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Evaluating land cover changes in Eastern and Southern Africa from 2000 to 2010 using validated Landsat and MODIS data

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ABSTRACT

In this study, we assessed land cover land use (LCLU) changes and their potential environmental drivers (i.e., precipitation, temperature) in five countries in Eastern & Southern (E & S) Africa (Rwanda, Botswana, Tanzania, Malawi and Namibia) between 2000 and 2010. Landsat-derived LCLU products developed by the Regional Centre for Mapping of Resources for Development (RCMRD) through the SERVIR (Spanish for "to serve") program, a joint initiative of NASA and USAID, and NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) data were used to evaluate and quantify the LCLU changes in these five countries. Given that the original development of the MODIS land cover type standard products included limited training sites in Africa, we performed a two-level verification/validation of the MODIS land cover product in these five countries. Precipitation data from CHIRPS dataset were used to evaluate and quantify the precipitation changes in these countries and see if it was a significant driver behind some of these LCLU changes. MODIS Land Surface Temperature (LST) data were also used to see if temperature was a main driver too.

Our validation analysis revealed that the overall accuracies of the regional MODIS LCLU product for this African region alone were lower than that of the global MODIS LCLU product overall accuracy (63–66% vs. 75%). However, for countries with uniform or homogenous land cover, the overall accuracy was much higher than the global accuracy and as high as 87% and 78% for Botswana and Namibia, respectively. In addition, the wetland and grassland classes had the highest user's accuracies in most of the countries (89%–99%), which are the ones with the highest number of MODIS land cover classification algorithm training sites.

Our LCLU change analysis revealed that Botswana's most significant changes were the net reforestation, net grass loss and net wetland expansion. For Rwanda, although there have been significant forest, grass and crop expansions in some areas, there also have been significant forest, grass and crop loss in other areas that resulted in very minimal net changes. As for Tanzania, its most significant changes were the net deforestation and net crop expansion. Malawi's most significant changes were the net deforestation, net crop expansion, net grass expansion and net wetland loss. Finally, Namibia's most significant changes were the net deforestation and net grass expansion.

The only noticeable environmental driver was in Malawi, which had a significant net wetland loss and could be due to the fact that it was the only country that had a reduction in total precipitation between the periods when the LCLU maps were developed. Not only that, but Malawi also happened to have a slight increase in temperature, which would cause more evaporation and net decrease in wetlands if the precipitation didn't increase as was the case in that country. In addition, within our studied countries, forestland expansion and loss as well as crop expansion and loss were happening in the same country almost equally in some cases. All of that implies that non-environmental factors, such as socioeconomics and governmental policies, could have been the main drivers of these LCLU changes in many of these countries in E & S Africa. It will be important to further study in the future the detailed effects of such drivers on these LCLU changes in this part of the world.

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Table 1
Examples of land cover datasets with coverage of East and Southern Africa.

No.	Dataset	Date – Ground Condition	Date – Publication	Original Source	Published as	Imagery used	Source Resolution	Coverage	No. Classes
1	Land Cover	1995–2002		FAO	Africover	Landsat TM	30 m	Regional	15–110, country dependent
2	Land Cover	1990–2000	1998	MDA	GeoCover	Landsat TM	30 m	Global	13
3	Land Cover	1989–1993	1990	Global Land Cover Facility	Landsat GeoCover	Landsat TM	30 m	Global	
4	Land Cover	1997–2000	2000	Global Land Cover Facility	Landsat GeoCover	Landsat ETM	30 m	Global	
5	Land Cover	2003		NGIA/ISCGM	GLCNMO	MODIS	1 km	Global	20
6	Land Cover	2008		NGIA/ISCGM	GLCNMO	MODIS	500 m	Global	20
7	Land Cover	2008		NGIA/ISCGM	Percent Forest Cover	MODIS	500 m	Global	3
8	Land Cover	2001–2013		NASA/USGS	MODIS LC-I	MODIS	500 m	Global	16
9	Land Cover	1990–2010	2015	SERVIR/RCMRD	East and Southern Africa Land Cover	Landsat TM	30 m	Regional	6, 13

1. Introduction

Land cover and land use (LCLU) changes have a direct impact on greenhouse gas (GHG) emissions (IPCC, 2000); and their accurate quantification is needed to estimate the contributions of the Land Use, Land Use Change and Forestry (LULUCF) sector in national GHG inventories. LCLU change, mainly due to deforestation, has been found to contribute to about 20% of the GHG emissions from anthropogenic sources (IPCC, 2000). LULUCF sector in general has an aggregate share of over 30% of the gross global emissions. In Africa, changes in land cover are in fact the biggest contributor, so it is especially important to track these changes there and quality LCLU maps are an important requirement for that. The quantification of land use change can be a complex and intensive task and needs comparable datasets and methodologies. Thus, countries in Eastern and Southern (E & S) Africa have been working together to overcome these challenges and achieve timely and sustainable accounting for the LULUCF component of the GHG inventory development (RCMRD, 2015).

In a collaborative effort to support countries in E & S Africa to develop their national GHG inventories, SERVIR (Spanish for "to serve"), a joint initiative between NASA and USAID, through its hub institution in E & S Africa, Regional Centre for Mapping of Resources for Development (RCMRD), partnered with the United Nations Framework Convention on Climate Change (UNFCCC) and other development partners. With the main goal of generating LCLU maps for several countries in this region. This initiative has become the first of its kind for multiple reasons. First, it provided a standardized methodology that was reviewed and approved by leading organizations in the topic. Second, it strongly engaged national organizations to build capacity and co-develop final LCLU maps derived from Landsat satellite data. Third, it generated multi-temporal, comparable datasets for the region and made the final products freely available online. Even though the main goal of these maps was to support the development of national GHG inventories, this wealth of information can also elucidate valuable understanding of the condition and over time changes of the land and forestry resources at the national and regional level in E & S Africa. These remotely sensed LCLU data applied the same analytical methods, which makes comparisons between countries and over time possible. So, RCMRD in collaboration with multiple organizations and with the aim of supporting countries in the development of their GHG inventories generated LCLU data for Rwanda, Botswana, Tanzania, Malawi, Namibia and Zambia based on 30 m Landsat satellite images. Dry season Imagery for the epochs: 2000 and 2010 (and 1990 for Malawi and Rwanda) were considered for processing. At the beginning of the land cover mapping activity in each country, a kickoff workshop was held. There, government representatives defined the land cover classes they were interested in. Originally, two classification schemes were used to generate these land cover datasets, one recommended by the Intergovernmental Panel on Climate Change (IPCC) to generate GHG inventories and another customized to national requirements. A supervised classification technique was originally implemented to produce country specific schema of land cover comprising 12–15 classes that were combined to obtain six major land cover categories recommended by the IPCC to generate GHG inventories (Forestland, Grassland, Cropland, Wetland, Settlement and Otherland), which we used in this study's analyses. Once the maps were originally developed, in situ data was collected in each country to help refine and validate the remote sensing-based land cover maps being produced. The initial draft maps, once completed, were sent to local experts in each country who could provide feedback about any misclassifications, and corrections were then made based on this feedback. A minimum user's accuracy (i.e., the probability of a satellite pixel being classified correctly) of 75% was considered acceptable, but high quality land cover maps were ultimately generated with accuracies between 80 and 92% for the six countries.

The current study further analyzes this LCLU data in relation with climatic information to help identify trends and drivers behind the major changes of land cover between 2000 and 2010. In addition, results of a higher-level validation using independent land cover and other satellite-derived datasets are also presented. This study focuses in five countries in E & S Africa: Botswana, Malawi, Namibia, Rwanda and Tanzania.

There are several LCLU products for Africa developed by a number of organizations from around the world (see Table 1), these products go from global, regional, national to local. The different methodologies, spatial and temporal resolutions, and geographic coverage discrepancies make the inter-comparison of all these LCLU products difficult. As a result, the understanding of land cover changes in Africa is challenging. If proven appropriate, global land cover products such as the yearly MODIS-derived LCLU product could be useful and provide valuable information of land cover change estimations in this part of the world.

RCMRD's Landsat-derived and NASA's Moderate-Resolution Imaging Spectroradiometer (MODIS) data were used in this study to evaluate and quantify the LCLU changes in five countries in E & S Africa. Given that the original development of the MODIS land cover type standard products included limited training sites in Africa (Friedl et al., 2002), we have also used the RCMRD's Landsat-derived LCLU products to revalidate these MODIS products in these five countries of E & S Africa. The primary MODIS land cover type product is a yearly 500-m product that was derived through an ensemble supervised decision-tree classification method (Friedl et al., 2010), and includes 11 natural vegetation classes, 3 developed and mosaicked land classes, and three non-vegetated land classes. Results from the ensemble decision trees are post-processed to correct classification results for

Table 2
User's accuracies of the RCMRD's Landsat-derived LCLU Scheme I classifications per country per year.

LCLU Class	User's Accuracy (Botswana_2000)	User's Accuracy (Botswana_2010)	User's Accuracy (Namibia_2000)	User's Accuracy (Namibia_2010)	User's Accuracy (Rwanda_2000)	User's Accuracy (Rwanda_2010)	User's Accuracy (Tanzania_2000)	User's Accuracy (Tanzania_2010)	User's Accuracy (Malawi_2000)	User's Accuracy (Malawi_2010)
Forestland	94	88	74	90	81	78	91	89	84	82
Grassland	93	93	91	91	78	81	93	93	77	61
Cropland	80	72	89	93	86	81	93	81	81	86
Wetland	83	98	84	100	98	92	97	95	96	99
Settlement	88	99	100	100	100	89	88	92	100	89
Otherland	94	94	89	81	100	100	75	52	33	69

biases inherent to the decision tree algorithm caused by specific properties of the training sample, and to exploit extant information related to the geographic distribution of global land cover. More details about the processing steps of this algorithm are provided elsewhere (Friedl et al., 1999, 2000, 2002; McIver and Friedl, 2001, 2002). This product has been used in several studies in the research literature and for different purposes and regions around the world. For example, Moreno-Madrinan et al. (2015) used this product to study the effect of land cover changes on water quality in watersheds in Central America. Fu and Tai (2015) used this product to study the impact of land cover changes on tropospheric ozone air quality and public health in East Asia. Vintrou et al. (2012) used this product for crop area mapping in West Africa. Ichoku et al. (2016) used this product and others to study the impacts of biomass burning on land cover dynamics in Northern Sub-Saharan Africa. And Gessner et al. (2012) used this MODIS land cover product as input data for regional climate modeling in West Africa. In this study, we have also used MODIS Land Surface Temperature (LST) data to also provide a first-level verification the MODIS LCLU data by applying spatial comparisons. Precipitation data from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset were used to evaluate and quantify the precipitation changes in these countries and see if it was a significant driver behind some of these LCLU changes. MODIS LST data were also used to see if temperature was a main driver too. If neither of these environmental drivers was significant, this could suggest that non-environmental drivers such as socio-economic changes (e.g. governmental agricultural policies, wars beginning/ending) could have influenced these LCLU changes.

In summary, the main goal of this study was to assess LCLU changes and their potential drivers in five countries in eastern & southern Africa (Rwanda, Botswana, Tanzania, Malawi and Namibia), using as reference the RCMRD's Landsat-derived LCLU maps. To that end, several remotely sensed datasets were used to quantify the LCLU changes and try to identify the possible environmental (e.g. precipitation, temperature) and/or socio-economic drivers behind such changes. So, the specific objectives of this study were:

- Evaluate the LCLU changes between 2000 and 2010 in E & S Africa using Landsat-derived and MODIS-derived data.
- Revalidate MODIS land cover type standard product in E & S Africa using Landsat-derived data, given the limited training sites in Africa that were used in the MODIS product's development.
- Evaluate potential environmental drivers (e.g. precipitation, temperature) behind LCLU changes between 2000 and 2010.

