently the focus of several multilateral agreements and other international processes, including Land Degradation Neutrality mechanism. SOC was clearly identified as one of the three sub-indicator of Sustainable Development Goals 15.3.1 "Proportion of land degraded over total land area".

There is currently no published soil organic carbon stock map in Mozambique. In LAUREL, developing a new soil carbon map or products on soil properties is beyond the scope of this project. Such studies involve gathering existing national soil database, carry out additional soil surveys at un-sampled locations and analyze each soil samples in a soil laboratory. Finally, spatial and ground data need to be processed using digital soil mapping (DSM) approach to provide spatially-explicit and operational products. All those steps require substantial amount time and important financial resources.

However, global and national initiatives can overcome these limitations and enable soil information integration into land degradation baseline and LANDSIM simulations. Those include:

- **SoilGrids[1] data portal**. This is an international initiative from the Global Soil Partnership which aims to provide high resolution soil properties maps at global scale using cutting-edge DSM methodologies and gathered and harmonized global soil database. Soil grid products are produced by International Soil Reference Information Centre (ISRIC) — World Soil Information.
- **National Soil Organic Carbon map**. To our knowledge there is currently a national SOC map under development from Mozambican Soil Research team including IIAM[2]. This map would be an important source of information since it would include national and recent soil inventory.

We used soilgrids data and soil organic carbon stocks. The outputs map we produced represents the levels of SOC storage (tons of soil organic carbon by hectare) at 250 m resolution for the 0 to 200 cm soil layer (Figure19).

[1] www.soilgrids.org, ISRIC, World Soil Information
[2] https://www.youtube.com/watch?v=ErVxM6bdmrE

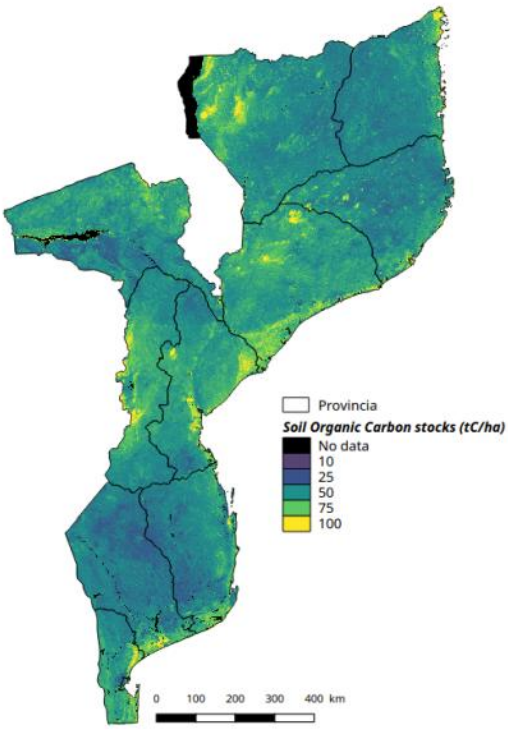



*Figure 19 : Soil Organic Carbon Stock map (tons C/ha) for 0-200 cm soil layer at 250 m resolution derived from SoilGrids database. Sediment export and retention maps for Mozambique (Mandle et al, 2016).*

*Table 14 : Soil Organic Carbon stocks statistics by Provinces.*

| | SOC stocks (tons/ha) | | | |
|---|---|---|---|---|
| **Province** | **mean** | **s.d.** | **min** | **max** |
| Niassa | 54 | 12 | 25 | 213 |
| Cabo Delgadao | 49 | 11 | 20 | 270 |
| Nampula | 49 | 11 | 23 | 206 |
| Zambesia | 60 | 11 | 28 | 257 |
| Tete | 53 | 11 | 20 | 203 |
| Manica | 58 | 13 | 24 | 229 |
| Sofala | 58 | 13 | 24 | 187 |
| Inhambane | 48 | 11 | 16 | 166 |
| Gaza | 44 | 11 | 19 | 219 |
| Maputo | 57 | 13 | 24 | 182 |
| Cidade de Maputo | 60 | 19 | 27 | 169 |
| **MOZAMBIQUE** | **54** | **12** | **16** | **270** |

From the Figure 19, one can observe very clear patterns of soil properties distribution. High SOC stock or "hot spot" (High Carbon Value) of soil carbon are mainly located in two type of area:

- On estuaries of large Mozambican rivers estuaries: on the estuary of Limpopo river in Gaza, around XaiXai city, on the estuary of Rio Pungoe in Sofala south of Beira city, and in the large estuary of Zambesia river. This is explained by ancient and current soil mineral particle (clay, loam) and organic matter deposit during flood events.
- On highlands and mountainous region, in Niassa around Lichinga city and forested landscape, in Manica west of Chimoio in the highlands and National Reserve of Chimanimani and some specific location in Zambesia, in the mountains around Gurue. This is explained by slower mineralization process due to reduced temperature and reduced soil biological activity. It may also coincide in many parts with areas with remaining forest (less accessible).

