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# From land productivity trends to land degradation assessment in Mozambique: Effects of climate, human activities and stakeholder definitions

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**Abstract**

Remote sensing observations such as normalized difference vegetation index (NDVI) trends can provide important insights into past and present land condition. However, they do not directly provide comprehensive information about our representation of land degradation and the processes at work. This study aimed to analyze vegetation productivity underlying factors in order to assess land degradation and to highlight the impact of definitions on its quantitative assessment, using Mozambique as case-study. Land productivity change were first analyzed using NDVI time-series (2000–2016), and a two-step framework was then used to understand the main factors of these productivity changes. The impact of land degradation's definition was assessed based on four types of stakeholder, with different priorities in terms of ecosystem services. The results show that 25% of the country display a significant land productivity decrease, while only 3% display a land productivity increase. A large part of these land productivity changes (>61% of the decrease, and >98% of the increase) is directly assigned to human activities, such as native forest growth or tree plantations (for the increase), or forest degradation, deforestation and loss of grassland productivity (for the decrease). We showed that the fraction of degraded land varies according to stakeholders' definitions, ranging from 12% to 20% of the Country, much less than the 39% estimated by Tier 1 United Nations Convention to Combat Desertification. This study provides a sound methodological framework for assessing land degradation status that could help stakeholders to design national and locally relevant land degradation mitigation policies or programmes.

KEYWORDS
land degradation, NDVI time series, RESTREND analysis, land productivity change, factor analysis, Mozambique

## 1 | INTRODUCTION

Land degradation is a widespread and worldwide phenomenon that impacts food security, ecosystem services and human well-being. In the past 5 years, many global and regional initiatives have been launched to halt land degradation and restore land. In the sustainable development goals (SDG) adopted by world leaders in 2015, target 15.3 states "...by 2030, combat desertification, restore degraded land

  

and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation neutral world". These initiatives push countries to set their own targets to reduce poverty, increase food security and nutrition and reduce land degradation for the coming decades. This first involves defining what constitutes land degradation, and then locating and developing a land degradation baseline at the national level in order to measure the progress made. However, despite the existence of international guidelines for monitoring land degradation (United Nations Convention to Combat Desertification [UNCCD]—methodology to report SDG indicator 15.3.1), some countries lack up-to-date and reliable estimates of the status and trend in land degradation. Reasons for this include the fact that the definition of land degradation may not be consensual, or because countries currently do not have the capacity to monitor land degradation (Higginbottom & Symeonakis, 2014).

The difficulty of estimating land degradation is illustrated by the meta-analysis conducted by Geist and Lambin (2004) who analyzed more than 130 case-studies about the underlying mechanisms of land degradation processes. They showed that land degradation is a complex process with various biophysical and socio-economic factors with no unique analytical framework for addressing land degradation at a global scale. The differences in definitions, indicators and even the perception of land degradation explain why estimates of the extent and severity of global land degradation vary from 15% to more than 66% (Higginbottom & Symeonakis, 2014; IUCN, 2015; Le et al., 2016; Van der Esch et al., 2017). For instance, the UNCCD bases land degradation on "the reduction of biological or economic productivity" (UNCCD, 2016), while for the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES, 2018), land degradation is mainly defined as a loss of biodiversity. A commonly agreed definition of land degradation could be the one given by UNEP (2007): "The decline or loss in ecosystem functions and services of a given territory that cannot fully recover unaided within decadal time scales". This raises the issue of disentangling changes over the long term from the impact of short-term fluctuations driven by seasonal pulse or single events (Cherlet et al., 2018). However, this definition does not explicitly address the difficulty in valuing and balancing ecosystem trade-offs. For instance, the conversion of natural ecosystems into human-oriented production ecosystems, such as agriculture, often creates benefits for society (food production services) but can simultaneously lead to a loss of biodiversity and other ecosystem services (Van der Esch et al., 2017). This example illustrates the subjective nature of any definition of land degradation, which largely explains the difficulty of estimating it at the global or national scales. Despite these difficulties, the international scientific community is actively working on assessing land degradation worldwide and using different approaches to degradation that can be grouped in three types: (i) expert opinion, (ii) remote sensing-based assessments and (iii) biophysical models (Gibbs & Salmon, 2015). Remote sensing has been recognized as a robust and large-scale monitoring tool for global assessments of land degradation (Dubovyk, 2017; Higginbottom & Symeonakis, 2014), through vegetation productivity, and land use/land cover change analysis. Technical implementation and guidelines for this approach have been recently published by the UNCCD (2017). As the vegetation productivity change observed over a long period of time is a good indicator of the ecosystem's response to natural or human pressures (Wessels et al., 2007; Yengoh et al., 2015), the normalized difference vegetation index (NDVI) trend, considered a proxy of net primary production, is one of the main indicators used to assess changes in vegetation productivity. Despite these commonly agreed best practices, the link between NDVI trends and land degradation is still not straightforward (Prince, 2019), particularly since it fails to characterize the cause of land degradation which can only be assessed using a dedicated analysis (Dubovyk, 2017).

Despite the abundant literature on vegetation productivity change analysis, few studies analyze the underlying factors of the changes observed. These factors can be climatic, anthropogenic or a combination of both (Evans & Geerken, 2004). To identify factors, studies use statistical analysis such as correlation analysis, regression analysis or principal component analysis (de Jong et al., 2013; EL-Vilaly et al., 2018; Krakauer et al., 2017; Yang et al., 2019) and, more recently, machine learning algorithms such as 'random forest' (Gichenje et al., 2019; Leroux et al., 2017). However, these analyses do not provide spatial and quantitative information on the contribution of each factor and thereby provide new, consistent insights for identifying priority areas of intervention for land restoration or conservation. At the global scale, Zhu et al. (2016) and Piao et al. (2019) have proposed a spatial distribution of the relative contribution of four factors ($C0_2$ fertilization, climatic factors, nitrogen deposition and land cover change) regarding the greening of the Earth and based on remote sensing observations coupled with an ecosystem model. Currently, the most widely used wall-to-wall approach to differentiate climatic from human-induced vegetation productivity change is the residual trend analysis proposed by Evans and Geerken (2004) and known as the RESTREND method (Wessels et al., 2007). This method consists of removing the effect of climate variability from the NDVI signal, using a trend analysis of the residuals between the observed NDVI and climatic data (mainly precipitation data). Other approaches to assess the relative role of rainfall variability or other factors in vegetation productivity change are based on a classification scheme using the outputs of NDVI trend analysis, residual trend analysis and correlation analysis with climate-related data (Leroux et al., 2017; Wang et al., 2017). While these studies make it possible to locate hot spots of changes in land condition and to separate the climatic influence of these changes from other factors (Bai et al., 2008; Le et al., 2016), they do not directly provide comprehensive information about land degradation. Therefore, to help decision makers to define targets and interventions to mitigate land degradation, there is an urgent need for up-to-date spatial information on land conditions and on the underlying factors of change at the national scale.

Mozambique is experiencing a rapid depletion of its natural resources (GoM, 2018). Moreover, the country is committed to setting targets to reach land degradation neutrality by 2030. Previous estimates for degraded areas in Mozambique can be found in the literature (Bai et al., 2008; Cherlet et al., 2018; Conservation International, 2018; Paganini et al., 2009). These range from 12% (Cherlet et al., 2018) to 42% (Paganini et al., 2009) depending on the study. As for estimates for the global scale as mentioned above, the large range of land degraded area estimates can be easily explained by differences in the period of analysis, the methodology, the input dataset used and the definition of land degradation. In order to produce a consistent, up-to-date spatial estimation of land degradation in Mozambique, a quantitative and comprehensive approach to land degradation is urgently needed.

The objective of this study is to analyze vegetation productivity underlying factors in order to assess land degradation and to highlight the impact of definitions on its quantitative assessment, using Mozambique as case study. Our approach is based on the premise that only an understanding of the processes underlying land productivity change can lead to a mapping of land degradation, and that this mapping is not unique but will depend on the ecosystem service targeted. To illustrate our point, we have implemented an approach based on proven NDVI trend analysis methods, which allows for the mapping of land productivity change factors. Then, for different stakeholder types, each with different objectives for conserving ecosystem services, we established rule scenarios that were used to convert the land productivity change factors map into land degradation estimations. Finally, we compare the results to the 15.3.1 indicator at the Mozambique scale, calculated according to the UNCCD standard approach.