2. Methodology

RCMRD's Landsat-derived and NASA's MODIS data were used in this study to evaluate and quantify the LCLU changes in five countries in eastern & southern Africa. There are multiple change detection methods used in the research literature that can be categorized as the following (Shah-Hosseini et al., 2015; Tewkesbury et al., 2015; Olthof and Fraser, 2014; Karnieli et al., 2014): (a) Images algebra (Dai and Khorram, 1998; Mas, 1999) (b) Change Vector Analysis (Vittek et al., 2014; Lambin and Strahlers, 1994); (c) Image transformation (Li and Yeh, 1998); (d) Post-classification comparison (Pang et al., 2014) (e) Direct classification (Zhou et al., 2014); and (f) Hybrid Change Detection methods (Shah-Hosseini et al., 2015). Examples of these techniques include kernel-based techniques, Hopfield neural network, Wavelet transform, Fourier transform, convolution filters, local variance, co-occurrence matrix, spatial autocorrelation, and fractal measurement (Shah-Hosseini et al., 2015; Al-Hamdan et al., 2014; Aleksandrowicz et al., 2014; Al-Hamdan et al., 2012; Hosseini et al., 2012; Celik and Ma, 2011; Camps-Valls and Bruzzone, 2009; Camps-Valls et al., 2008; Pajares, 2006; Guorui et al., 2006). However, since one of the objectives of this paper was to revalidate MODIS land cover type standard product

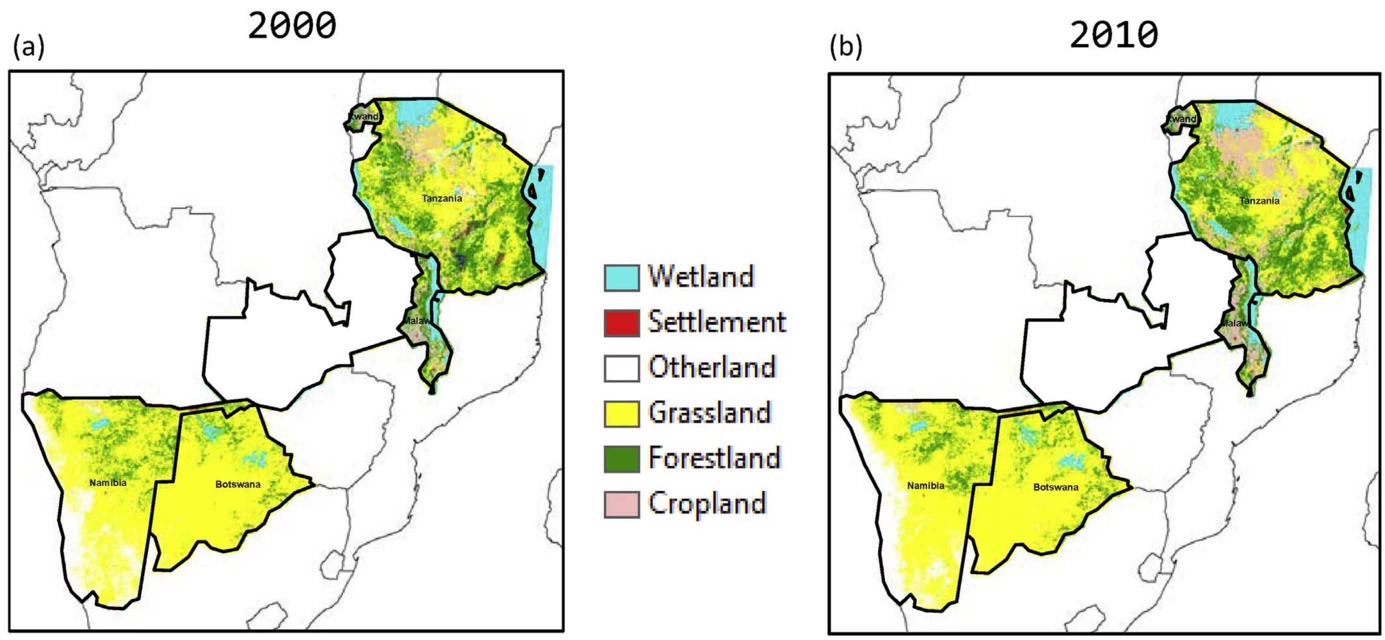

Fig. 1. Landsat-derived LCLU data for (a) 2000 and (b) 2010.

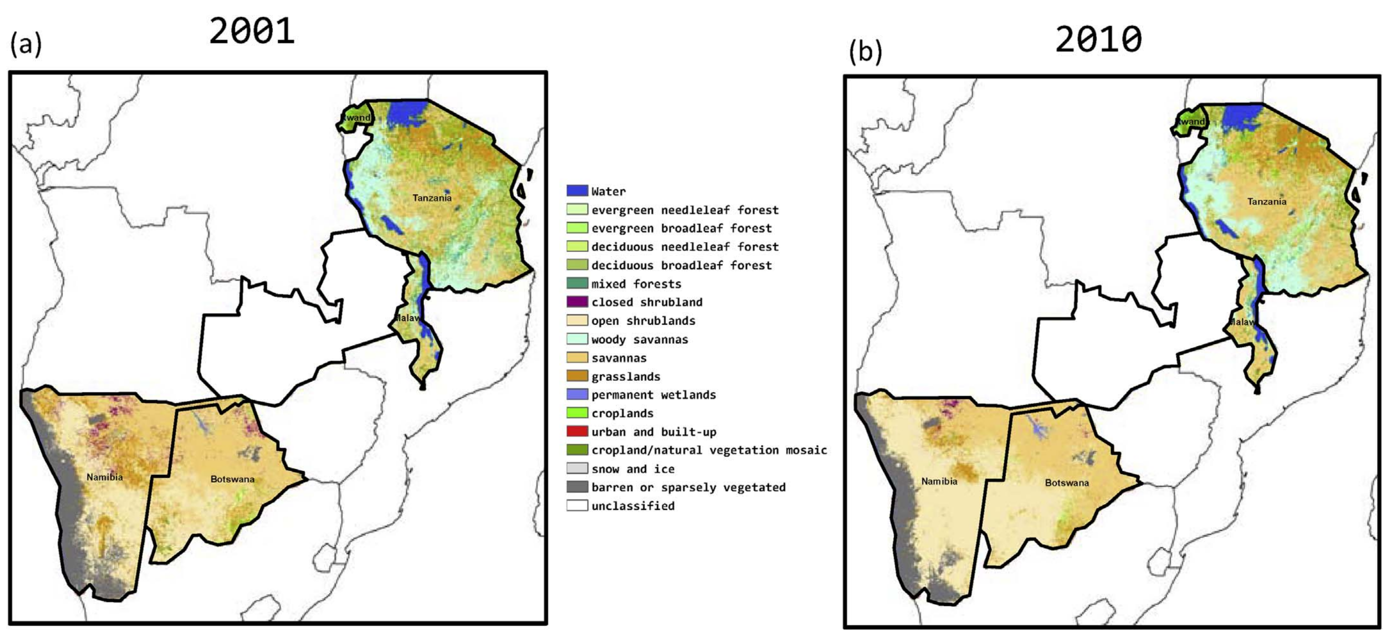

Fig. 2. MODIS LCLU data for (a) 2001 and (b) 2010.

in Eastern & Southern Africa using Landsat-derived data, we needed to be consistent in the change detection methods and the data used. Thus, we looked at the direct change percentages per unified major LCLU classes using standard and available products for both satellite sensors (MODIS and Landsat) and a straightforward statistical method that can be applied to these standard products.

But first, a two-level verification/validation of the MODIS land cover product in this part of the world was performed given the limited training sites in Africa that were used in the MODIS product's original development. First, MODIS LST data were used to verify the MODIS LCLU data by applying spatial comparisons and identifying the mean LST for different MODIS LCLU classes. The second level of validation involved using the previously rigorously validated RCMRD's Landsat-derived LCLU products to revalidate these MODIS products in these five countries of E & S Africa. The MODIS and Landsat-derived LCLU products did not employ the same classification scheme, so it was necessary to remap their classes to a common classification scheme for comparison between the two products. In other words, in order to be able to compare the MODIS LCLU products to the RCMRD's Landsat-derived LCLU products, we have remapped the MODIS LCLU classes to those of RCMRD's based on their matching definitions given in Friedl et al. (2002) and RCMRD's workshops reports (RCMRD, 2015). For consistency purposes, we have also resampled the RCMRD's Landsat-derived 2000 and 2010 LCLU products from 30 m to 500 m using the "majority" or "most dominant" class technique. In order to assess the classification accuracy of the MODIS LCLU products in these countries

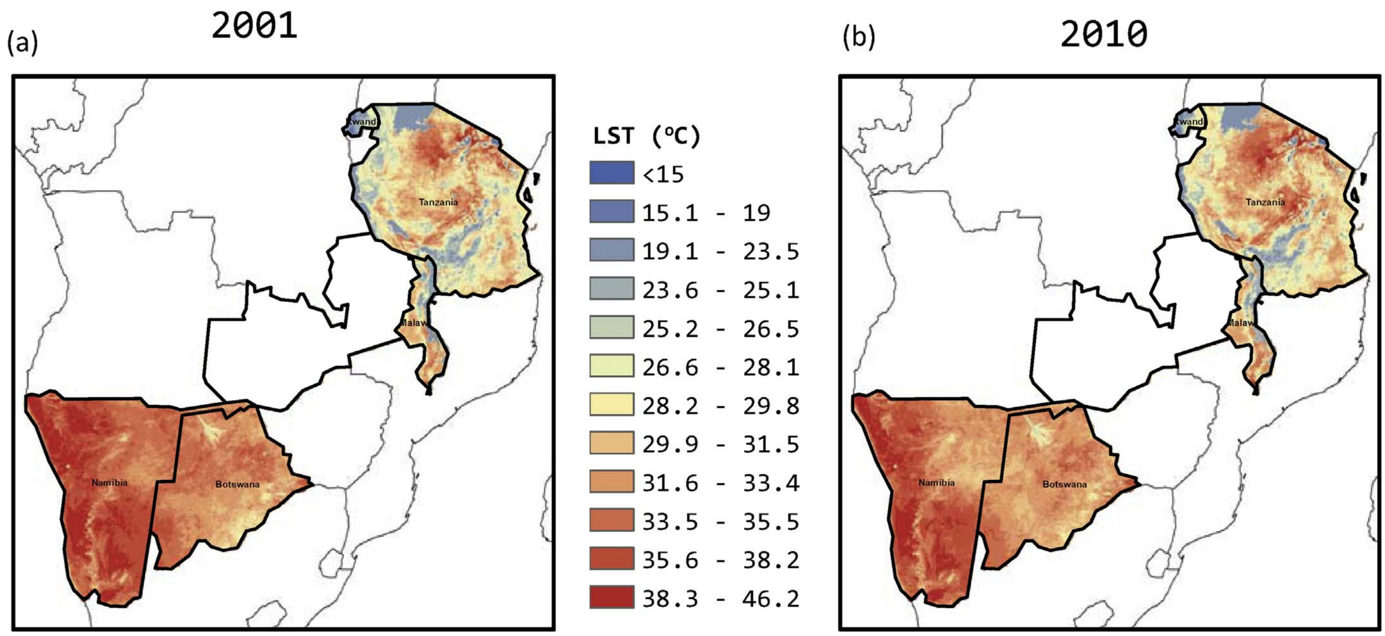

Fig. 3. MODIS mean annual LST data for (a) 2001 and (b) 2010.