## 5.3 Soil erosion

Many quantified and spatially explicit soil erosion methods exist, the most common approach being the Revised Universal Soil Loss Equation (RUSLE), developed in 1965 by Wischmeier and Smith to predict long time average soil losses in run-off from specific field areas in specified cropping and management systems. We based on analysis on two recent studies (2013 and 2016) that both used the RUSLE method, and were conducted in South Africa and Mozambique:

- **Soil erosion prelimininary study in Mozambique** (Mandle et al., 2016). This study conducted in 2016 by Natural Capital Assessment program was a first attempt to derive soil erosion and sedimentation information using thethe Revised USLE method and the Invest Software. To our knowledge this study was not continued, but another National Capital Assessment program is currently being developed.
- **RUSLE application in a South African watershed** (Breetzke et al., 2013). This study proposed to compare to famous method for soil erosion assessment in several catchments in South Africa. Authors made a great analysis, especially providing reference values for each of 6 factors of USLE, especially on the Crop and Management factors (C).

The RUSLE method disaggregates the erosion process into 5 factors. Initially developed in the USA, this method has been applied in many studies around the world for rapid assessment of erosion hazard. The RUSLE equation is as follow (see Table 15 and Table 16 for the factors description and dataset used):

$$A = R \times K \times LS \times C \times P$$

*Table 15. The RUSLE factors and datasets used in this analysis.*

| USLE factors | Description | Dataset used and calculation |
|---|---|---|
| A | Mean annual soil loss (t $ha^{-1}$ $yr^{-1}$ ) | |
| R | Rainfall and runoff erosivity index | Rainfall data from WorldClimt (v1.2) of 1 km resolution. Calculation were performed using GRASS r.usele R algorithm. |
| K | Soil erodibility factor | Soil texture (sand, silt and clay) 250 m soil properties map from soilgrid dataset |
| LS | Slope and length of slope factor | SRTM 30 m Digital Elevation Model . Calculation were performed using Grass r.watershed algorithm. |
| C | Cropping – Management factor | Data and look-up-table as indicated in Mandle et al, (2016 ) and Breetzke et al (2013) as presented in Table . Land Cover map is the LAUREL LULC 2016 (April version, presented in this report) |
| P | Erosion control factor practice | set to 1 |

*Table 16. C factors used applied for the LAUREL LULCC map classes.*

| Land use and land cover 2016 | Crop and management factor (C) | Erosion control factor (P) |
|---|---|---|
| Forest | 0,018 | 1 |
| Mangrove | 0,001 | 1 |
| Grassland | 0,021 | 1 |
| Crop | 0,180 | 1 |
| Other land | 0,000 | 1 |
| Wetland | 0,000 | 1 |
| Settlement | 0,130 | 1 |

*Table 17. Statistics area report on erosion hazard in Mozambique.*

| Erosion hazard | Hectares | % |
|---|---|---|
| Very low (0-1 t/ha) | 74 153 627 | 96,4% |
| Low (1-4 t/ha) | 2 453 694 | 3,2% |
| Moderate (4-10 t/ha) | 250 233 | 0,3% |
| High (10-25 t/ha) | 59 995 | 0,1% |
| Very high (>25 t/ha) | 9 326 | 0,0% |