## 2 | MATERIAL AND METHODS

### 2.1 | Study area: Mozambique

Mozambique is located on the southeast coast of Africa bordered by the Indian Ocean in the east (Figure 1). The country has an area of 799,380 km$^2$, with mainly lowland regions in the east and a few mountainous regions in the west of the country, reaching heights of up to 2,436 m. The climate is tropical to subtropical, with a semiarid region in the southern provinces and two seasons, a dry cool season from April to September and a rainy hot season from October to March. Average annual rainfall ranges from 300 to 1,000 mm in the southern region and from 1,000 to 2000 mm in the northern region (Figure 1b). Average annual temperatures range from 20 to 27°C in the lowlands and 15–25°C at the highest altitudes (GoM, 2002; Figure 1c). Mozambique's population was estimated at 28 million in 2015, with the northern provinces of Nampula and Zambezia being the most populous (INE, 2018). The agricultural sector employs more than 80% of the Mozambican population and accounts for 32% of the country's GDP (Armand et al., 2019). The Country still has a large proportion of natural forest, mainly *Miombo* woodland, covering more than 40% of the Country (GoM, 2018; Figure 1a). Forests play an important role in the Country's economy, mainly in rural areas, and represent a source of energy (firewood, charcoal), construction material, non-timber forest products and nutrients for small-scale agriculture (Chidumayo & Gumbo, 2010; GoM, 2018). However, Mozambique's natural resources are rapidly depleting: about 267,000 ha of forests per year were lost between 2003 and 2013,

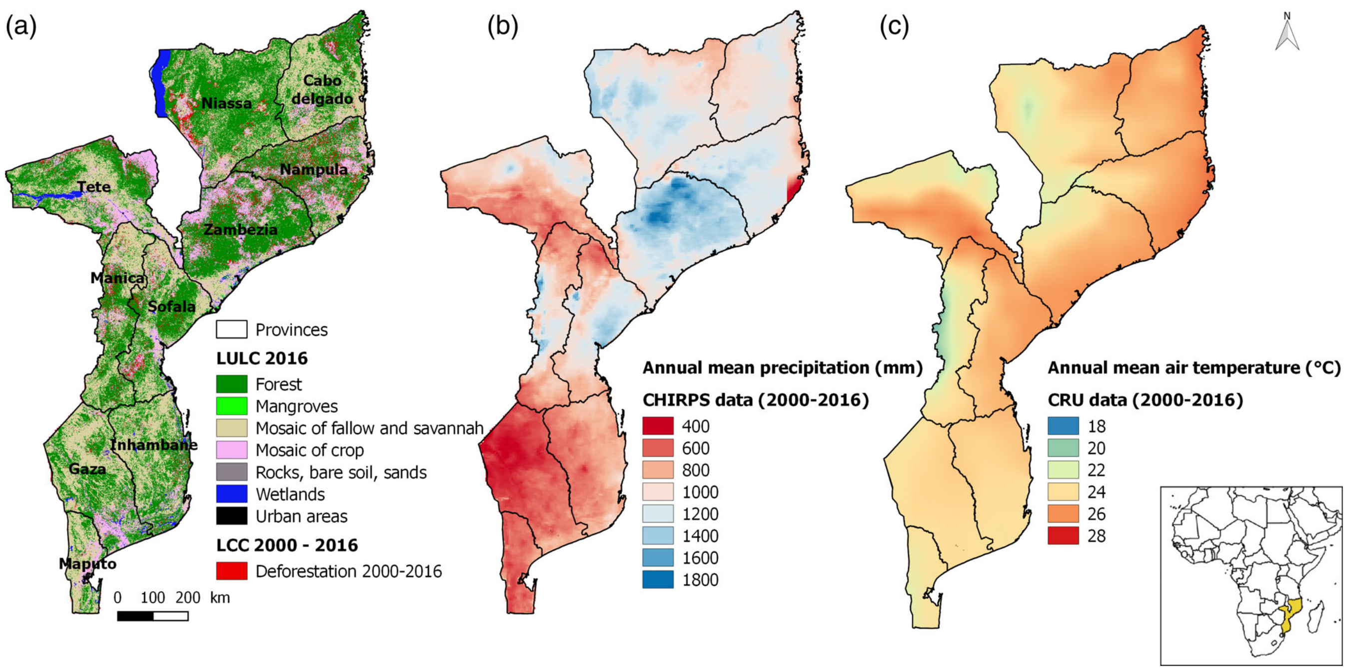


**FIGURE 1** Environment and climate in Mozambique: (a) 2000–2016 land use and land cover change map (Grinand et al., 2018) and province limits; (b) Annual mean rainfall (mm) over the 2000–2016 period (CHIRPS data; Funk et al., 2015); (c) Annual mean air temperature (°C) over the 2000–2016 period (CRU data) [Colour figure can be viewed at wileyonlinelibrary.com]

mainly to slash-and-burn agriculture and urban expansion (GoM, 2018). In addition, some areas are prone to high soil fertility depletion, which reduces the potential for productive agriculture (Folmer et al., 1998).

## 2.2 | Data collection and pre-processing

### 2.2.1 | MODIS NDVI time-series

The NDVI trends maps were derived from the 16-day MODIS NDVI products (MOD13Q1 Collection 6) available at a 250 m spatial resolution (Didan et al., 2015). The MODIS product was selected because it provides a regular and long-term record of vegetation condition that can be used to detect change. The MODIS product is considered the most reliable NDVI record available (Higginbottom & Symeonakis, 2014). MODIS NDVI time-series were downloaded using the NASA's Application for Extraction and Exploring Analysis Ready Samples (*App*EEARS). The images time-series covers the 2000–2016 period and the entire Country. The MODIS product is corrected for molecular scattering, ozone absorption and aerosol (Didan et al., 2015). However, residual noise may persist and disturb the NDVI signal. In order to reduce this noise, the NDVI 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). Then, for each pixel, we calculated the annual cumulated NDVI (expressed as 'annual NDVI' in this study) by summing the bi-monthly NDVI values over each climatic year (August *n-1* to July *n*).

### 2.2.2 | Climate data

In the *Miombo* ecoregion, vegetation dynamics are controlled mainly by the rainfall and temperature variability (Campbell, 1996; Chidumayo, 2005).

We used rainfall estimates derived from satellite imagery as Mozambique's rain gauge network is sparse with gaps in the temporal records (Toté et al., 2015). Rainfall data were obtained from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) rainfall estimates (Funk et al., 2015). CHIRPS products were chosen because they have a high spatial and temporal resolution. Furthermore, CHIRPS data 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°, ~5.4 km) monthly precipitation dataset, starting from 1981 to near-present, which combines satellite imagery with in situ station data to create gridded rainfall time-series (Funk et al., 2015). CHIRPS data were downloaded for the 2000–2016 period using the 'heavyRain' R package (Detsch, 2018) and cumulated over the climatic year (August *n-1* to July *n*). These data were resampled using the nearest neighbour resampling method at 250 m to allow for the comparison with MODIS NDVI data.

Air temperature data were obtained from the Climate Research Unit Time-Series (CRU TS v.4.03) dataset (Harris et al., 2014), a global monthly gridded time series dataset that covers the 1901–2018 period at 0.5° resolution (~50 km). CRU data are based on weather station measurements. The average maximum temperature was calculated per climatic year (August *n-1* to July *n*) for the 2000–2016 period, and were resampled using the nearest neighbor resampling method to the MODIS NDVI data spatial resolution of 250 m.

### 2.2.3 | Land use and land cover data

We used a national land use and land cover change (LULCC) map from 2000 to 2016 produced from a mosaic of cloud-free Landsat images at 30 m resolution (Grinand et al., 2018). The nomenclature of the map is composed of six IPCC land cover categories (forest, cropland, grassland, mangrove, wetland and other land) for 2000 and 2016, and one land cover change category (three periods of deforestation between 2000 and 2016). The overall accuracy of the LULCC map is 81%. This LULCC map was resampled to the MODIS NDVI image resolution (250 m) using a category majority filter for the six IPCC land cover categories and by calculating the percentage of deforestation (2000–2016 period) for the land cover change categories. This choice makes it possible to keep information on deforestation over small areas that would be removed with a majority filter and provide another layer of information.

### 2.2.4 | Ground observations

Ground observations were collected in order to understand the underlying factors in land productivity changes. Through interviews (open-ended questionnaires) and field observations we collected information on current and past land use and land cover, vegetation characteristics, natural external pressures (drought, flooding, cyclones and so forth) and the impact of human activities (e.g., cultivation, grazing, fire and logging). A total of 330 ground observations were made in four provinces (Inhambane, Manica, Zambezia and Nampula) in April and November 2018 (dry season), in areas characterized by different changes in land productivity. The observations were complemented by visual interpretation of very high resolution satellite images available on Google Earth.