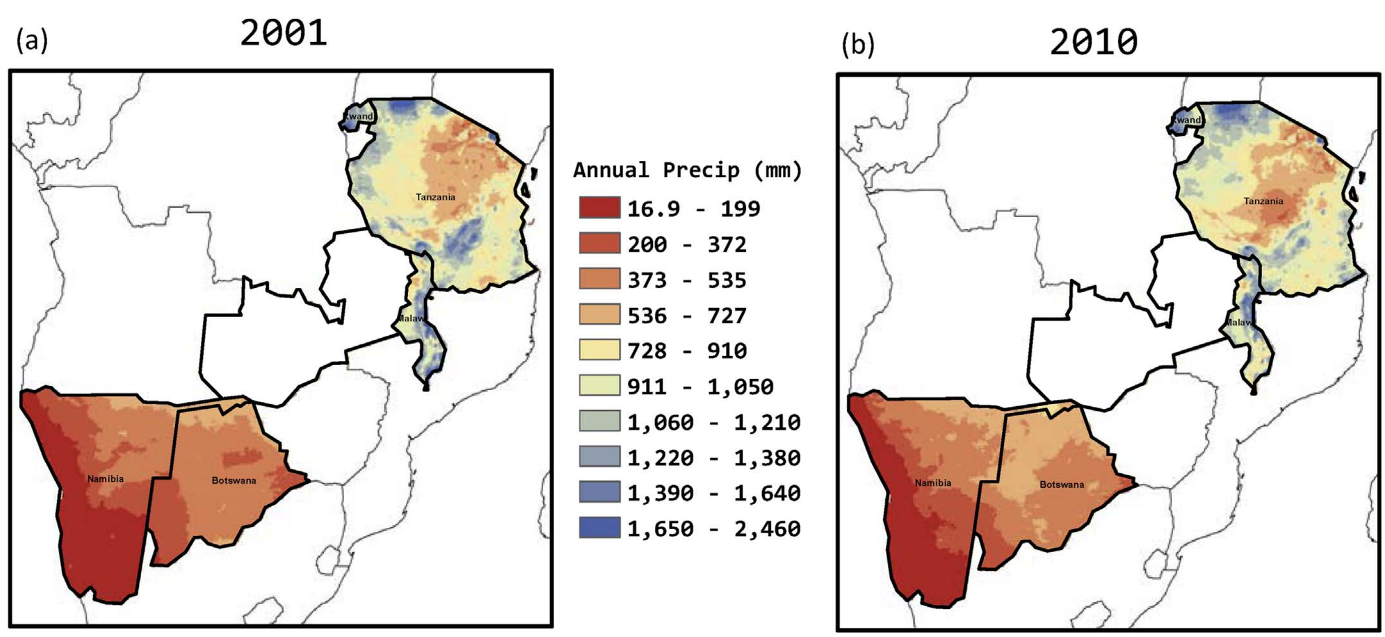

Fig. 4. CHIRPS total annual precipitation data for (a) 2001 and (b) 2010.

in E & S Africa, we have created the confusion matrix using the remapped MODIS-derived LCLU and resampled Landsat-derived LCLU data and computed the Overall Accuracy (Campbell, 1996; Foody, 2002), assuming that the resampled Landsat-derived LCLU are the "true" LCLU representation. Precipitation data from the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) dataset were used to evaluate and quantify the precipitation changes in these countries and see if it was a significant driver behind some of these LCLU changes. MODIS LST data were also used to see if temperature was a main driver too. To that end, we computed and used the total precipitation and mean LST per country for the years around the LCLU epochs of 2000 and 2010.

3. Datasets

3.1. RCMRD's Landsat-derived LCLU products (summary of classification methodology)

RCMRD in collaboration with multiple organizations and with the aim of supporting countries in the development of their GHG inventories generated LCLU data for Rwanda, Botswana, Tanzania, Malawi, Namibia and Zambia based on 30 m Landsat satellite images. Dry season Imagery for the epochs: 2000 and 2010 (and 1990 for Malawi and Rwanda) were considered for processing. Following necessary pre-

Table 3
Remapping of MODIS and Landsat LCLU to a common classification.

MODIS Original LCLU IGBP Class	Remapped Class Matching RCMRD's Landsat-derived LCLU Scheme I Class
Water	Wetland
Evergreen Needleleaf Forest	Forestland
Evergreen Broadleaf Forest	Forestland
Deciduous Needleleaf Forest	Forestland
Deciduous Broadleaf Forest	Forestland
Mixed Forest	Forestland
Closed Shrublands	Forestland
Open Shrublands	Grassland
Woody Savannas	Forestland
Savannas	Grassland
Grasslands	Grassland
Permanent Wetlands	Wetland
Croplands	Cropland
Urban and built-up	Settlement
Cropland/Natural vegetation mosaic	Cropland
Snow and Ice	Otherland
Barren or Sparsely Vegetated	Otherland

processing procedures, the Maximum Likelihood algorithm supervised classification technique was implemented to produce country specific schema of land cover comprising 12–15 classes which were combined to obtain the six Intergovernmental Panel on Climate Change (IPCC) land cover categories required to implement the GHG inventorying. Because of the fragmented nature of land cover within the E & S Africa countries, slight modifications of the processing procedures were implemented to suit country conditions guided by the locally obtained auxiliary data. Further post processing was performed to edit the land covers as appropriate, including ground truthing following random sampling procedures to validate and establish the accuracy of the land cover products. A minimum user's accuracy (i.e., the probability of a satellite pixel being classified correctly) of 75% was considered acceptable. Accuracies however differed for the different schemas: Scheme II (country specific) had more Land Cover categories and slightly Lower Accuracies than the Scheme I (IPCC) categories that had only six classes. This would further differ between epochs. As shown in Table 2, 2010 epoch was found to generally have better user's accuracies since validation was done based on in-situ data complimented with data from other sources. It was only possible to obtain in-situ data for the contemporary year.

All processing procedures were implemented as outlined in the implementation guide developed by the Regional Center for Mapping of Resources for Development and available at RCMRD (2015). The Landsat-derived 2000 and 2010 LCLU products for our study area are shown in Fig. 1.

3.2. MODIS-derived LCLU products (summary of classification methodology)

The MODIS Land Cover Type product (MCD12Q1) contains five global land cover classification schemes, which describe land cover properties derived from observations spanning a year's input of Terra- and Aqua-MODIS data. The primary land cover scheme, which was used in this study, it's the most similar to RCMRD's Landsat-derived classification schemes, identifies 17 land cover classes defined by the International Geosphere Biosphere Programme (IGBP). It includes 11 natural vegetation classes, 3 developed and mosaicked land classes, and three non-vegetated land classes. Collection 5 of this product is a yearly 500-m product that was derived through an ensemble supervised decision-tree classification method (Friedl et al., 2010). Results from the ensemble decision trees are post-processed to correct classification results for biases inherent to the decision tree algorithm caused by specific properties of the training sample, and to exploit extant information related to the geographic distribution of global land cover. More details about the processing steps of this algorithm are provided elsewhere (Friedl et al., 1999, 2000, 2002; McIver and Friedl, 2001, 2002). The MODIS-derived 2001 and 2010 LCLU products for our study area are shown in Fig. 2.

3.3. MODIS land surface temperature data

The MODIS data collections are derived from both the NASA Terra and Aqua MODIS instruments, and temporally span from 2000 until present. The calibration for the 16 thermal emissive bands is on-orbit using observations of a temperature-controlled blackbody and deep space (Wenny et al., 2013). Terra descends (ascends) the equator

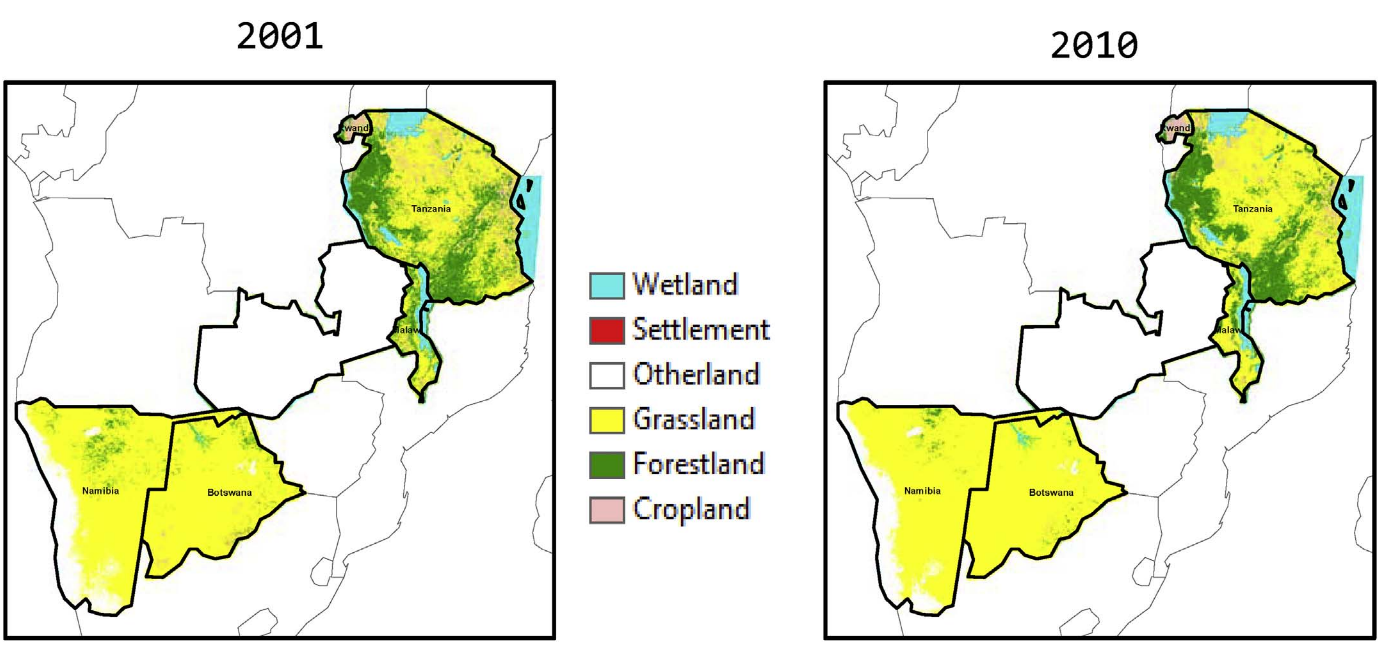

Fig. 5. Remapped MODIS-derived LCLU (~500 m spatial resolution).