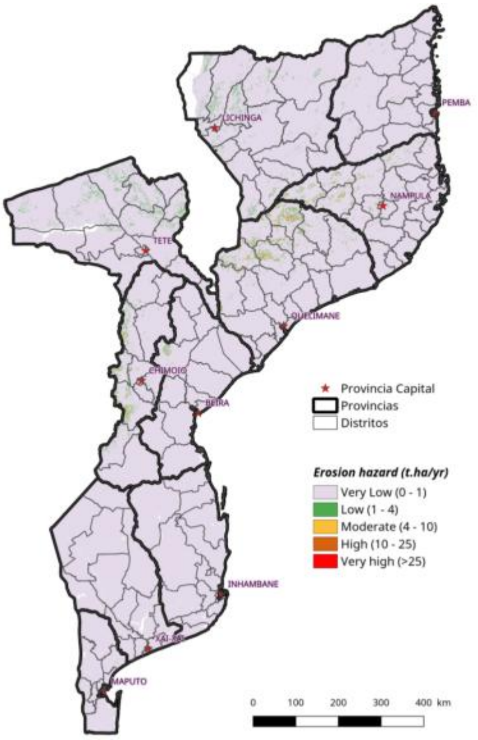



*Figure 20. Erosion hazard map in Mozambique.*

The Mozambique soil erosion hazards are presented in Table 17 and Figure 20. From this preliminary analysis, we observed that the extension of erosion is limited, restricted to small patch of mountainous areas in Mozambique, thanks to a dominant flat and low land landscape. This also reflects the initial discussion on soil erosion relative importance in Mozambique during the kick-off mission.

## 5.4 Biodiversity

The decline or loss in biodiversity is a globally agreed indicator of land degradation (IPBES, 2018). Biodiversity studies based on forest cover and structure provide a mean to rapidly assess this complex indicator. However ecological researches do not have an agreed and quantified measurement and often fail to capture biodiversity gradient due to forest type and species composition. Quantitative and observation-based biodiversity studies enable to estimate agreed biodiversity indicators such as richess of Shannon index. However it requires a large amount of field records, which takes years and is expensive and consequently there is a lack of available data and knowledge regarding species occurrence and distribution.

New spatial modeling tools that combine biodiversity's observations with environmental variables enable to provide rapid, large-scale, current and future biodiversity distribution patterns. These tools can produce species distributions maps and produce scenarios of biodiversity evolution under climate of land use change.

A similar tool based on Species Distribution Models (SDMs) is under development as part of an ongoing project in Madagascar (BioSceneMada[3] - collaboration with CIRAD). The final goal of this study is to support the identification of high priority areas for biodiversity conservation. The methodology is based on 6 steps : 1) collect biodiversity observations; 2) Derive and select the relevant environnemental variables; 3) Model species distribution using SDMs; 4) Combine all the results (# models, # species); 5) Apply land use change and climate change scenarios; 6) Assess hot spots of biodiversity and priorities of conservation (Figure 21).

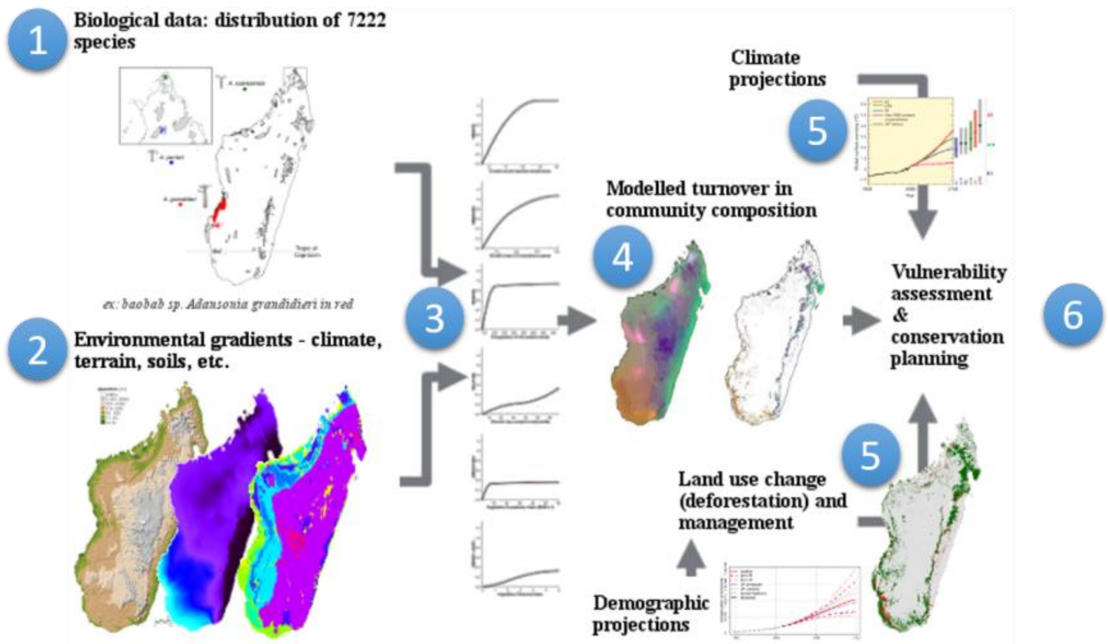



*Figure 21 : Methodology to produce scenarios of biodiversity evolution under climate change (BioSceneMada project)*

