LONG-TERM LAND COVER AND LAND USE CHANGE DETECTION IN THE KILOMBERO FLOODPLAIN (TANZANIA) USING MULTITEMPORAL METRICS-BASED COMPOSITING

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ABSTRACT

Land cover and land use changes have great impact on the hydrological characteristics of the Kilombero floodplain wetland (Tanzania) and its surroundings. Conservation interests meet the wetland's ecosystem function as a site for growing food production. The system, processes and ecosystem responses are, however, not yet fully understood. We make use of Landsat data to assess long-term land cover and land use changes in the catchment. In this paper we describe an approach to circumvent the challenge of frequent cloud cover and to consider the dynamics of the wetland during the classification. The approach results in temporal composites for four different decades and hierarchically organized maps including two levels of detail and providing information about dynamic classes.

1. INTRODUCTION

Food demand and processes of land conversion from natural to cultivated land have been accelerating in East Africa over the past decades. The main drivers might be rapid population growth and economic development. Land cover information of the region at reasonable spatial scales is often inconsistent, outdated, incomplete or simply not available [1]. Remote sensing is a valuable means to assess land cover and land use and their changes since the datasets cover the last decades, the time where many changes of the society and its land took place. It is obvious that land cover and land use changes have great impact on the hydrological characteristics of wetlands and their surroundings. To quantify these effects accurate land cover and land use information is needed. On the other hand, food demand increases with increasing population. For long time agriculture was limited to uplands whereas recent studies try to assess the potential of wetlands as future food production zones in Africa. Consequently, land cover and land use changes take place not only in the catchment of wetlands but also within the wetlands. Quantification of long-term changes will allow to reconciling conservation with food production. The GlobE research project (https://www.wetlands-africa.de/) aims at multiscale analyses of wetlands in East Africa. The work presented here explores land cover and land use changes at catchment scale. The first objective is to generate cloudfree image composites that reflect the dynamics within wetlands and at the same time circumvent the challenge of frequent cloud cover in the tropics. The second objective is to generate a classification approach that provides useful maps to different disciplines such as hydrology, ecology, or soil sciences.

2. STUDY SITE

The study site is the Kilombero catchment in south-east Tanzania in the Tropics of East Africa. The Kilombero floodplain is a huge wetland and one of the four core test sites of the GlobE project. It experiences pressure from increasing agricultural use and land use changes. Traditional crop is rain-fed rice. Recently, cultivation of cash crops such as sugarcane, and other commercial land uses such as teak plantations increased. Teak plantations are concentrated south of the Kilombero river, industrial forms of (cash crop) agriculture have been visible north of the river. Irrigation recently appeared in parts of the catchment. The floodplain is surrounded by mountain ranges with the Udzungwa mountains reaching up to 2.567 m. The floodplain itself is located about less than 250 m. The mountains are dominated by forests whereas the flat floodplain is dominated by agricultural land, different savanna types and grassland. The areas south of the Kilombero river are dominated by miombo forests. The Kilombero floodplain is also an important corridor and plays a major role in the connectivity of the Udzungwa mountains north of Kilombero and the Selous Game Reserve south-east of the river [2].

3. DATA AND METHODS

For the present study we use Landsat data for four reference dates over the past four decades. Inconsistent datasets with gaps due to frequent cloud coverage are common for the tropics. However, compositing of moderate resolution data such as Landsat [3] is an option to generate cloudfree datasets. Most of the compositing approaches select cloudfree observations that are closest to a predefined day of year (DOY). In case no appropriate observation is available, data from other years are considered as well. In the present study we make use of an alternative compositing approach but