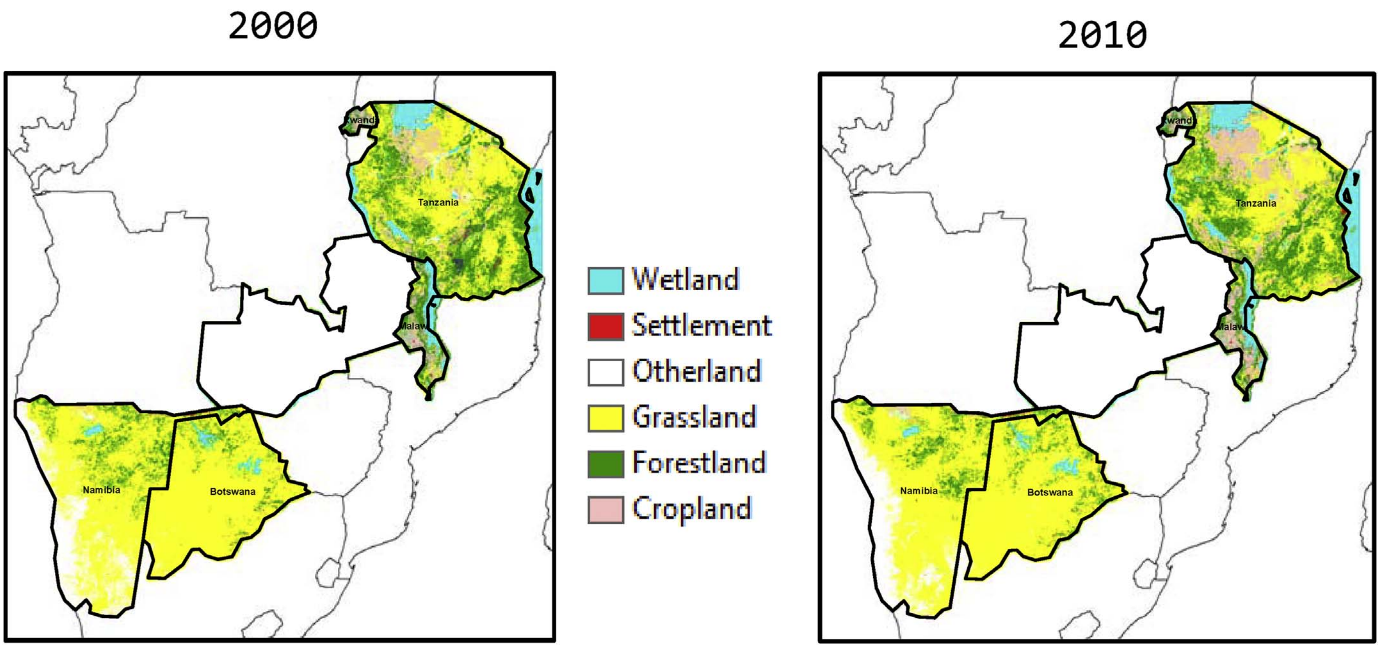

Fig. 6. Resampled Landsat-derived LCLU from 30 m to ~500 m.

around 10:30 A.M. (10:30 P.M.) local time. In contrast, Aqua descends (ascends) the equator at 1:30 P.M. (1:30 A.M.) local time. MODIS instruments provide a number of environmental products including land cover/land use change, net primary productivity, leaf area index, emissivity values, and surface temperature. The daily Terra MOD11A1 product is the daytime LST product collected by the Terra instrument at spatial resolutions of 1 km over global land surfaces under clear-sky conditions (Level 3, Collection 5). The MODIS 2001 and 2010 mean annual LST data were computed from these daily MODIS LST data for our study area, and are shown in Fig. 3.

3.4. CHIRPS precipitation data

Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) is a 30+ year quasi-global rainfall dataset. Spanning (50°S–50°N, 180°E–180°W), starting in 1981 to near-present, CHIRPS incorporates 0.05° (~5 km) resolution satellite imagery with in-situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring (Funk et al., 2014). The CHIRPS 2001 and 2010 total annual precipitation data for our study area are shown in Fig. 4.

3.5. Remapped MODIS-LCLU and resampled Landsat-LCLU for comparison purposes

As previously mentioned, we have mapped the MODIS and Landsat-derived LCLU products to a common classification scheme (Table 3). We have remapped the MODIS LCLU classes to those of RCMRD's based on their matching definitions given in Friedl et al. (2002) and RCMRD's workshops reports (RCMRD, 2015). The remapped MODIS-derived 2001 and 2010 LCLU products for our study area are shown in Fig. 5. We have also resampled the RCMRD's Landsat-derived 2000 and 2010 LCLU products from 30 m to 500 m using the "majority" or "most dominant" class technique, and they are shown in Fig. 6.

4. Results and discussion

As previously mentioned, RCMRD's Landsat-derived and NASA's MODIS data were used in this study to evaluate and quantify the LCLU changes in five countries in eastern & southern Africa. But first, a two-level verification/validation of the MODIS land cover product in these five countries was performed given the limited training sites in Africa that were used in the MODIS product's original development. First, as a first-level verification of the MODIS LCLU data, a spatial analysis comparing the MODIS Land Surface Temperature (LST) among the different MODIS Land Cover Land Use (LCLU) classes revealed a positive conclusion. As shown in Fig. 7 and as expected, the barren or sparsely vegetated lands had the highest LSTs in all the countries, while water had the lowest LSTs. Forests had lower LSTs than grasslands and croplands, and evergreen forests had lower LSTs than deciduous forests.

The second level of validation involved using the previously rigorously validated RCMRD's Landsat-derived LCLU products to revalidate these MODIS products in these five countries of E & S Africa. To that end and for consistency, we have remapped the MODIS LCLU classes to those of RCMRD's based on their matching definitions and resampled the RCMRD's Landsat-derived LCLU products from 30 m to 500 m. Comparing the changes in the remapped MODIS LCLU classes to the corresponding ones of the resampled Landsat-derived data revealed a positive conclusion. As shown in Figs. 9 and 10 , the LCLU classes generally matched reasonably well. For instance, as shown in Fig. 9, the Landsat-derived classification showed that the grassland comprised ~90% of Botswana's land around 2000. On the other hand, as shown in Fig. 10, the corresponding class in the 2001 remapped MODIS LCLU data comprise ~93%, which is very similar to that of the Landsat classification. Also, the Landsat-derived classification showed that the grassland comprised ~47% of Tanzania's land around 2000. On the other hand, the corresponding class in the 2001 remapped MODIS LCLU data comprise ~49%, which is very similar to that of the Landsat classification. Also, the Landsat-derived classification showed that the forestland comprised ~24% of Tanzania's land around 2000. On the other hand, the corresponding class in the 2001 remapped MODIS LCLU data comprise ~28%, which is close to that of the Landsat classification. In addition, the Landsat-derived classification showed that the wetland comprised ~24% of Malawi's land around 2000. On the other hand, the corresponding class in the 2001 remapped MODIS LCLU data comprise ~22%, which is similar to that of the Landsat classification. The previous analyses confirmed our confidence with both LCLU products. This can be considered as a

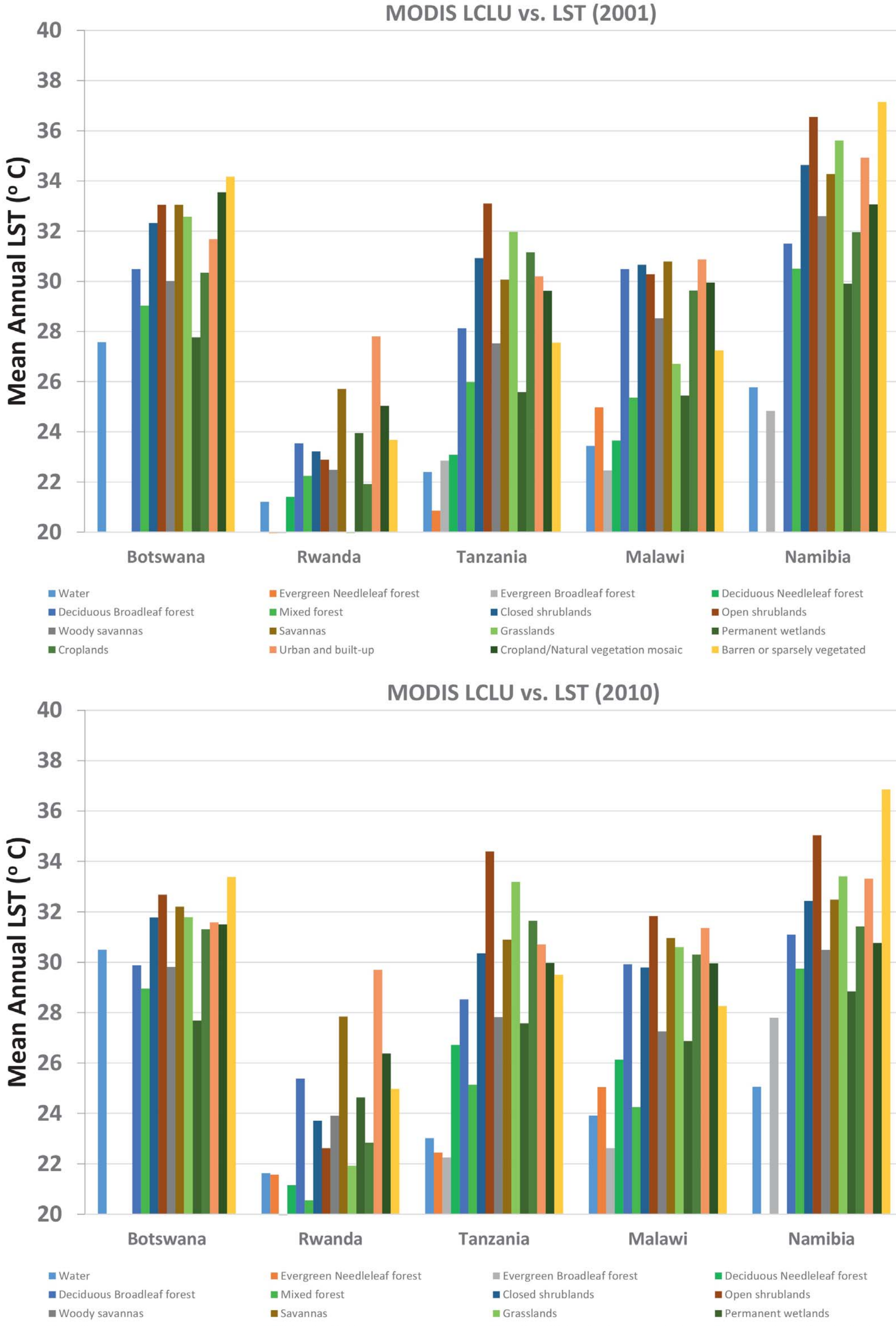

Fig. 7. MODIS LCLU versus LST per country for (a) 2001 and (b) 2010.

validation of MODIS LCLU product, whose development included limited training sites in Africa (Friedl et al., 2002). To further assess the classification accuracy of these MODIS LCLU products in Africa, we have created the confusion matrix using the remapped MODIS-derived LCLU and resampled Landsat-derived LCLU data and computed the Overall Accuracy (Campbell, 1996; Foody, 2002), assuming that the resampled Landsat-derived LCLU are the "true" LCLU representation. Fig. 11 shows the procedure for calculating the classification overall and user's accuracies and Tables 4 and 5 show the confusion matrices and all the computed accuracies for 2001 and 2010 respectively. The overall accuracies of the regional MODIS LCLU product for this African region were 63.2% and 66.4%, for 2001 and 2010 respectively, which are lower than that of the global MODIS LCLU product overall accuracy of 75% (Friedl et al., 2002). The user's accuracies (the probability that