## 2.3 | Data analysis

Data analysis was conducted in three steps (Figure 2).

### 2.3.1 | Land productivity change analysis

*NDVI trend analysis*

Land productivity changes were analyzed using a statistical trend analysis applied to each pixel of the 16-year annual MODIS NDVI time series. The statistical trend analysis is based on an ordinary-least

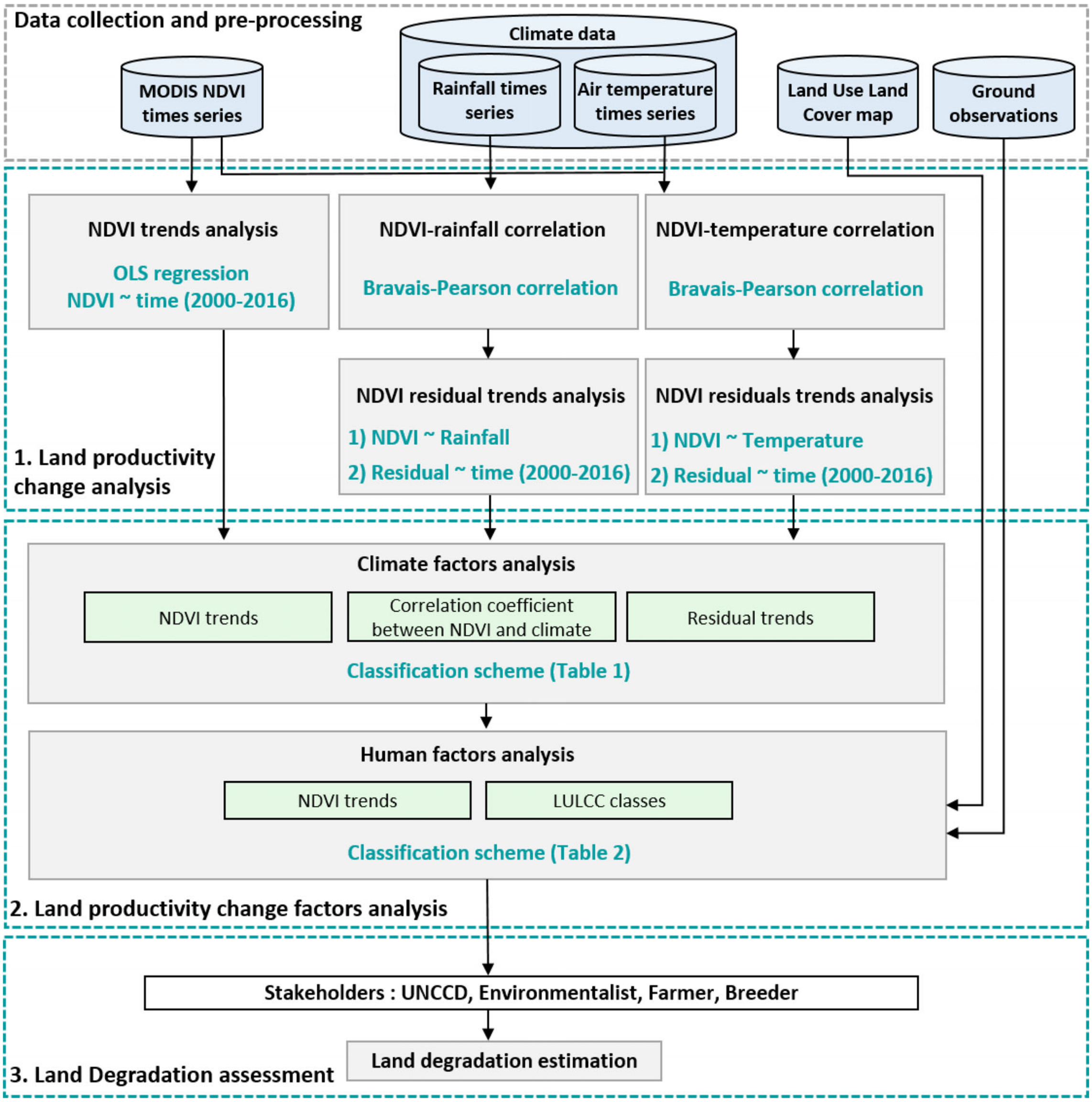


**FIGURE 2** Flowchart of the approach used in this study [Colour figure can be viewed at wileyonlinelibrary.com]

square (OLS) regression. OLS quantified NDVI value changes (dependent variable) against time (independent variable). A positive slope coefficient indicates a productivity increase and a negative slope coefficient indicates a productivity decrease. The significance of the slope coefficient was determined using the $P$-value, at a 95% confidence level ($P$-value < .05). Each pixel was then classified in three NDVI trend types: significant increase or decrease in productivity and non-significant changes.

*NDVI-climate data correlation*

We calculated the Bravais–Pearson correlation coefficient between annual cumulated NDVI value and annual cumulated rainfall value and annual average maximum temperature value over the 2000–2016 period for each pixel. The correlation was considered statistically significant at the 95% level ($P$-value < .05, corresponding to $r$ = 0.50 and $r$ = –0.50). In this study, we only considered positive NDVI-rainfall and negative NDVI-temperature correlations, because they represent the most observed correlations in southern Africa according to Ichii et al. (2002).

*NDVI residual trend analysis*

We used a residual analysis of the productivity-climate relationship known as the RESTREND method (Evans & Geerken, 2004; Wessels et al., 2007) to separate climate and other factors in NDVI changes. Pixels with no significant NDVI-climate data correlation were excluded from the RESTREND analysis as suggested by Wessels et al. (2012). This robust and widely accepted method consists of (i) calculating an OLS regression between the annual cumulated NDVI value and the annual cumulated rainfall value or annual average maximum temperature per pixel and (ii) performing for each pixel a new OLS regression on the model residuals (the difference between the observed NDVI value and the predicted NDVI value) with respect to time. Trends in the residuals were then interpreted as the part of the vegetation productivity that is not explained by rainfall or temperature inter-annual variability.

#### 2.3.2 | Land productivity change factor analysis

*Climate factor analysis*

In this study, we consider that changes in productivity are mainly related to climate and human factors (which includes all factors related to land management and their environmental impacts). This analysis aims to identify the productivity changes induced by rainfall or temperature trends from those changes induced by human factors. We followed Leroux et al.'s method (2017) which suggests a classification scheme based on the slope of the NDVI trend, the coefficient of correlation between NDVI and rainfall and NDVI and temperature, the slope and significance of the NDVI rainfall and NDVI temperature residuals trends (*P*-value < .05) (Table 1). As a result, pixels were classified into three categories (1) NDVI changes through rainfall and/or temperature change only, (2) NDVI changes through rainfall and/or temperature change and human factors, (3) NDVI changes through human factors. The assumption used is, for example, for a positive NDVI trend, if a positive trend can still be observed after the removal of the climate effect in the NDVI residual trends, then the change in land productivity can be explained by more than rainfall and temperature inter-annual variability alone. For a significant correlation between NDVI and rainfall and/or temperature, the vegetation productivity changes are explained by rainfall and/or temperature and human factors when the sign of the slope of the NDVI and NDVI residual trends are the same. On the contrary, vegetation productivity change can be explained mainly by rainfall and/or temperature when the sign of the slope of the NDVI and NDVI residual trends are opposite or the trend is not-significant (*P*-value > .05). If there is no correlation between NDVI and rainfall and NDVI and temperature, vegetation productivity is driven only by human factors.

*Human factor analysis*

To produce the final map of land productivity change factors, we further analyzed the 'human factors' category produced previously. We used the LULCC map to identify potential factors of change due to human activities. We proposed a pixel classification scheme based on the slope of the NDVI trend and the LULCC categories (Table 2). Each change factor represents the main potential factor based on ground observations for productivity changes related to each LULCC category.