This methodology has been applied in Mozambique using the open-source GBIF dataset for different taxonomic groups: amphibians, reptiles and mamals (after pre-processing and cleaning steps) and 7 climatic variables (WorldClim data) and the Laurel LULCC 2016 map to derive forest cover (%). Five SDMs (Random Forest, Maxent, Artificial Neural Network, Generalized Additive Model, and Generalized Linear Model) were applied and their outputs combined to drive the species distribution map.

Due to a lack of biodiversity observations (only few data are available on open/public database and usable) results are preliminary and need to be completed. However, an exemple is presented in the Figure 22 and show the potential of the methodology to: 1) map species current ecological niche, 2) exploring future and potential distribution of the species, assessing hot spot of biodiversity and 3) calculating composite biodiversity index based of individuals maps. This indicator can be used then for

[3] https://bioscenemada.cirad.fr

modeling loss of biodiversity under climate of land use change and derived indicator of land degradation.

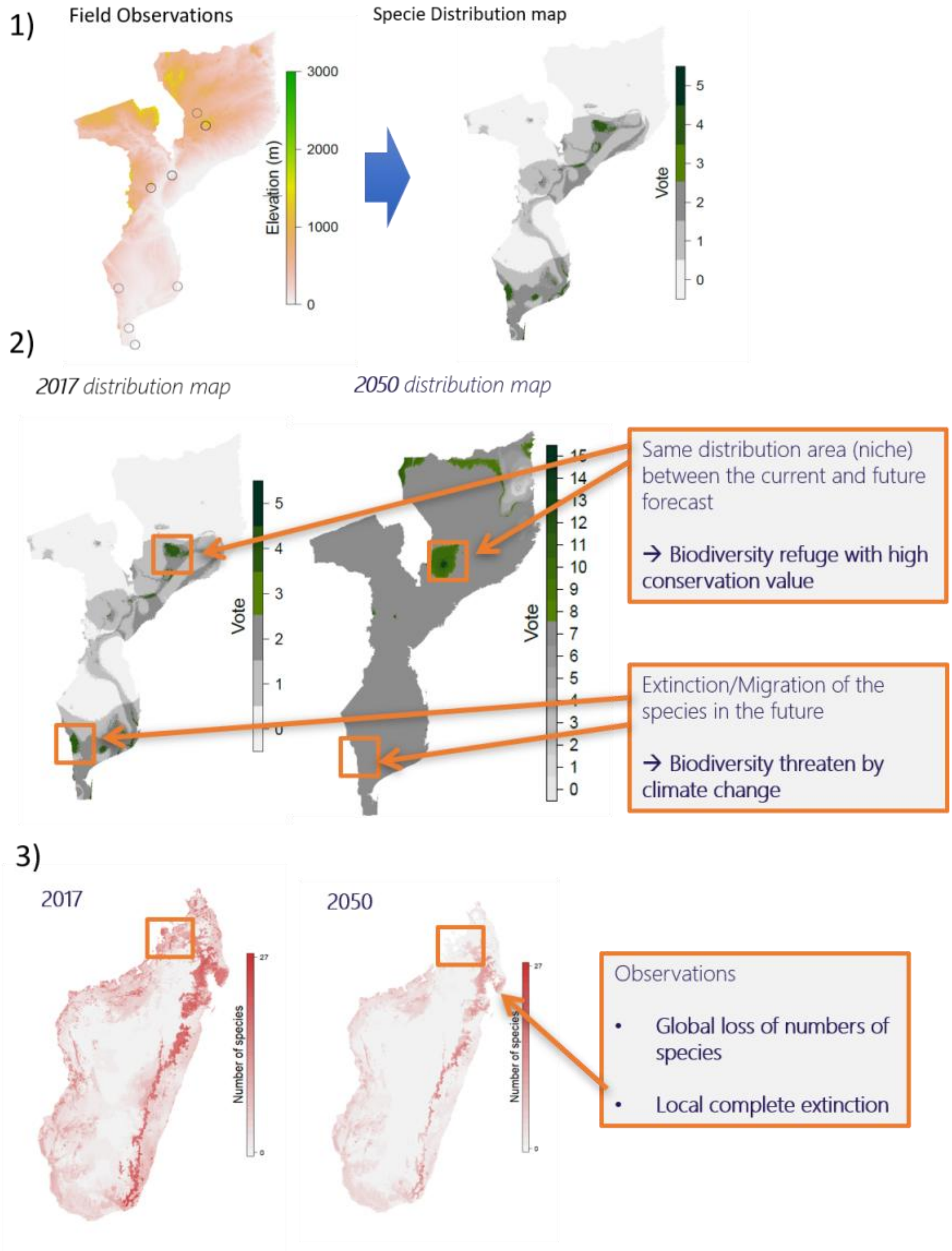



*Figure 22 : Main results of the spatial modelling tool*

Futhermore, this tool can be used to identify the Key Biodiversity Areas (KBAs) in Mozmabique. KBAs are defined as "sites that contribute significantly to the global persistence of biodiversity, in terrestrial, freshwater and marine ecosystems". The concept of KBA was developed following the observation that site conservation was one of the most effective ways to reduce the loss of global biodiversity, and that it was therefore essential to identify the sites where unique biodiversity must be protected immediately. Sites are considered as global KBAs if they contain one or more biodiversity elements that meet one or more of the 11 criteria listed in the KBA IUCN Global Standard (IUCN, 2016). These KBA criteria and their associated quantitative thresholds are standardized worldwide. They can be applied to species and ecosystems and are grouped into five categories: threatened biodiversity; geographically restricted biodiversity; ecological integrity; biological processes; and irreplaceability.