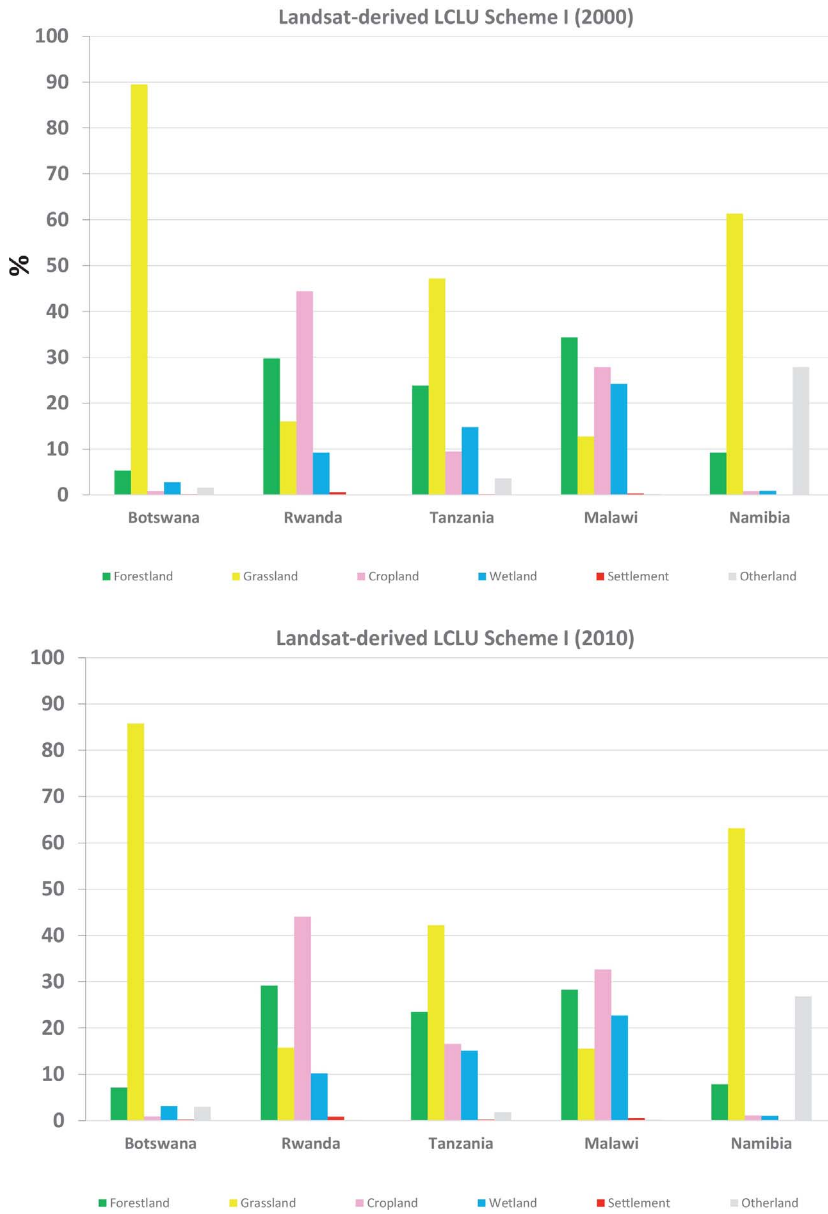

Fig. 8. Landsat-derived LCLU data percentages per country for (a) 2000 and (b) 2010.

the assessed LCLU classes actually match what they are from the reference data) range from 19%-96% and 35%-92% for 2001 and 2010 respectively, with the wetland class having the highest accuracy and the cropland class having the lowest accuracy. The lower accuracies of 2001 compared to 2010 could be due to the fact that the 2010 Landsat-derived LCLU products were more rigorously validated than those of 2001. In addition to this regional accuracy analysis, we have also performed the accuracy analysis on a country-by-country basis for both 2001 and 2010. Tables 6–15 show the confusion matrices and all the computed accuracies for each country for 2001 and 2010 respectively. Table 16 shows a listed summary of the overall accuracy per country, and Table 17 shows a listed summary of the LCLU classes for the top two user's accuracies. Botswana and Namibia had the best overall accuracies (78%–87%), while Rwanda, Tanzania and Malawi had the lowest (45%–55%). This could be due to the fact that Botswana and Namibia are the most homogeneous land cover among the five studies countries as shown in Figs. 5 and 6. Thus, even if they have just a few classification algorithm training sites and even if these sites are clustered in one part of the country, as it is the case in the MODIS land cover classification algorithm as shown in Friedl et al. (2002), these few sites would still be good representatives of the dominant land cover types within these homogenous countries. On the other hand, not only are the training sites that were used in creating the MODIS land cover product fewer in Rwanda, Tanzania and Malawi than those in Botswana and Namibia, but also they are more clustered within countries that are more heterogeneous in terms of land cover types. This is consistent with other studies in the literature that demonstrated that the accuracy of classification methods are generally reduced by increasing land cover heterogeneity (Tran et al., 2014; Lechner et al., 2009; Smith et al., 2003, 2002). Among the countries of the highest overall accuracies, Botswana had even higher overall accuracies than those of Namibia's, which could be due to the fact that the number of training sites that were used in creating the MODIS land cover product was higher in Botswana than that in Namibia and these sites were more spatially distributed within Botswana as well. It's apparent that the number of training sites has also affected the user's accuracies for the

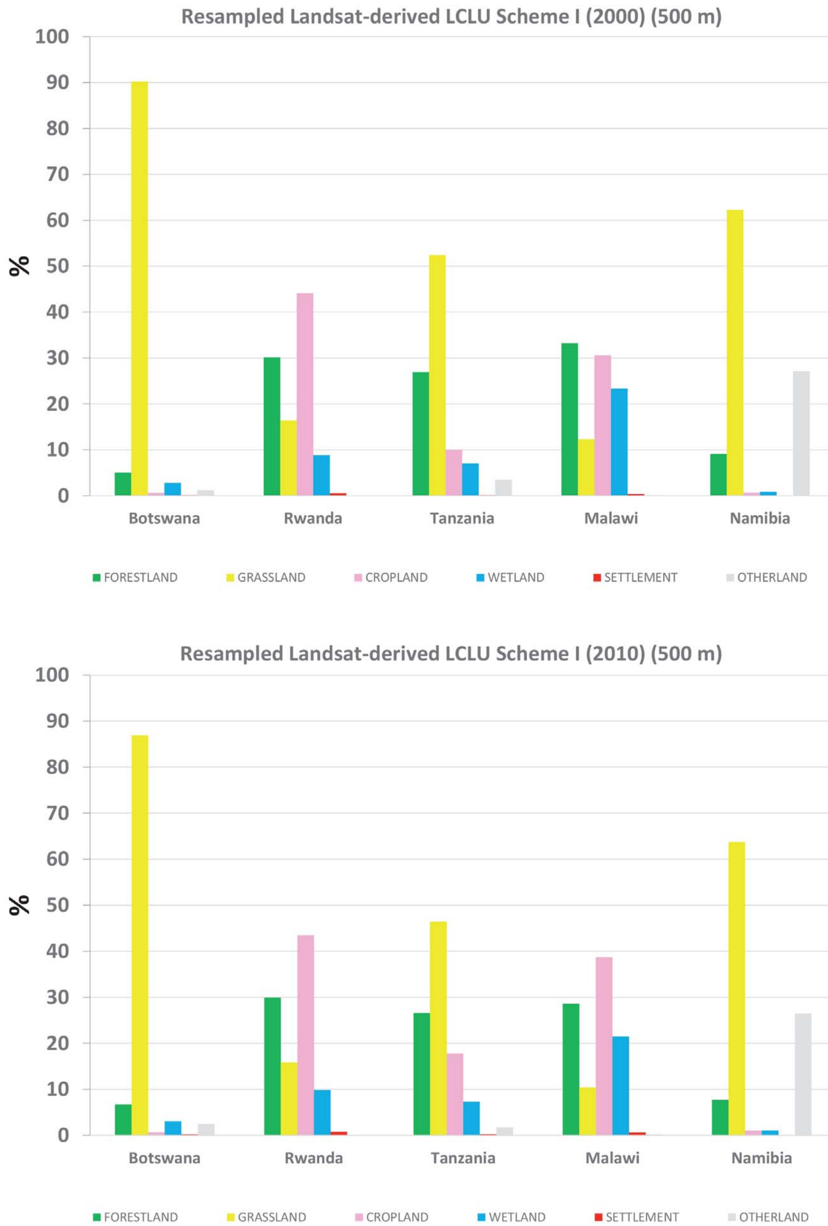

Fig. 9. Resampled Landsat-derived LCLU data percentages per country with a spatial resolution of 500 m for (a) 2001 and (b) 2010.

different LCLU classes as well. Our results showed that the wetland and grassland classes had the highest user's accuracies in most of the countries (89%–99%), and these classes are the ones with the highest number of MODIS land cover classification algorithm training sites in Africa as shown in Friedl et al. (2002).

We decided to perform the LCLU change analyses based on the Landsat-derived LCLU products, which have higher spatial resolution than the MODIS LCLU product. Based on the Landsat-derived data and as shown in Figs. 1 and 8, we can see that Botswana is dominated by grassland with some forestland and wetland; Rwanda is dominated by cropland and forestland with some grassland and wetland; Tanzania is dominated by grassland and forestland with some wetland and cropland; Malawi is dominated by forestland, cropland and wetland with some grassland; and Namibia is dominated by grassland and other land (mainly bare land) with some forestland. Also, as shown in Figs. 12–14, the majority of each country's area had no land cover change between 2000 and 2010 with 85%, 80%, 70%, 68%, and 65% for Botswana, Malawi, Namibia, Rwanda, and Tanzania, respectively. Tanzania had the largest amount of absolute change, followed by Namibia, Botswana, Malawi and Rwanda. Also, Tanzania was the one with the largest amount of change as percentage of its size as well, but it was followed by Rwanda, Namibia, Malawi and Botswana in this case. As shown in Fig. 14, the largest amount of absolute forestation between 2000 and 2010 took place in Tanzania, followed by Namibia, Botswana, Malawi and Rwanda. However, significant deforestation also happened in many of these countries with the largest being in Tanzania, followed by Botswana, Namibia, Malawi and Rwanda. The largest amount of absolute cropland expansion took place in Tanzania, followed by Malawi, Rwanda, Botswana and Namibia. However, some cropland loss also happened in many of these countries with the largest being in Tanzania, followed by Rwanda, Malawi, Botswana and Namibia. As for the grassland, the largest amount of absolute grass expansion took place in Namibia, followed by Tanzania, Botswana, Malawi, and Rwanda. However, significant grass loss also happened in many of these

Fig. 10. Remapped MODIS LCLU data percentages per country for (a) 2001 and (b) 2010.

countries with the largest being in Namibia, followed by Tanzania, Botswana, Malawi and Rwanda. Finally, the largest amount of absolute wetland expansion took place in Botswana, followed by Tanzania, Namibia, Rwanda and Malawi. However, some wetland loss also happened in many of these countries with the largest being in Malawi, followed by Namibia, Tanzania, Botswana and Rwanda. The net changes in forestland, grassland, and wetland as an absolute area and as a percentage of the respective country's size are shown in Fig. 15. Both Tanzania and Malawi had the highest net forest reduction and crop expansion as a percentage of their respective country's size, but Tanzania had much higher net absolute numbers. Malawi had the highest net wetland reduction among all the studied countries in terms of both absolute areal numbers and percentage of their respective country's size. Botswana had the highest net grass reduction and wetland expansion among all the studied countries in terms of both absolute areal numbers and percentage of their respective country's size. Namibia on the other hand had the highest net grass expansion among all the studied countries in terms of both absolute areal numbers and percentage of their respective country's size. As for settlements, there was no significant changes whatsoever in all countries.