#### 2.3.3 | Land degradation assessment

We tested the impact of stakeholder type perceptions on the assessment of degraded land at the national scale. We defined four types of stakeholders, based on the prioritization of ecosystem services, with its own definition: the 'default' UNCCD definition, and three definitions for hypothetical types of stakeholders targeting different ecosystem services and referred hereafter as 'environmentalists', 'farmers' and 'breeders'. The definitions served to establish four scenarios of

**TABLE 1** Classification scheme for the climate factors, based on NDVI and NDVI residual (RESTREND) trends, and on the correlation coefficients between NDVI and rainfall, and NDVI and air temperature.

| NDVI trends (*P*-value < .05) | Correlation coefficient NDVI-rainfall | Residual trends rainfall (*P*-value < .05) | Correlation coefficient NDVI-temperature | Residual trends temperature (*P*-value < .05) | Categories of change factors |
|---|---|---|---|---|---|
| Decrease (slope < 0) | $r > 0.50$ | Slope > 0 or n.s[a] | $r > -0.50$ | | Rainfall change |
| | $r < 0.50$ | | $r < -0.50$ | Slope > 0 or n.s | Temperature change |
| | $r > 0.50$ | Slope > 0 or n.s | $r < -0.50$ | Slope > 0 or n.s | Rainfall and temperature change |
| | $r > 0.50$ | Slope < 0 | $r > -0.50$ | | Rainfall change + human factors |
| | $r < 0.50$ | | $r < -0.50$ | Slope < 0 | Temperature change + human factors |
| | $r > 0.50$ | Slope < 0 | $r < -0.50$ | Slope < 0 | Rainfall and temp. change + human factors |
| | $r < 0.50$ | | $r > -0.50$ | | Human factors |
| Increase (slope > 0) | $r > 0.50$ | Slope < 0 or n.s | $r > -0.50$ | | Rainfall change |
| | $r < 0.50$ | | $r < -0.50$ | Slope < 0 or n.s | Temperature change |
| | $r > 0.50$ | Slope < 0 or n.s | $r < -0.50$ | Slope < 0 or n.s | Rainfall and temperature change |
| | $r > 0.50$ | Slope > 0 | $r > -0.50$ | | Rainfall change + human factors |
| | $r < 0.50$ | | $r < -0.50$ | Slope > 0 | Temperature change + human factors |
| | $r > 0.50$ | Slope > 0 | $r < -0.50$ | Slope > 0 | Rainfall and temp. change + human factors |
| | $r < 0.50$ | | $r > -0.50$ | | Human factors |

Abbreviation: NDVI, normalized difference vegetation index.
[a]n.s, non-significant (*P*-value > .05).

**TABLE 2** Classification scheme for human factors, based on NDVI trends and LULCC categories.

| NDVI trends (*P*-value <.05) | LULCC categories | Categories of change factors |
|---|---|---|
| Decrease (slope < 0) | Forest 2000 and Deforestation >10% | Deforestation |
| | Forest 2000 and 2016 | Forest degradation |
| | Cropland 2000 and 2016 | Agricultural productivity decline |
| | Grassland 2000 and 2016 | Grassland productivity decline |
| | Mangrove 2000 and 2016 | Mangrove degradation or deforestation |
| | Urban area 2016 | Urban expansion or densification |
| | Other land use 2016 | Others (undifferentiated multiple factors) |
| Increase (slope > 0) | Forest 2016 | Native forest growth or plantations |
| | Cropland 2000 and 2016 | Agricultural productivity increase or fallow regrowth |
| | Grassland 2000 and 2016 | Grassland productivity increase |
| | Mangrove 2000 and 2016 | Mangrove growth |
| | Urban area 2016 | Urban greening |
| | Other land use 2016 | Others (undifferentiated multiple factors) |

Abbreviations: LULCC, land use and land cover change; NDVI, normalized difference vegetation index.

rules that were used to convert the map of land productivity into four distinct land degradation estimations (Table 3).

UNCCD defines land degradation as the reduction or loss of the biological or economic productivity of all land use resulting from human activities (UNCCD, 2016). In this case, any decrease in land productivity, except that attributed solely to climate, is considered as land degradation. The 'environmentalist' definition is similar to the UNCCD one, except that it includes the climate trend as a cause of land degradation and leaves out the reduction or loss of cropland productivity. In turn, 'farmers' and 'breeders' are only concerned by the reduction or loss of cropland and grassland productivity, respectively, resulting from human activities or climatic variabilities and leaves out the reduction or loss of natural vegetation productivity.

## 2.4 | Comparison with the 15.3 SDG indicator

In order to place our study in the international context of the SDG, we compared our results with the indicator 15.3.1 ('Proportion of land that is degraded over total land area'), calculated according to the UNCCD recommendations. To do this, we used the Trends. Earth platform (Conservation International, 2018) developed to support countries in analyzing data to prepare for their reporting commitments to the UNCCD. We used the Tier1 (global default) data provided by the platform: MODIS NDVI, CHIRPS rainfall data and ESA CCI Land cover and Soil Grids (ISRIC), for the 2001–2015 period.

# 3 | RESULTS

## 3.1 | Land productivity change

Around 71.5% of the country (55.55 Mha) shows no significant land productivity change over the period (Figure 3). Some 25.3% (19.71 Mha) of the total area shows a decrease in land productivity. By contrast, 3.2% (2.49 Mha) shows an increase in land productivity, mainly in the Niassa and Cabo Delgado Provinces in the north of the Country. Except for these two provinces, all provinces are characterized by large areas of decreased land productivity (between 56.2% and 17.2% of the total provincial area) and small areas of increased land productivity (between 3.1% and 0.9%).

The results of the NDVI-climate data correlation analysis showed that 19.2% and 15.4% of the country exhibited significant positive NDVI-rainfall and negative NDVI-temperature relationships, respectively, during the 2000–2016 period (see Figure 4). Spatial patterns of NDVI-climate correlation are spatially heterogeneous, with high values concentrated in the semi-arid region of the southern provinces.

RESTREND analysis applied on pixels marked by significant positive NDVI-rainfall and negative NDVI-temperature correlations, resulted in a large majority of 'stable' pixels after climate correction (78.8% and 85.4% of these processed pixels have no significant trends; Table 4), indicating that the NDVI trends of these 'correlated' pixels are largely explained by rainfall and temperature inter-annual variability. Among the significant residual trends suggesting the influence of factors other than climate, 3.8% and 2.0% of the total area have decreasing trends, while 0.3% of the total area has an increasing trend with rainfall correction and 0.3% has an increasing trend with temperature correction.

## 3.2 | Land productivity change factors analysis

We observed that 19.7% of the decreasing trend over the 2000–2016 period can be explained by climate variability alone (rainfall or temperature), 61% by human factors alone and 19.4% by climatic variability combined with human factors (Table 5, Figure 5). The spatial distribution of factors shows that climatic variability is the dominant factor in NDVI change in the southern provinces (Figure 5). Forest, cropland and grassland are the main land use categories that

**TABLE 3** Four land degradation scenarios based on the list of land processes expected to produce degraded land (ticked column), according to stakeholder type definitions.

| | UNCCD | Environmentalist | Farmer | Breeder |
|---|---|---|---|---|
| Climate change + others (decrease trends) | ✓ | ✓ | ✓ | ✓ |
| Climate change (decrease trends) | | ✓ | ✓ | ✓ |
| Native forest growth or plantation | | | | |
| Agricultural productivity increase | | | | |
| Fallow regrowth | | | | |
| Grassland productivity increase (herbaceous species) | | | | |
| Grassland productivity increase (woody species) | | | | ✓ |
| Mangrove productivity increase or regrowth | | | | |
| Urban greening | | | | |
| Deforestation | ✓ | ✓ | | |
| Forest degradation | ✓ | ✓ | | |
| Agricultural productivity decline | ✓ | | ✓ | |
| Grassland productivity decline | ✓ | | | ✓ |
| Mangrove degradation or deforestation | ✓ | ✓ | | |
| Urban expansion or densification | ✓ | ✓ | ✓ | ✓ |
| Others (decrease trends) | ✓ | | | |

Abbreviation: UNCCD, United Nations Convention to Combat Desertification.

display significant NDVI trends (decreases and increases) between 2000 and 2016 (Table 5, Figures 6 and 7). Forest degradation and deforestation represent a large proportion of the decreasing trend (19.3% and 13.2% of the decreasing trend, respectively). The areas characterized by a decrease potentially due to deforestation are mainly located in Zambezia Province (Figure 6). The decline in grassland and cropland productivity represented 17.7% and 7.9% of the of the overall decrease trend, respectively.

Regarding positive trends, climate variability alone (rainfall or temperature) is responsible for 0.2% of the trend over the 2000–2016 period (Table 5, Figure 5), human factors for 98.1% and climatic variability combined with other factors for 1.7%. We observed that native forest growth or commercial plantations account for 51.6% of the total increase trend, mainly in the northern part of the country (Table 5, Figure 7). A large proportion of grassland experienced an increase in vegetation productivity, accounting for 22.6% of the total NDVI increase trend. Increased agricultural productivity or fallow regrowth in cropland represented 17.1% of the total increase trend.

### 3.3 | Land degradation assessment

Results show that the estimation of the degraded land area ranges between 11.9% and 20.3% of the country depending on the stakeholder type (Figure 8). The fractions of degradation attributed to different factors clearly show the difference in the ecosystem service prioritized. Indicator 15.3.1. is much higher, with 39% of degraded land in Mozambique.