In Mozambique, the 21 terrestrial, freshwater and marine KBAs cover 2 640 674 ha or 3.3% of the national territory (Figure 23). They are listed in the official World Database of Key Biodiversity Areas[4], managed by BirdLife International and KBA Partnership. There is an heterogeneous distribution of KBAs across the country (Figure 23). The Sofala province has the largest KBAs cover with 885 000 ha or 13% of the province, and the province of Cabo Delgado does not present any KBA. The Zambezia province has the largest number of KBAs (5 KBAs).

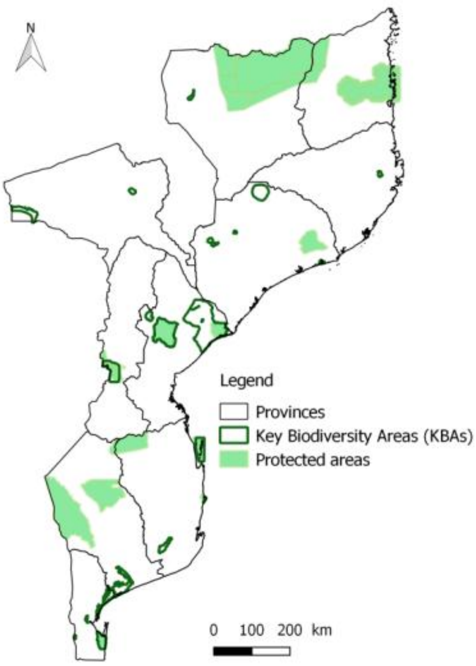



*Figure 23. KBA map of Mozambique, version 2017, overlay over the Protected Area Network.*

Mozambique is one the few countries in southern Africa that still has a significant portion of natural forest. Miombo forest is the most extensive forest type, covering approximately two thirds of the country. This formation is characterized by a high floristic richness and a strong endemism (Campbell, 1996). Miombo forests in Mozambique host several threatened or endangered wildlife and floristic species and

4 http://www.keybiodiversityareas.org/home

are facing multiple threats (climate, deforestation, degradation). However, several sites are not officially considered as KBA, but meet one or more of the criteria listed in the KBA Standard. So, there is a need for in-depth assessment and the identification of new KBAs in Mozambique.

# 6 CONCLUSION

The Land Degradation Baseline presented in this report is the first of his kind in Mozambique and enable to provide important base map for the simulation prototype: the LULCC map and Land Productivity Change map. The drivers' analysis enables to go deeper into the cause of change, using a simple approach, and enable to efficiently use that information in land use planning and interventions.