As for the drivers behind these changes, it was noticed that Malawi was the only country of a total precipitation decrease between the periods of 1999–2001 and 2009–2011 as shown in Fig. 16, which also happened to have a slight increase in LST as shown in Fig. 7, and this may explain the significant wetland loss in this country as shown in Figs. 14 and 15. In addition, within our studied countries, forestland expansion and loss as well as crop expansion and loss were happening in the same country almost equally in some cases. All of that implies that non-environmental factors, such as socioeconomics and governmental policies, could be mainly driving these changes.

5. Summary and conclusions

In this study, we assessed LCLU changes and their potential

Actual Class / **Predicted Class**

	Forestland	Grassland	Cropland	Wetland	Seetlement	Otherland	Total
Forestland	N_{FF}	N_{FG}	N_{FC}	N_{FW}	N_{FS}	N_{FO}	N_{F+}
Grassland	N_{GF}	N_{GG}	N_{GC}	N_{GW}	N_{GS}	N_{GO}	N_{G+}
Cropland	N_{CF}	N_{CG}	N_{CC}	N_{CW}	N_{CS}	N_{CO}	N_{C+}
Wetland	N_{WF}	N_{WG}	N_{WC}	N_{WW}	N_{WS}	N_{WO}	N_{W+}
Seetlement	N_{SF}	N_{SG}	N_{SC}	N_{SW}	N_{SS}	N_{SO}	N_{S+}
Otherland	N_{OF}	N_{OG}	N_{OC}	N_{OW}	N_{OS}	N_{OO}	N_{O+}
Total	N_{+F}	N_{+G}	N_{+C}	N_{+W}	N_{+S}	N_{+O}	N

$$Overall\ Accuracy = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100$$

$$User's\ Accuracy = \frac{n_{ii}}{n_{i+}} \times 100$$

$$Producer's\ Accuracy = \frac{n_{ii}}{n_{+i}} \times 100$$

Fig. 11. Overall Accuracy calculation using the confusion matrix. The highlighted elements represent the main diagonal of the matrix that contains the cases where the classifications agree, whereas the off-diagonal elements contain those cases where there is a disagreement.

Table 4
Confusion matrix (error matrix) using remapped 2001 MODIS and resampled Landsat LCLU data and measures of accuracy for the whole regional area.

Remapped_MODIS	Landsat_Forestland	Landsat_Grassland	Landsat_Cropland	Landsat_Wetland	Landsat_Settlement	Landsat_Otherland	Total	User's Accuracy (%)
Forestland	1973524	1409672	161613	116745	1291	21051	3683896	53.6
Grassland	1485489	6236218	541952	95374	8703	524314	8892050	70.1
Cropland	229883	533584	189276	22506	4135	32655	1012039	18.7
Wetland	4687	9197	781	462449	17	3129	480260	96.3
Settlement	1554	2670	1328	198	3866	156	9772	39.6
Otherland	220	284688	45	46662	327	645209	977151	66.0
Total	3695357	8476029	894995	743934	18339	1226514	15055168	
Producer's Accuracy	53.4	73.6	21.1	62.2	21.1	52.6		
$Overall\ Accuracy = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100$	= 63.2 %							

Table 5
Confusion matrix (error matrix) using remapped 2010 MODIS and resampled Landsat LCLU data and measures of accuracy for the whole regional area.

Remapped_MODIS	Landsat_Forestland	Landsat_Grassland	Landsat_Cropland	Landsat_Wetland	Landsat_Settlement	Landsat_Otherland	Total	User's Accuracy (%)
Forestland	2112088	932295	199812	108827	1147	9528	3363697	62.8
Grassland	1541097	6365991	999734	106007	16247	458326	9487402	67.1
Cropland	141151	278730	246627	15577	6762	7674	696521	35.4
Wetland	15774	26977	2663	540833	44	3191	589482	91.7
Settlement	863	2142	1775	203	4654	129	9766	47.7
Otherland	127	101440	103	48486	428	681920	832504	81.9
Total	3811100	7707575	1450714	819933	29282	1160768	14979372	
Producer's Accuracy	55.4	82.6	17.0	66.0	15.9	58.7		
$Overall\ Accuracy = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100$	= 66.4%							

Table 6
Confusion matrix (error matrix) using remapped 2001 MODIS and resampled Landsat LCLU data and measures of accuracy for Botswana.

Remapped_MODIS	Landsat_Forestland	Landsat_Grassland	Landsat_Cropland	Landsat_Wetland	Landsat_Settlement	Landsat_Otherland	Total	User's Accuracy (%)
Forestland	9755	48628	236	8524	35	40	67218	14.5
Grassland	122262	2325413	15370	31134	2204	27144	2523527	92.1
Cropland	3830	62279	1278	974	585	4806	73752	1.7
Wetland	128	274	4	10929	0	1	11336	96.4
Settlement	62	566	74	10	764	7	1483	51.5
Otherland	9	1595	0	23536	2	164	25306	0.6
Total	136046	2438755	16962	75107	3590	32162	2702622	
Producer's Accuracy (%)	7.2	95.4	7.5	14.6	21.3	0.5		
$Overall\ Accuracy = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100$	= 86.9 %							

Table 7
Confusion matrix (error matrix) using remapped 2001 MODIS and resampled Landsat LCLU data and measures of accuracy for Namibia.

Remapped_MODIS	Landsat_Forestland	Landsat_Grassland	Landsat_Cropland	Landsat_Wetland	Landsat_Settlement	Landsat_Otherland	Total	User's Accuracy (%)
Forestland	34912	77946	620	1040	9	631	115158	30.3
Grassland	309226	2012535	24551	10299	705	389521	2746837	73.3
Cropland	2587	6721	127	197	1	313	9946	1.3
Wetland	109	1149	9	288	13	1916	3484	8.3
Settlement	71	611	24	14	329	54	1103	29.8
Otherland	135	282962	29	20545	309	644742	948722	68.0
Total	347040	2381924	25360	32383	1366	1037177	3825250	
Producer's Accuracy (%)	10.1	84.5	0.5	0.9	24.1	62.2		

$$Overall\ Accuracy = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100 = 70.4\ \%$$

Table 8
Confusion matrix (error matrix) using remapped 2001 MODIS and resampled Landsat LCLU data and measures of accuracy for Tanzania.

Remapped_MODIS	Landsat_Forestland	Landsat_Grassland	Landsat_Cropland	Landsat_Wetland	Landsat_Settlement	Landsat_Otherland	Total	User's Accuracy (%)
Forestland	575723	609285	41445	14266	420	19557	1260696	45.7
Grassland	446058	1291611	288997	12915	2544	104562	2146687	60.2
Cropland	147641	375801	104924	7313	1617	27094	664390	15.8
Wetland	2662	1880	258	269927	2	1096	275825	97.9
Settlement	871	781	630	44	1131	87	3544	31.9
Otherland	64	123	11	1777	1	295	2271	13.0
Total	1173019	2279481	436265	306242	5715	152691	4353413	
Producer's Accuracy (%)	49.1	56.7	24.1	88.1	19.8	0.2		

$$Overall\ Accuracy = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100 = 51.5\ \%$$

Table 9
Confusion matrix (error matrix) using remapped 2001 MODIS and resampled Landsat LCLU data and measures of accuracy for Rwanda.

Remapped_MODIS	Landsat_Forestland	Landsat_Grassland	Landsat_Cropland	Landsat_Wetland	Landsat_Settlement	Landsat_Otherland	Total	User's Accuracy (%)
Forestland	12049	1428	5134	2353	13	1	20978	57.4
Grassland	6857	5376	10571	861	54	30	23749	22.6
Cropland	15236	11847	34460	1357	327	17	63244	54.5
Wetland	335	123	249	5377	0	0	6084	88.4
Settlement	46	1	31	4	225	0	307	73.3
Otherland	5	1	1	162	0	0	169	0.0
Total	34528	18776	50446	10114	619	48	114531	
Producer's Accuracy (%)	34.9	28.6	68.3	53.2	36.3	0.0		

$$Overall\ Accuracy = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100 = 50.2\ \%$$

Table 10
Confusion matrix (error matrix) using remapped 2001 MODIS and resampled Landsat LCLU data and measures of accuracy for Malawi.

Remapped_MODIS	Landsat_Forestland	Landsat_Grassland	Landsat_Cropland	Landsat_Wetland	Landsat_Settlement	Landsat_Otherland	Total	User's Accuracy (%)
Forestland	89166	16551	33664	6304	157	208	146050	61.1
Grassland	74624	43741	106526	9404	947	505	235747	18.6
Cropland	17556	6840	26562	4090	679	59	55786	47.6
Wetland	103	87	40	107250	0	102	107582	99.7
Settlement	37	26	122	17	190	0	392	48.5
Otherland	5	1	3	200	0	7	216	3.2
Total	181491	67246	166917	127265	1973	881	545773	
Producer's Accuracy (%)	49.1	65.0	15.9	84.3	9.6	0.8		

$$Overall\ Accuracy = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100 = 48.9\ \%$$

Table 11
Confusion matrix (error matrix) using remapped 2010 MODIS and resampled Landsat LCLU data and measures of accuracy for Botswana.

Remapped_MODIS	Landsat_Forestland	Landsat_Grassland	Landsat_Cropland	Landsat_Wetland	Landsat_Settlement	Landsat_Otherland	Total	User's Accuracy (%)
Forestland	5544	13910	74	2448	10	117	22103	25.1
Grassland	173478	2308418	16260	35682	4397	65946	2604181	88.6
Cropland	1187	22646	969	723	164	586	26275	3.7
Wetland	1083	3382	8	20634	0	45	25152	82.0
Settlement	58	482	43	14	833	53	1483	56.2
Otherland	0	568	0	22600	30	230	23428	1.0
Total	181350	2349406	17354	82101	5434	66977	2702622	
Producer's Accuracy	3.1	98.3	5.6	25.1	15.3	0.3		

$$Overall\ Accuracy = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100 = 86.5\ \%$$

Table 12
Confusion matrix (error matrix) using remapped 2010 MODIS and resampled Landsat LCLU data and measures of accuracy for Namibia.

Remapped_MODIS	Landsat_Forestland	Landsat_Grassland	Landsat_Cropland	Landsat_Wetland	Landsat_Settlement	Landsat_Otherland	Total	User's Accuracy (%)
Forestland	8333	31504	736	1034	4	55	41666	20.0
Grassland	284513	2293600	37494	11836	1066	328082	2956591	77.6
Cropland	1876	9602	379	155	3	83	12098	3.1
Wetland	402	2361	32	4110	21	2021	8947	45.9
Settlement	102	516	35	6	398	43	1100	36.2
Otherland	26	100532	17	22346	354	681299	804574	84.7
Total	295252	2438115	38693	39487	1846	1011583	3824976	
Producer's Accuracy	2.8	94.1	1.0	10.4	21.6	67.3		
$Overall\ Accuracy = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100$	= 78.1 %							

Table 13
Confusion matrix (error matrix) using remapped 2010 MODIS and resampled Landsat LCLU data and measures of accuracy for Rwanda.