## 4 | DISCUSSION

### 4.1 | The role of climate and human activities on land productivity change

In this article, we have implemented an approach based on proven NDVI trend analysis methods, which allows factors of land productivity change to be mapped. The calculation of land productivity trends is based on a trajectory indicator of the NDVI annual mean which has proved, using local expertise, to be the best approach to reflect land changes when compared with more sophisticated ones (Teich et al., 2019). Compared with the UNCCD approach, we used linear regressions and calculated the annual mean over the climatic year (August *n-1* to July *n*) rather than the civil year as recommended by Montfort et al. (2019). Although linear regression is widely used for NDVI trend analysis, sometimes it cannot comply with the OLS statistical assumptions (de Beurs & Henebry, 2005) and can be a limitation of this study. However, some authors have shown that linear regression can be consistent with the OLS hypotheses in some cases and results with linear and non-parametric such as Mann–Kendall trends tests are very similar (Jamali et al., 2014; Wessels et al., 2012). Furthermore, the use of the non-parametric method does not generally outperform the parametric method for identifying trends (Jamali et al., 2012). Concerning the factor analysis, based on in situ observations and scientific literature, two categories of factors were studied: climate (rainfall and air temperature) and human factors (land management) (Boisvenue & Running, 2006; Zhu et al., 2016).

Our results show that a large proportion of land in Mozambique is characterized by no significant trend in land productivity (72%),

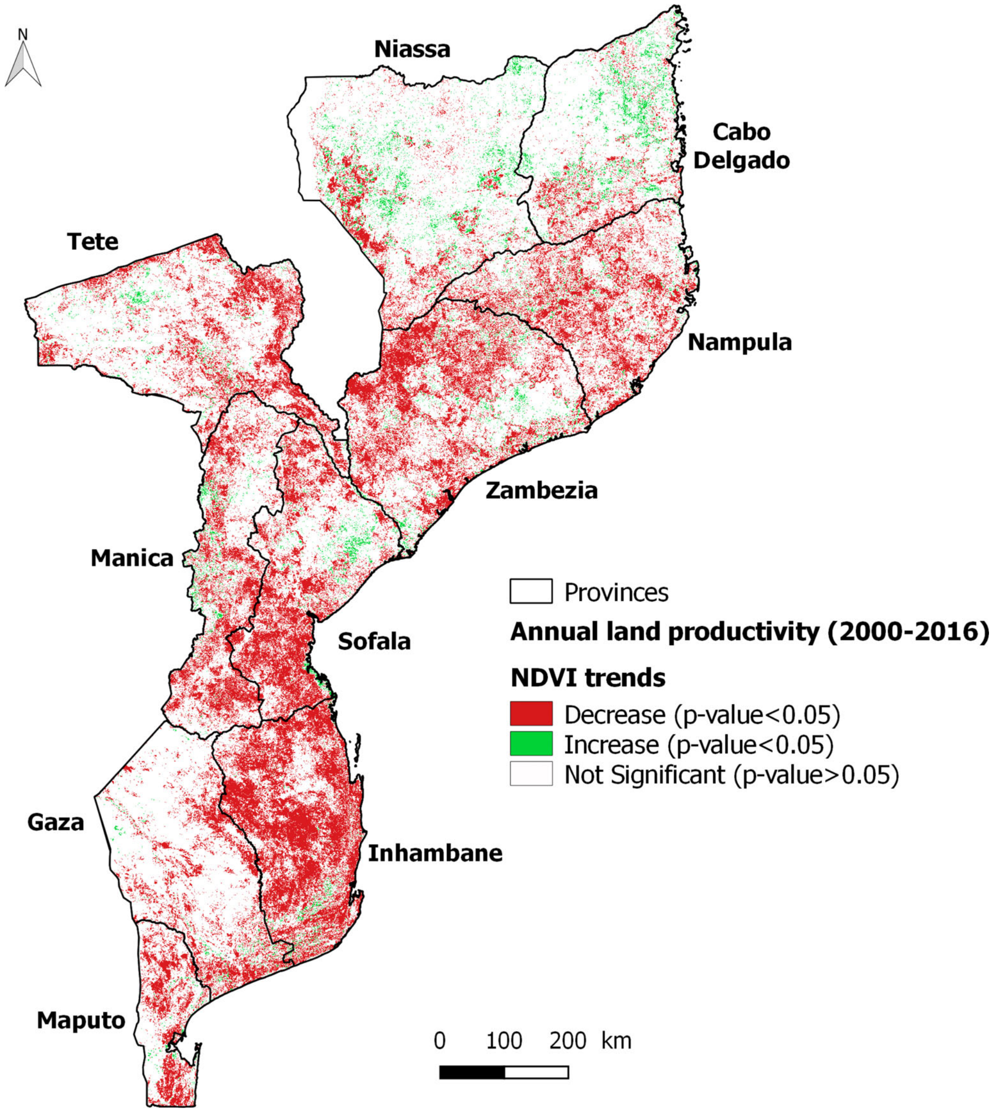


**FIGURE 3** Annual land productivity trend without climate correction maps of Mozambique calculated for the 2000–2016 period [Colour figure can be viewed at wileyonlinelibrary.com]

while the rest of the territory is mainly dominated by a decrease (25%), alongside an increase (3%) in land productivity. The decreasing proportion is of the same order of magnitude as the 28% reported by Bai et al. (2008) for Mozambique in the 1981–2003 period. We also showed that a large majority of the land productivity decrease (61%) was due to only human factors that 19.7% involved only climatic variables, and 19.4% was explained by both climate and human factors.

The correlations between annual climate variables (rainfall and air temperature) and the mean annual NDVI calculated over the climatic year indicate that for at least 15% of the Country, the land productivity dynamic is dependent on the climate trend. It is interesting to note that the inclusion of the air temperature variable in the climatic driver analysis increases the share of trends in land productivity explained by climatic factors (around 9% of the decrease in land productivity is explained by temperature alone), as shown by Burrell et al. (2019). This is particularly true in the southern provinces of Mozambique, such as the semiarid Inhambane province, characterized by a large decrease in land productivity. The role of temperature in land productivity trends over recent years is globally explained by the average air temperature increase of 0.6°C observed between 1960 and 2006 (Winthrop et al., 2018). Similar studies carried out in the Sahel region (Dardel et al., 2014; Fensholt et al., 2012; Herrmann et al., 2005; Hickler et al., 2005), where rainfall is the main limiting factor for vegetation growth, reached the same conclusion on the impact of climate on land productivity trends.

Despite the important role of climate in land productivity changes, human activities remain the dominant factor in land productivity change in Mozambique, explaining at least 61% of the decrease observed at the national scale. This result is consistent with recent studies that showed the prominent role of human land-use management in global vegetation change (Chen et al., 2019; Song et al., 2018). The main human activities reducing land productivity were forest degradation and deforestation. Illegal and legal logging, firewood and charcoal production and fires were reported to be the most important causes of forest degradation (GoM, 2018; Sitoe et al., 2012). Controlled and uncontrolled fires are widespread in Mozambique (Sitoe et al., 2012) and are reported to impact 30 million hectares of forest and other land (38%) each year (Hoffmann