The NDVI trend analysis shows that a large proportion of the country **(77%) is characterized by an overall stable trend**, meaning there is no significant change in terms of vegetation productivity over the period. **Among the significant trends, 19% of the total area have negative NDVI Trends**, **with clear spatial patterns of decreasing trends in Inhambane, Zambezia and Nampula provinces**. On the other hand, **only 3% and of the total area displayed increase trends**, mainly observed along the Zambezia and Sabi rivers and in the Maputo, Niassa and Cabo Delgado provinces.

In the final LULCC map for 2000, 2005, 2010 and 2016 we observed an overall land use pattern of **45.0% (35.8 Mha) of dry forest, 37.0% (29.3 Mha) of grassland and fallow, 13.7% (10.8 Mha) of cropland 2.0% (1.6 Mha) of wetlands, 1.3% (1 Mha) of other categories (rocks, sands, or bare soils), 0.3% (271,000 ha) of Mangroves, and 0.1% (673.1 ha) of urban areas**. These values are broadly in agreement with the National Land Use and Land Cover maps for 2016 currently being finalized by the GoM. The **deforestation over the 2000-2016 period is estimated to have been 207,272 ha per year**.

Land degradation and its consequences have in general not been included in prior quantitative scenario studies assessing global environmental change and their scale and severity are therefore largely unknown to policymakers. The method is based on the latest guidance of international UN conventions, the state-of-art Earth observation technology and draws upon the multi-factor and multi-scale WAD approach. This allows for the identification of environmental and socio-economic drivers that can lead to land degradation. The LAUREL land degradation products are designed to help decision-makers identify the constraints and opportunities for the conservation, restoration and the sustainable management of land resources, and to be used as inputs to the Land use change simulation platform prototype (LandSIM).

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# 8 Annex – Abstracts

## Submitted to IGARSS

### MAPPING AND CHARACTERIZING LAND CONDITIONS TO BETTER ESTIMATE LAND DEGRADATION: A CASE STUDY OF MOZAMBIQUE

*Montfort Frédérique[1], Bégué Agnès[2], Leroux Louise[3], Cambule Armindo[4], Remane Ivan[4] Grinand Clovis[1]*

[1] Nitidae, 500 rue Jean-François Breton, 34093, Montpellier, France
[2] UMR TETIS, CIRAD, 500 rue Jean-François Breton, 34093, Montpellier, France
[3] UPR AIDA, CIRAD, CSE Fann Residence, Dakar, Sénégal
[4] Eduardo Mondlane University, Faculty of Agronomy and Forest Engineering, CP 257 Maputo, Mozambique

### Abstract

This study aimed at providing a comprehensive spatially-explicit land conditions baseline taking Mozambique as an example. Land productivity trends were analyzed using NDVI time series (2001-2016), before and after climate correction (RESTREND method), and a land cover map, to study changes in vegetation dynamics. We found no significant change in land productivity for more than 76% of the country. However, we observed clear spatial patterns of decreasing productivity trend in Inhambane, Nampula and Zambezia provinces and, to a lesser extent, increasing productivity trend in Maputo, Niassa and Cabo Delgado provinces. The joint analysis of the rainfall-corrected NDVI trends and the dominant land covers enables to better describe the land conditions, and thus is a step forward in estimating land degradation status that could help Mozambican stakeholders to design national and local relevant land degradation mitigation policies or programs.

***Keywor**ds — Land productivity trends, NDVI time series, RESTREND analysis, Land use/land cover.*

# SENSITIVITY ANALYSIS OF LAND PRODUCTIVITY CHANGE CALCULATION IN MOZAMBIQUE

*Montfort Frédérique[1], Bégué Agnès[2], Leroux Louise[3], Grinand Clovis[1]*

[1] Nitidae, 500 rue Jean-François Breton, 34093, Montpellier, France
[2] UMR TETIS, CIRAD, 500 rue Jean-François Breton, 34093, Montpellier, France
[3] UPR AIDA, CIRAD, CSE Fann Residence, Dakar, Sénégal

## Abstract

Land productivity change is one of three indicators used to assess land degradation for reporting on Sustainable Development Goal (SDG) 15.3.1. This study aimed to analyze the sensitivity of this indicator to three parameters (i) the period of analysis, (ii) the rainfall dataset used for climate correction, and (iii) the annual NDVI integration period (civil year vs climatic year). We observed that the spatial pattern and values of the resulting land productivity indicators greatly differ according to these three parameters, questioning the comparability of SDG indicator 15.3.1 between countries in different agroclimatic zones.

***Keywords* —** Trend analysis, NDVI time series, RESTREND analysis, land degradation, SDG, LDN