Remapped_MODIS	Landsat_Forestland	Landsat_Grassland	Landsat_Cropland	Landsat_Wetland	Landsat_Settlement	Landsat_Otherland	Total	User's Accuracy (%)
Forestland	9271	1689	2294	1823	16	4	15097	61.4
Grassland	2358	4456	4349	798	29	42	12032	37.0
Cropland	22370	11842	42972	2187	622	61	80054	53.7
Wetland	261	170	166	6368	3	1	6969	91.4
Settlement	20	3	44	6	235	0	308	76.3
Otherland	0	0	0	76	0	0	76	0.0
Total	34280	18160	49825	11258	905	108	114536	
Producer's Accuracy	27.0	24.5	86.2	56.6	26.0	0.0		
$Overall\ Accuracy = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100$	= 55.3 %							

Table 14
Confusion matrix (error matrix) using remapped 2010 MODIS and resampled Landsat LCLU data and measures of accuracy for Tanzania.

Remapped_MODIS	Landsat_Forestland	Landsat_Grassland	Landsat_Cropland	Landsat_Wetland	Landsat_Settlement	Landsat_Otherland	Total	User's Accuracy (%)
Forestland	614128	488773	67967	15250	266	8372	1194756	51.4
Grassland	464700	1329729	564054	23003	4817	59736	2446039	54.4
Cropland	79149	204411	143212	8217	3680	6481	445150	32.2
Wetland	4812	5433	990	269604	11	895	281745	95.7
Settlement	396	772	1004	46	1300	21	3539	36.7
Otherland	74	329	53	2783	4	388	3631	10.7
Total	1163259	2029447	777280	318903	10078	75893	4374860	
Producer's Accuracy	52.8	65.5	18.4	84.5	12.9	0.5		
$Overall\ Accuracy = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100$	= 53.9 %							

Table 15
Confusion matrix (error matrix) using remapped 2010 MODIS and resampled Landsat LCLU data and measures of accuracy for Malawi.

Remapped_MODIS	Landsat_Forestland	Landsat_Grassland	Landsat_Cropland	Landsat_Wetland	Landsat_Settlement	Landsat_Otherland	Total	User's Accuracy (%)
Forestland	73761	12292	9169	1758	76	194	97250	75.8
Grassland	71161	37704	176525	4688	2298	635	293011	12.9
Cropland	10854	6742	25344	1555	732	207	45434	55.8
Wetland	476	149	398	108979	7	47	110056	99.0
Settlement	36	18	127	9	190	12	392	48.5
Otherland	25	6	16	341	2	0	390	0.0
Total	156313	56911	211579	117330	3305	1095	546533	
Producer's Accuracy	47.2	66.3	12.0	92.9	5.7	0.0		
$Overall\ Accuracy = \frac{\sum_{k=1}^{q} n_{kk}}{n} \times 100$	= 45.0 %							

Table 16
Summary of overall accuracy per country for MODIS LCLU data.

Country	Overall Accuracy for 2001 (%)	Overall Accuracy for 2010 (%)
Botswana	87	87
Namibia	70	78
Rwanda	50	55
Tanzania	52	54
Malawi	49	45

environmental drivers (i.e., precipitation, temperature) in five countries in eastern & southern Africa (Rwanda, Botswana, Tanzania, Malawi and Namibia) between 2000 and 2010. RCMRD's Landsat-derived and

Table 17
Summary of LCLU classes for the top two user's accuracies for MODIS LCLU data.

Country	LCLU Classes for Top Two User's Accuracies for 2001 (%)	LCLU Classes for Top Two User's Accuracies for 2010 (%)
Botswana	Wetland (96%)	Grassland (89%)
	Grassland (92%)	Wetland (82%)
Namibia	Grassland (73%)	Otherland (85%)
	Otherland (68%)	Grassland (78%)
Rwanda	Wetland (88%)	Wetland (91%)
	Settlement (73)	Settlement (76)
Tanzania	Wetland (98%)	Wetland (96%)
	Grassland (60%)	Grassland (54%)
Malawi	Wetland (100%)	Wetland (99%)
	Forestland (61%)	Forestland (76%)

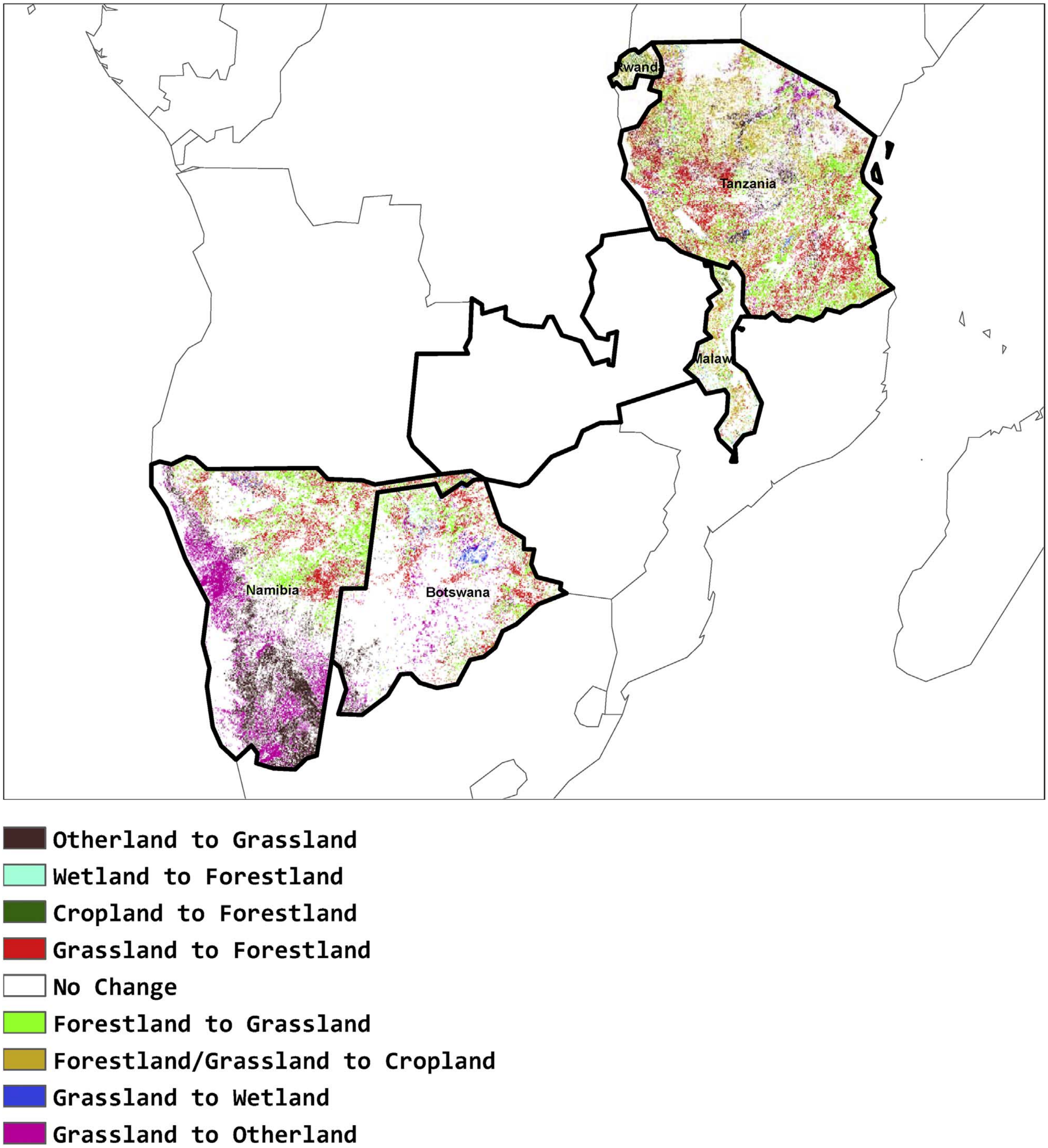

Fig. 12. LCLU changes between 2000 and 2010 using Landsat-derived LCLU data.

NASA's MODIS data were used to evaluate and quantify the LCLU changes in these five countries. Given that the original development of the MODIS land cover type standard products included limited training sites in Africa, we performed a two-level verification/validation of the MODIS land cover product in these five countries. As a first-level verification of the MODIS LCLU data, a spatial analysis comparing the MODIS LST among the different MODIS LCLU classes, which revealed reasonable results. The second level validation involved using the previously rigorously validated RCMRD's Landsat-derived LCLU products to revalidate these MODIS products in these five countries of E & S Africa. In order to be able to perform this validation, we used a common classification scheme and spatial resolution. Precipitation data from CHIRPS dataset were used to evaluate and quantify the precipitation changes in these countries and see if it was a significant driver behind some of these LCLU changes. MODIS LST data were also used to see if temperature was a main driver too. If neither of these environmental drivers was significant, this could suggest that non-environmental drivers such as socio-economic changes (e.g. governmental agricultural

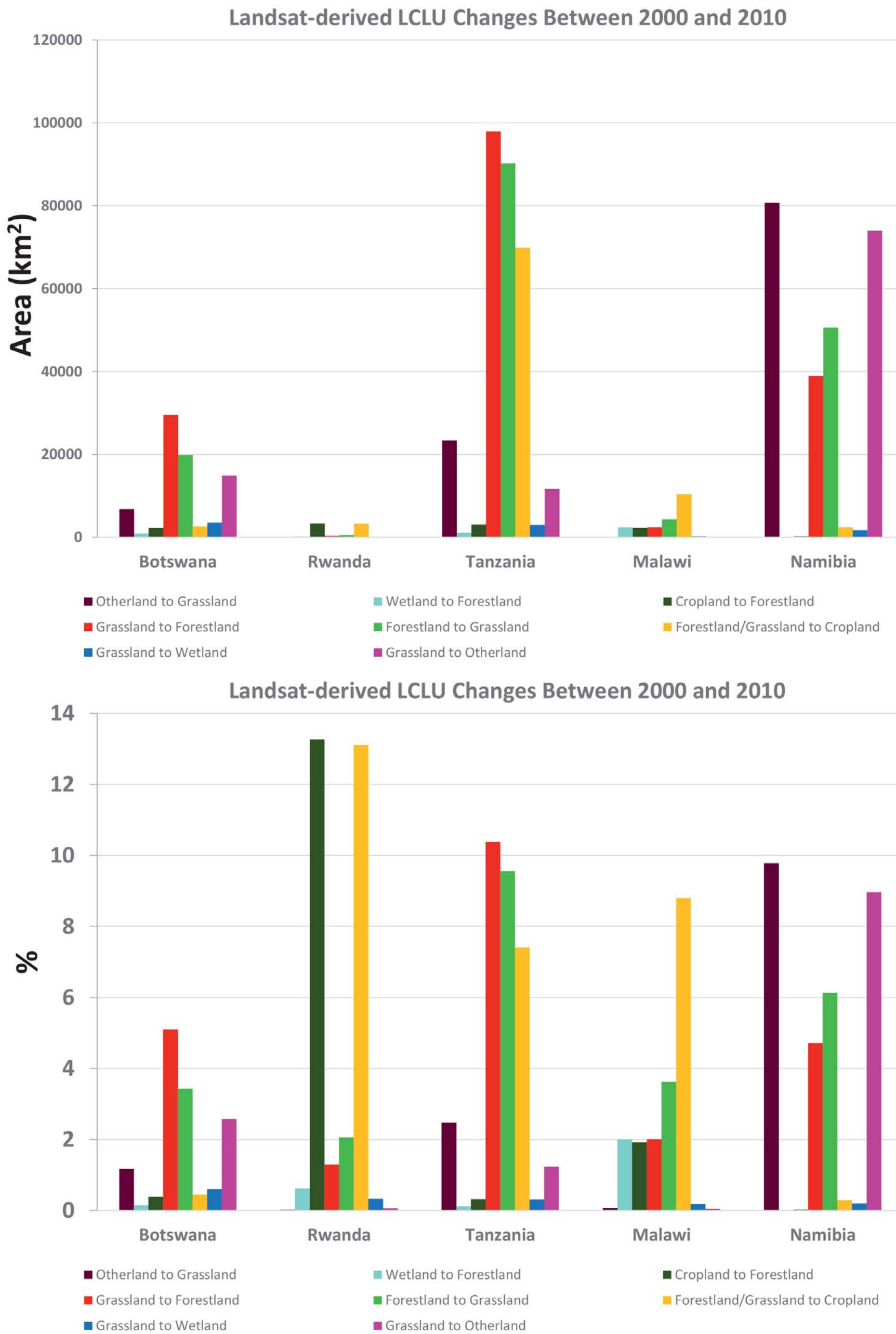

Fig. 13. Landsat-derived LCLU changes between 2000 and 2010 per country: (a) km^2, (b) % of country size.

policies, wars beginning/ending) could have influenced these LCLU changes.