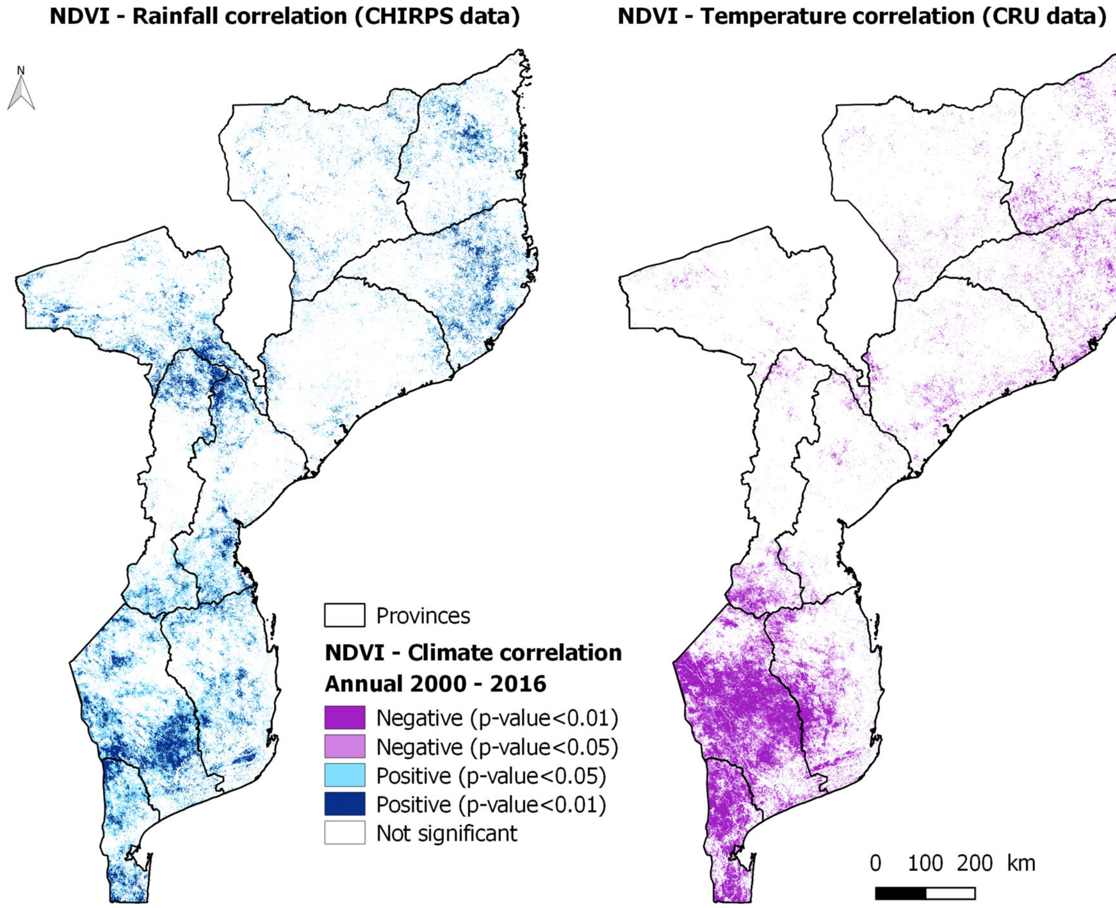


**FIGURE 4** NDVI-rainfall and NDVI-temperature relationship during the 2000–2016 period (Bravais–Pearson coefficient, statistically significant at the 95% level or $r$ = 0.50 or $r$ = −0.50) [Colour figure can be viewed at wileyonlinelibrary.com]

**TABLE 4** Distribution of land productivity trends after climate correction (Rainfall data: CHIRPS; Temperature data: CRU) in Mozambique, calculated for the 2000–2016 period.

| | Rainfall | | Temperature | |
|---|---|---|---|---|
| Residual trends | Area (ha) | % total area | Area (ha) | % total area |
| Decrease ($P < .05$) | 2,971,992 | 3.8 | 1,551,248 | 2.0 |
| Increase ($P < .05$) | 198,737 | 0.3 | 207,929 | 0.3 |
| Not significant | 11,778,078 | 15.1 | 10,265,643 | 13.1 |
| Total | 14,948,807 | 19.2 | 12,024,820 | 15.4 |

et al., 2009). Locally, *Miombo* aboveground woody biomass is negatively affected by frequent and high intensity fires (Ribeiro et al., 2008; Ryan & Williams, 2011; Saito et al., 2014). Regarding the second factors concerning forest areas, this is in line with the recently published Forest Reference Emission Level (GoM, 2018) that reported a high rate of deforestation of 267,000 ha per year during the 2003–2013 period. Shifting cultivation was reported to be the major cause of deforestation in Mozambique. The Zambezia and Nampula provinces are particularly characterized by decreasing trends due to deforestation, forest degradation and fires. These provinces have the Country's highest rural population density and had the country's highest deforestation rates between 2003 and 2013 (GoM, 2018). Furthermore, the Zambezia and Nampula Provinces also have extended cropland (mostly small-scale farms), but a large part of this cropland is characterized by reduced productivity. We interpreted this decline in terms of potential soil erosion and soil fertility depletion due to agricultural practices (Folmer et al., 1998). This can greatly affect agricultural productivity and, consequently, the national economy and food security. This factor could guide the choice of areas for priority interventions for the restoration or management of land resources.

Finally, the increase in land productivity (3% of Mozambique's territory) is almost entirely driven by human factors (>98%). It was observed in native forest (51.6%), grassland (22.6%) and cropland

**TABLE 5** Distribution of main factors of land productivity change in Mozambique, calculated for the 2000–2016 period.

| NDVI trends | Categories of climate and human change factors | | Hectares | % increase or decrease | |
|---|---|---|---|---|---|
| Decrease ($P$ < .05) | Climate | Rainfall change | 1,655,803 | 8.4 | 19.7 |
| | | Temperature change | 1,714,529 | 8.7 | |
| | | Rainfall and temperature change | 518,659 | 2.6 | |
| | Climate + human | Rainfall change + human factors | 1,527,625 | 7.8 | 19.4 |
| | | Temperature change + human factors | 917,456 | 4.7 | |
| | | Rainfall and temp. change + human factors | 1,350,427 | 6.9 | |
| | Human | Forest degradation | 3,806,104 | 19.3 | 61.0 |
| | | Grassland productivity decline | 3,490,382 | 17.7 | |
| | | Deforestation | 2,601,731 | 13.2 | |
| | | Agricultural productivity decline | 1,555,429 | 7.9 | |
| | | Mangrove degradation or deforestation | 44,259 | 0.2 | |
| | | Urban expansion or densification | 13,879 | 0.1 | |
| | | Others (undifferentiated multiple factors) | 511,499 | 2.6 | |
| Increase ($P$ < .05) | Climate | Rainfall change | 5,353 | 0.2 | 0.2 |
| | | Temperature change | 634 | 0.03 | |
| | | Rainfall and temperature change | 0 | 0 | |
| | Climate + human | Rainfall change + human factors | 35,353 | 1.4 | 1.7 |
| | | Temperature change + human factors | 7,780 | 0.3 | |
| | | Rainfall and temp. change + human factors | 227 | 0.01 | |
| | Human | Native forest growth or plantation | 1,283,180 | 51.6 | 98.1 |
| | | Grassland productivity increase | 563,010 | 22.6 | |
| | | Agriculture productivity increase or fallow regrowth | 394,324 | 17.1 | |
| | | Mangrove productivity increase or regrowth | 35,094 | 1.4 | |
| | | Urban greening | 1,408 | 0.1 | |
| | | Others (undifferentiated multiple factors) | 164,644 | 5.3 | |

(17.1%) and can be attributed to land management changes. Locally, Niassa and Cabo Delgado Provinces displayed an increase that can be explained by forest regeneration or plantation, and grassland management or bush encroachment (Brandt et al., 2017; O'Connor et al., 2014; Stevens et al., 2016). Indeed, these two provinces have the largest conservations areas in Mozambique and are characterized by low human population densities. This situation, together with favorable climatic conditions, could explain the increase in land productivity.

As highlighted previously, to extend the factor analysis, more ground surveys would help grasp more subtle or local factors (Brandt et al., 2015; Leroux et al., 2017; Mbow et al., 2015). Then, the use of statistical or regression methods would make it possible to add these variables (distance to river, fire occurrence, topography, etc.)—including socio-economic ones (population density, distance to market, cattle density, etc.)—in land productivity trend models and then to produce a quantitative analysis of the factors (Leroux et al., 2017). Another improvement could be the dissociation between herbaceous and woody vegetation changes in order to provide additional information on productivity change factors (Brandt et al., 2016). Recently, approaches based on passive microwave vegetation optical depth (Tian et al., 2016), or long-term and short-term sensitivity changes between satellite vegetation indices and rainfall data (Kaptué et al., 2015) have been suggested to assess woody or herbaceous changes.

## 4.2 | From land productivity change to land degradation: A question of perception

In this study, we showed that understanding the processes underlying land productivity change is a necessary step prior to mapping land degradation, and that this map is not unique but depends on the ecosystem service being targeted. Indeed, this study adds to the large body of literature on land degradation by highlighting the impact of the perception of land degradation on its assessment. Previous studies (Hobbs, 2016; IUCN, 2015; Van der Esch et al., 2017) mentioned that estimations of land degradation vary greatly due to the divergence in definition and perception, but in this article we were able to illustrate and quantify these divergences by simulating four stakeholder types.

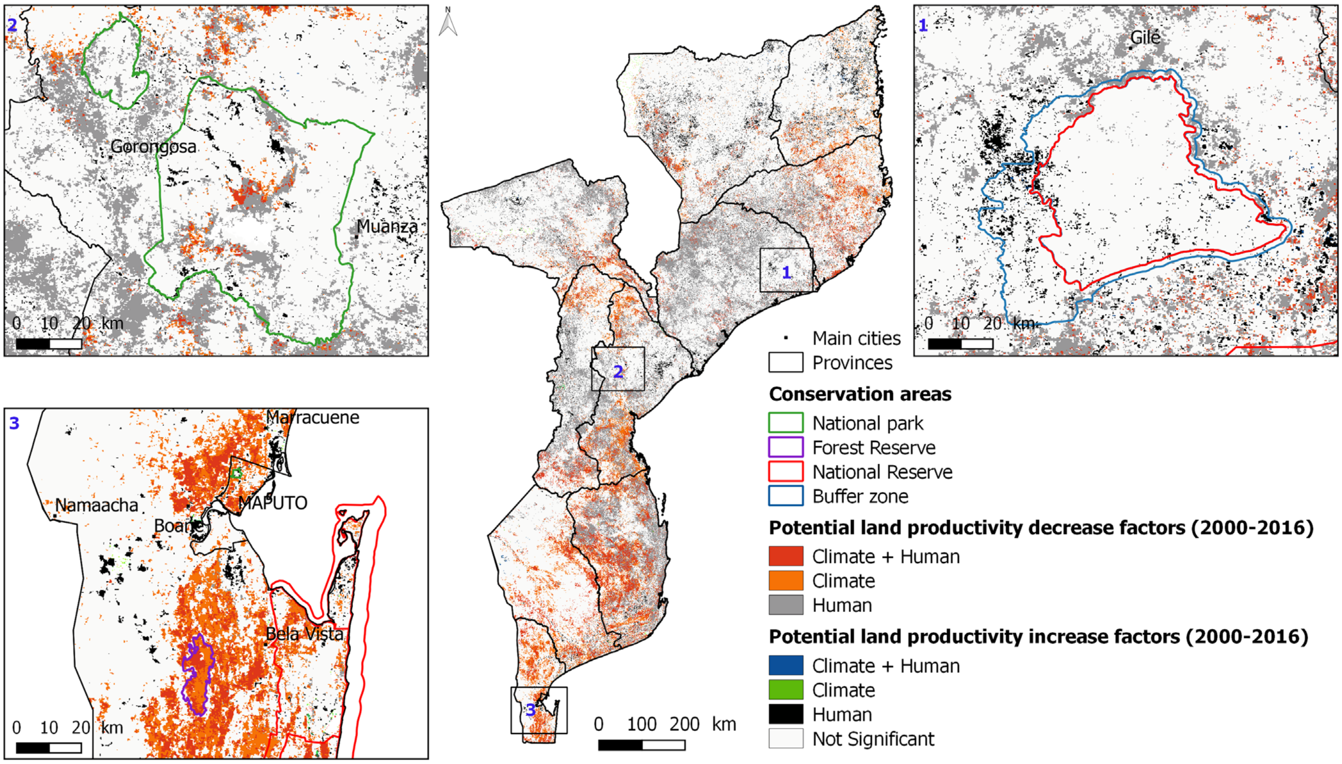


**FIGURE 5** Spatial distribution of the climate factors of the NDVI trends (Rainfall and temperature change are regrouped for clarity) [Colour figure can be viewed at wileyonlinelibrary.com]

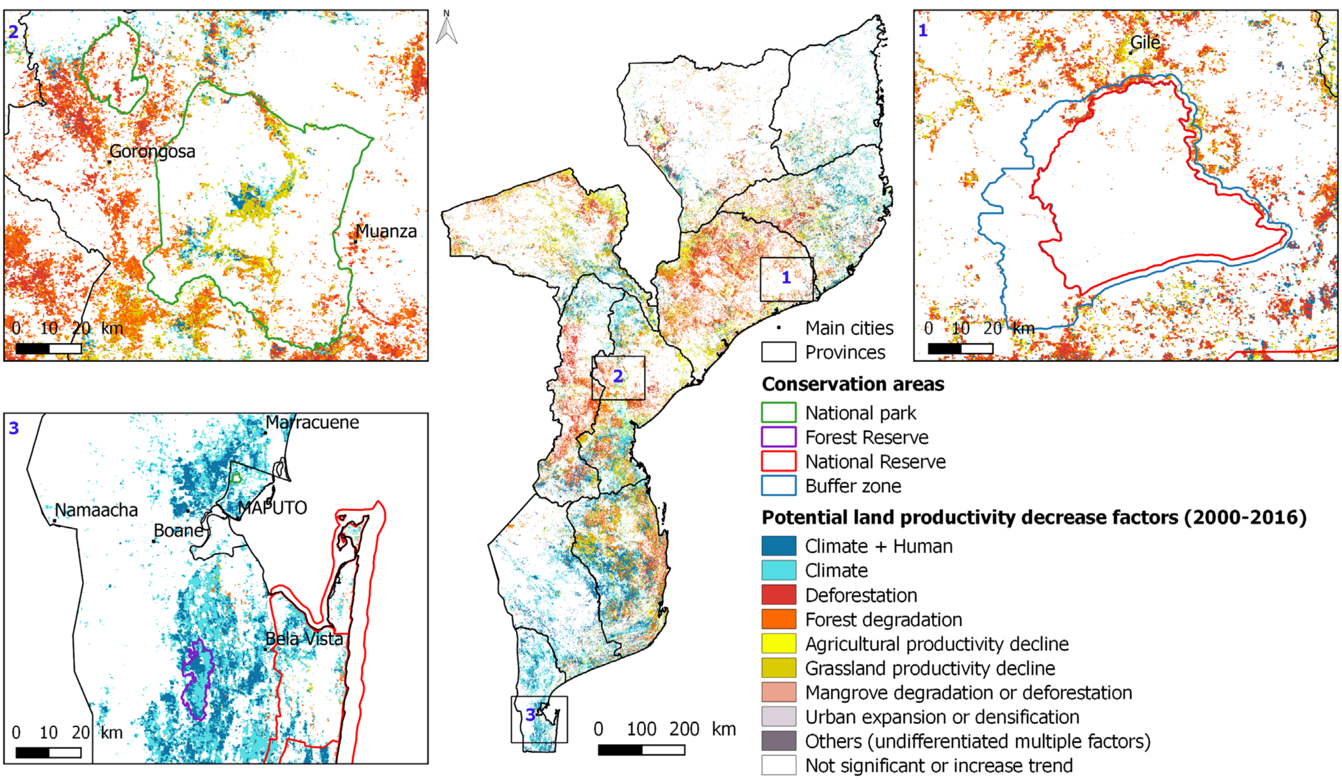


**FIGURE 6** Spatial distribution of the main factors of land productivity decreases [Colour figure can be viewed at wileyonlinelibrary.com]