Our validation analysis revealed that the overall accuracies of the regional MODIS LCLU product for this African region alone were lower than that of the global MODIS LCLU product overall accuracy (63–66% vs. 75%). However, for countries with uniform or homogenous land cover, the overall accuracy was much higher than the global accuracy and as high as 87% and 78% for Botswana and Namibia, respectively. In addition, the wetland and grassland classes had the highest user's accuracies in most of the countries (89%–99%), which are the ones with the highest number of MODIS land cover classification algorithm training sites.

Our LCLU change analysis revealed that Botswana's most significant changes were the net reforestation, net grass loss and net wetland expansion. For Rwanda, although there have been significant forest, grass and crop expansions in some areas, there also have been significant forest, grass and crop loss in other areas that resulted in very minimal net changes. As for Tanzania, its most significant changes were the net deforestation and net crop expansion. Malawi's most significant changes were the net deforestation, net crop expansion, net

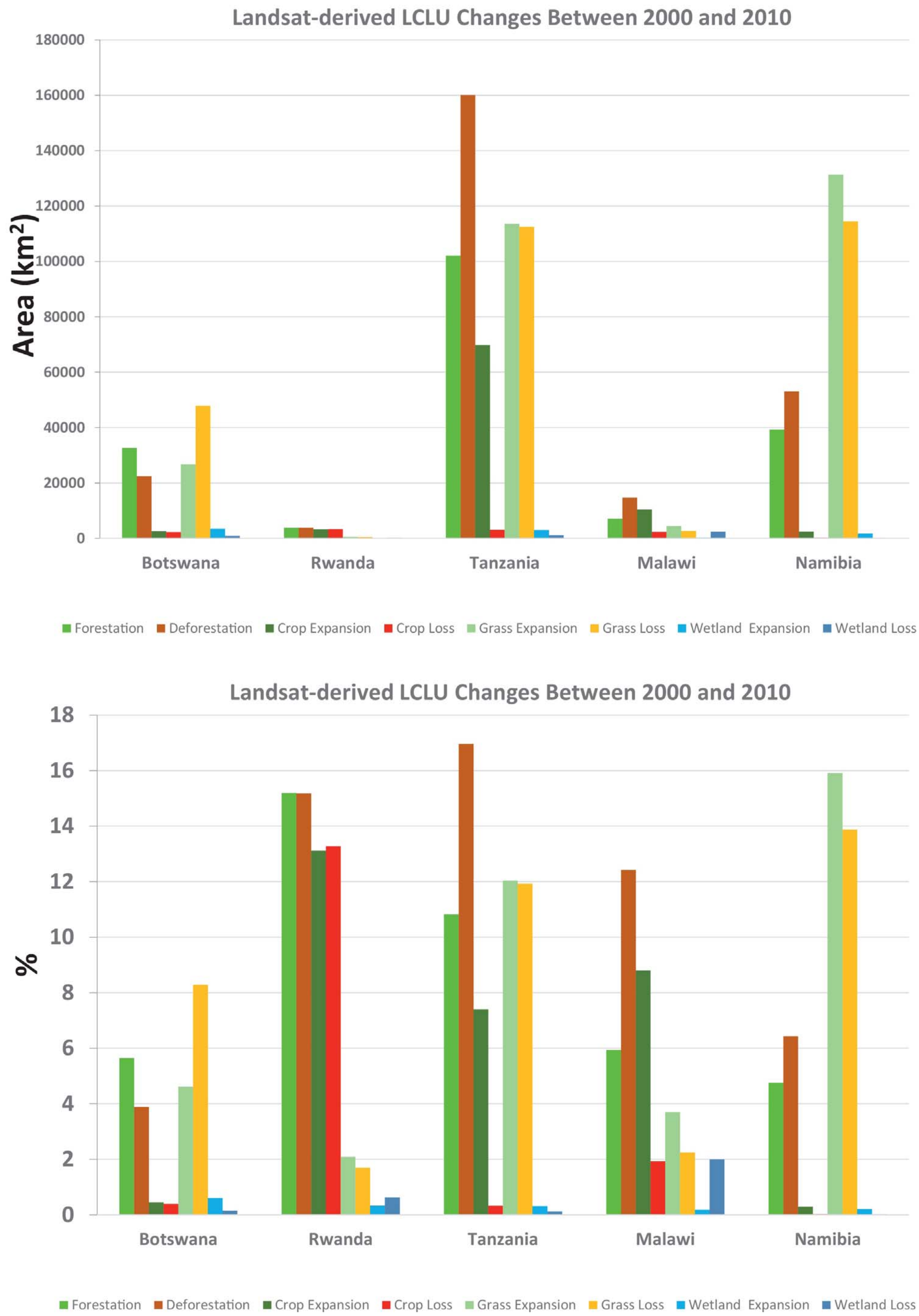

Fig. 14. Forestland, cropland and grassland changes between 2000 and 2010 per country: (a) km^2, (b) % of country size.

grass expansion and net wetland loss. Finally, Namibia's most significant changes were the net deforestation and net grass expansion.

The only noticeable environmental driver was in Malawi, which had a significant net wetland loss and could be due to the fact that it was the only country that had a reduction in total precipitation between the periods when the LCLU maps were developed. Not only that, but Malawi also happened to have a slight increase in temperature, which would cause more evaporation and net decrease in wetlands if the precipitation didn't increase as was the case in that country. In addition, within our studied countries, forestland expansion and loss as well as crop expansion and loss were happening in the same country almost equally in some cases. All of that implies that non-environmental factors, such as socioeconomics and governmental policies, could have been the main drivers of these LCLU changes in many of these countries in eastern and southern Africa. It will be important to further study in the future the detailed effects of such drivers on these LCLU changes in this part of the world. In addition, the assessment of longer-term (> 10 years) climatic variables including air temperature, precipitation, water vapor, surface radiation, and others could provide additional information about the relationship between the climatic variability and land cover changes in this region.

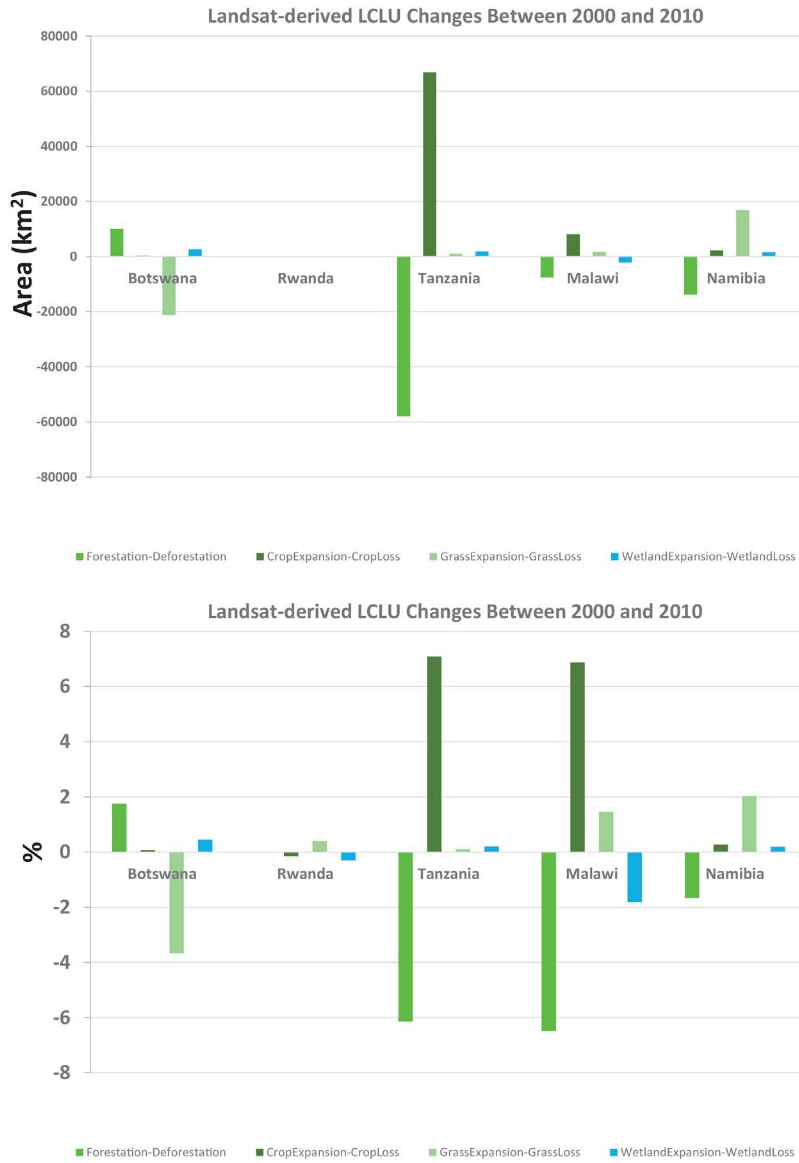

Fig. 15. Forestland, cropland and grassland net changes between 2000 and 2010 per country: (a) km^2, (b) % of country size.

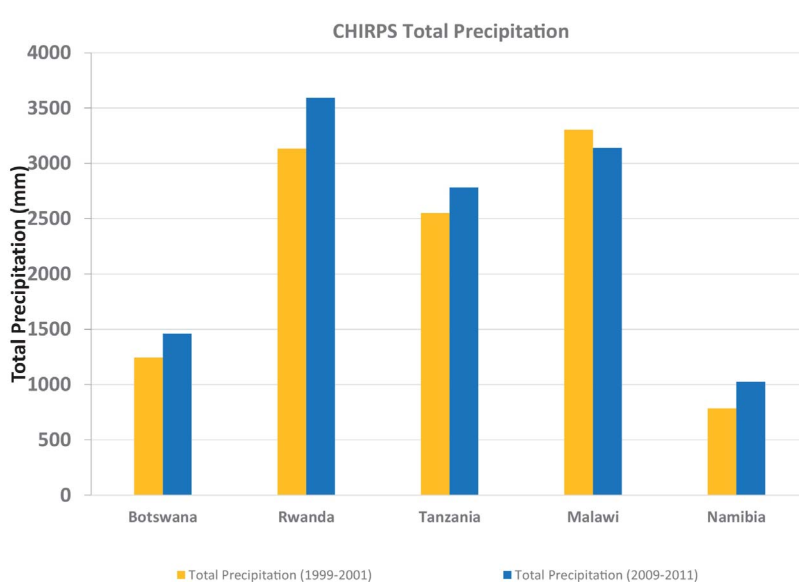

Fig. 16. Total precipitation per country for 1999–2001 and 2009–2011.

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