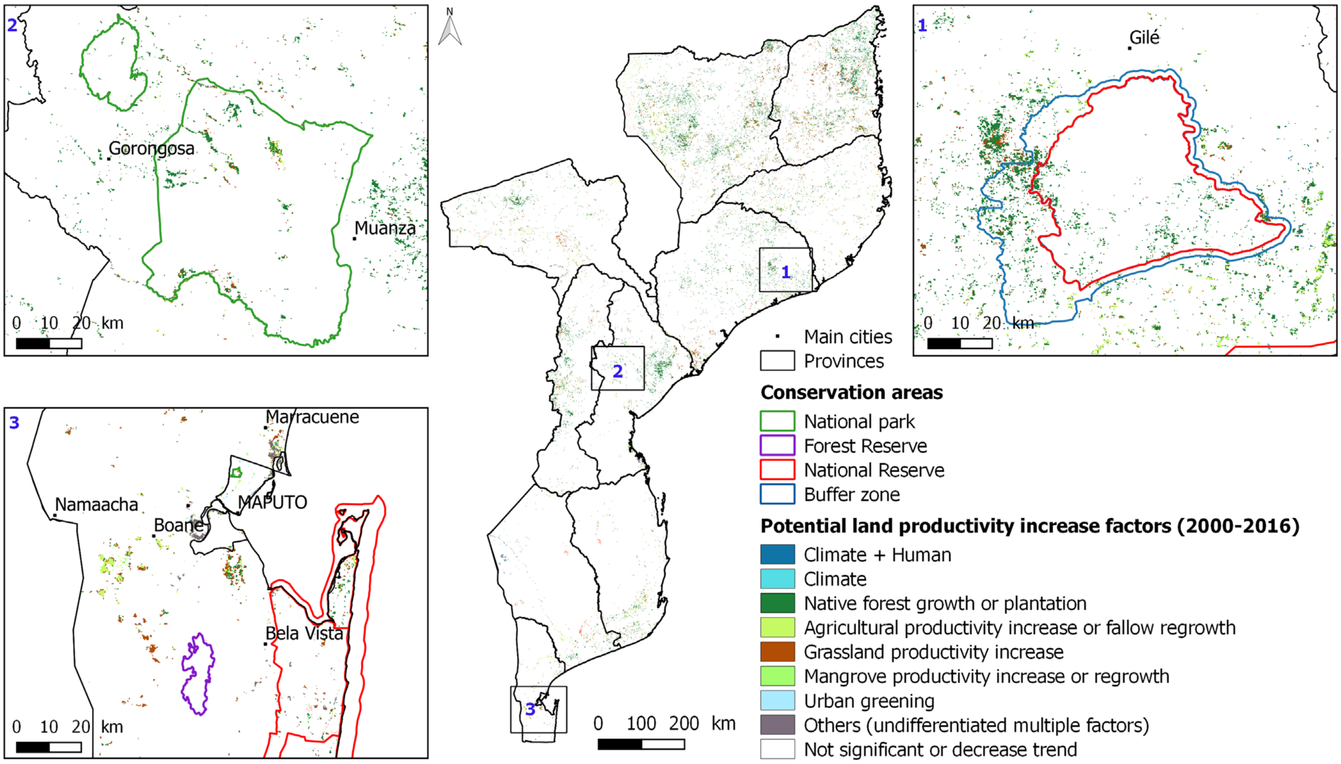


**FIGURE 7** Spatial distribution of the main factors of land productivity increases [Colour figure can be viewed at wileyonlinelibrary.com]

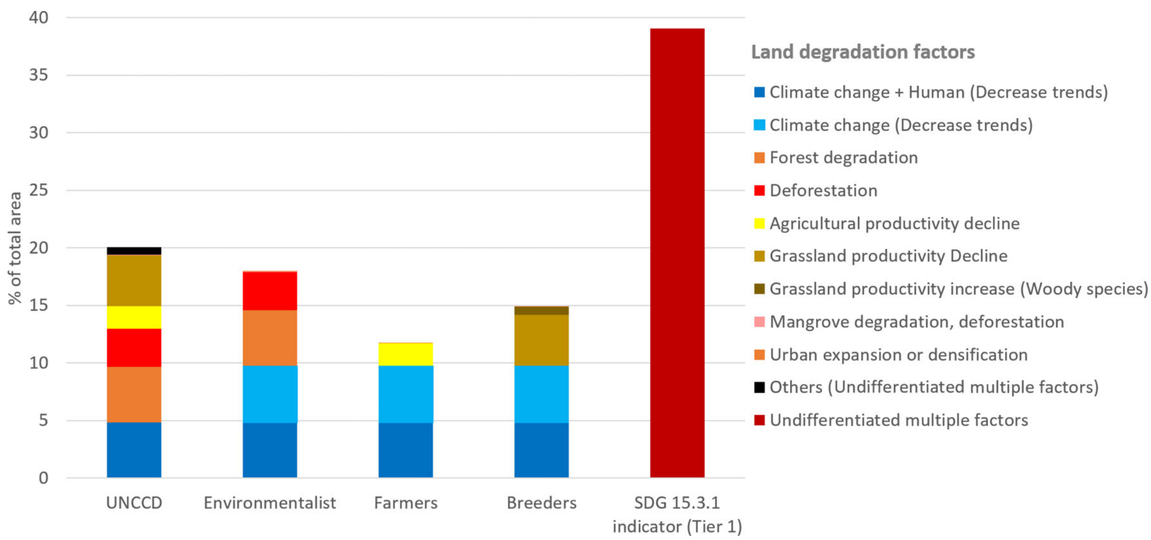


**FIGURE 8** Distribution of the fraction of degraded land in Mozambique as a function of the main factors, and for each stakeholder type and proportion of degraded land (2001–2015) calculated using the UNCCD default method (SDG 15.3.1 indicator) [Colour figure can be viewed at wileyonlinelibrary.com]

These four theoretical groups had their own targeted ecosystem services that were converted into indicators of change (biodiversity loss, reduced human and animal food production), durability of the change (temporary or permanent; Prince, 2019), and integration or non-integration of climate trends. These indicators were used to build four scenarios of land processes that, combined with the land productivity factors map, produced four different degraded land maps. Based on the scenarios, the proportion of degraded land varies between 11.9% (farmers) and 20.3% (UNCCD stakeholders) of the national territory, which is much smaller than the value of the indicator 15.3.1. (39%) computed with Trends Earth using Tier 1 data over Mozambique.

The difference between UNCCD stakeholder estimations of degraded land (20.3%) and indicator 15.3.1. (39%) can be explained by the difference in the LULC datasets that were used (Tier 1 vs. Tier 2) and by the NDVI period of integration (climate vs. civil year). As previously stated by different studies (Burrell et al., 2018; Montfort et al., 2019), the results are highly dependent on the choice of input data, namely, the LULC, climatic and NDVI datasets.

Considering the four stakeholder types, the differences in the assessment of the proportion of land which is degraded comes from the different weights of the human factors in land productivity changes. Indeed, climate (and climate plus human) has the same weight for all scenarios, counting for around 10% of degraded land for the whole Mozambique territory, while human factors depend on land management or absence of management. For example, an increase in the productivity of grassland cover can come from intensified rangeland management, or from bush encroachment. Bush encroachment is the most probable explanation in Mozambique, where pasture management is low (Marblé, 2012) and is therefore a sign of land degradation for breeders, while it can be interpreted as land restoration for other stakeholders due to increasing aboveground carbon stocks (Ayalew & Mulualem, 2018). Similarly, increasing land productivity due to commercial plantations can be seen as a benefit in terms of the land's economic productivity, but also as a loss of biodiversity if plantations replace natural ecosystems (Bremer & Farley, 2010; process of deforestation, for example). On the other hand, a decrease in cropland productivity will be a sign of land degradation for farmers, but not for the other stakeholders as long as it does not affect biodiversity. These examples illustrate the ambiguity and limits of UNCCD and IPBES definitions that do not consider the trade-off among various ecosystem services for land degradation assessment as highlighted by Van der Esch et al. (2017). Our results support the conclusions of previous studies on the fact that land productivity trends in terms of degradation and/or restoration of environmental conditions is not straightforward. An illustration of this difficulty is the contradictory results found in the literature. For example, Herrmann et al. (2014) found no strong correlation between NDVI trends and the perceptions of environmental conditions among the local population in Senegal, and Gonzalez-Roglich et al. (2019) showed recently that the land productivity indicator was able to detect at global scale the effect of many sustainable land management practices as increases in primary productivity over time.

### 4.3 | Towards a land degradation common reporting framework

Understanding changes in the productive capacity of land is critical for assessing the impact of land management interventions, its long-term sustainability and climate-derived impacts which could affect ecosystem resilience and human livelihoods (Teich et al., 2019).

Contrary to the UNCCD approach (which does not dissociate factors), the method we proposed further tackles our understanding of the factors influencing changes in vegetation productivity and reflects the land condition without any negative judgment and making a direct link with land degradation. The final interpretation of land conditions (land degradation or land restoration) is made according to local stakeholders' knowledge and views as illustrated in this article.

Variability in the estimation and location of land degradation may have impacts on the identification of these areas, and the constraints and opportunities for their restoration and the sustainable management of land resources. A single definition of land degradation would not meet with global consensus due to the site-specific nature and context of land degradation. One suggestion could be that each country develop its own definition—or definitions—of land degradation, as for the forest definition in the reduction of emissions from deforestation and forest degradation, conservation, sustainable management and restoration of carbon stocks (REDD+) mechanism. These definitions could be developed from the collection of information on the perceptions of representative stakeholders.

## 5 | CONCLUSIONS

In this study, we characterized and mapped factors in land productivity changes over the 2000–2016 period in order to produce elements that make it possible to establish a land degradation estimation at the country scale, using remote sensing data. Overall, our study evidenced that land productivity decreased and threatened one-quarter of Mozambique between 2000 and 2016. We showed that a large part of this negative trend could be mainly related to anthropogenic activities compared with climate change factors. We demonstrated from hypothetical study cases that some of the subjectivity in the assessment of degradation relates to the use and goal under consideration.

This study provides a consistent, up-to-date and spatial estimation of land degradation in Mozambique, which can help decision-makers to design national and locally relevant land degradation mitigation policies or programs to reach land degradation neutrality by 2030. The novelty of this study was to better describe land conditions and discuss some improvements to the existing UNCCD methods for assessing land degradation. Our findings highlight that applying NDVI trend analysis for land degradation assessments remains a challenge both in implementation and interpretation. For effective policies to combat land degradation there is a need for research to develop or improve methodologies and agreements on definitions.

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