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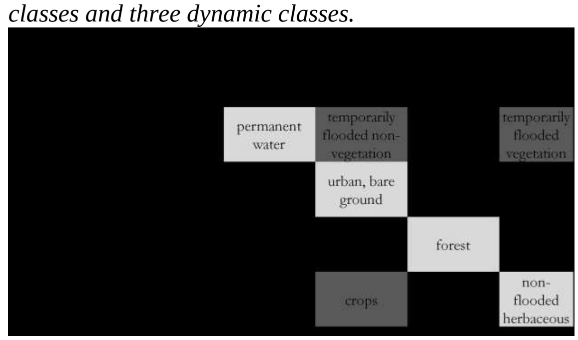
had to consider multiyear data as well to achieve coverage of the whole catchment. Instead of selecting best suited observations we consider all cloudfree observations of predefined periods and calculate multitemporal metrics such as maximum, minimum, mean, median, standard deviation and percentiles per pixel and per band (multitemporal metrics). Landsat 4, 5, 7, and 8 data are used to generate land cover and land use maps for 1984, 1994, 2004, and 2014. Each period refers to at least two water years to allow for the assessment of flood extent and non-permanent land cover classes such as flooded grasslands (e.g., reference year 2014 includes images taken between January 1, 2013 and December 31, 2015). The surface reflectance product provided by USGS was used as input (http://earthexplorer.usgs.gov/). Unusable data (i.e., clouds, cloud shadows, no data) were masked by applying the Fmask mask file that is attached to each product. Fmask is an efficient method to discriminate clouds, cloud shadows, snow, water, and clear land pixels [4]. Dry and rainy season were separated based on rainfall data and the assumption that it takes several weeks after the first rains before the water is concentrated in the drainage system (i.e., a time lag is assumed). Multitemporal metrics were calculated for dry and rainy season from the pixels that were identified as clear land or water. By using percentiles, the impact of missed clouds and cloud shadows was reduced. The multitemporal metrics of each period and dry and rainy season, respectively, were subjected to a supervised Random Forest classification [5] using the EnMap toolbox [6]. The digital elevation model at 30 m spatial resolution acquired during the SRTM (shuttle radar topography mission) campaign was included in the classification. Training samples were taken during a field trip in 2015 and were complemented by UAV (Unmanned Aerial Vehicle) image interpretation. The spatial resolution of the UAV data is approximately 30 cm. The data were acquired at three different times of the hydrological year: i) parallel to the 2015 field trip, ii) in May 2014, and iii) in September 2014. The classification was performed in a two level approach. The first level distinguishes between water, bare soil, forests and other vegetation. Deriving these classes for dry and rainy season separately allows to combining them afterwards and thereby discriminating between stable classes that show the same land cover during the whole hydrological year and dynamic classes that change land cover depending mainly on water supply. The concept of dynamic classes was used e.g. by [7,8] to account for dynamic processes taking place in wetlands. The combination of the four basic classes results in four stable and three dynamic classes as shown in Tab. 1. These are permanent water, temporarily flooded non-vegetation, urban and bare ground, crops, temporarily flooded vegetation, non-flooded vegetation, forests. Fig. 1 shows how these classes can be broken down to a more detailed second level including the classes permanent water, temporarily flooded non-vegetation, temporarily flooded herbaceous, non-flooded herbaceous, urban, bare ground, crops, mountain forest, degraded mountain forest, miombo forest, gallery forest, and teak plantation.

Table 1: Combination of four land cover classes of dry and rainy season to seven basic classes (four stable classes and three dynamic classes.



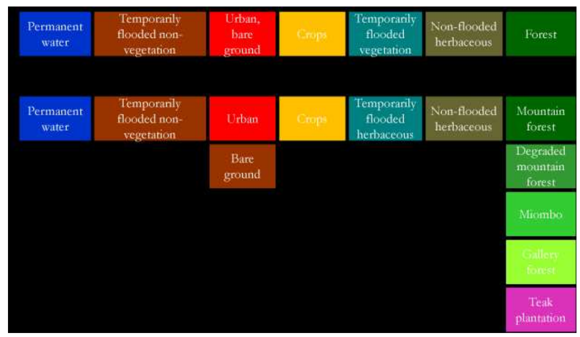


Figure 1: General scheme of hierarchical class construction with combined results from dry and rainy season (from Level 1 to Level 2).

4. RESULTS

The results of the compositing for reference year 2014 can be seen in Fig. 2. Panels a) and c) show false color composites in band combination 7-4-2 (band naming after Landsat 5) for the dry and rainy season, respectively. Panels b) and d) show the number of cloudfree input images per pixel. Obviously, there are huge differences among the different areas inside and outside the catchment. The continental areas north-west of the Kilombero catchment are less cloud-contaminated than the catchment itself. The Kilombero catchment seems to be a kind of cloud trap. The frequent cloud coverage is caused by high evaporation rates in the floodplain and high transpiration rates in the mountain ranges in the north and the south-east of the catchment. It can be seen that the rainy season composite still contains some artefacts that may result from cloud shadows in the western regions. However, the flood extent was well captured. During the rainy season cloud coverage seems to be more dominant in the

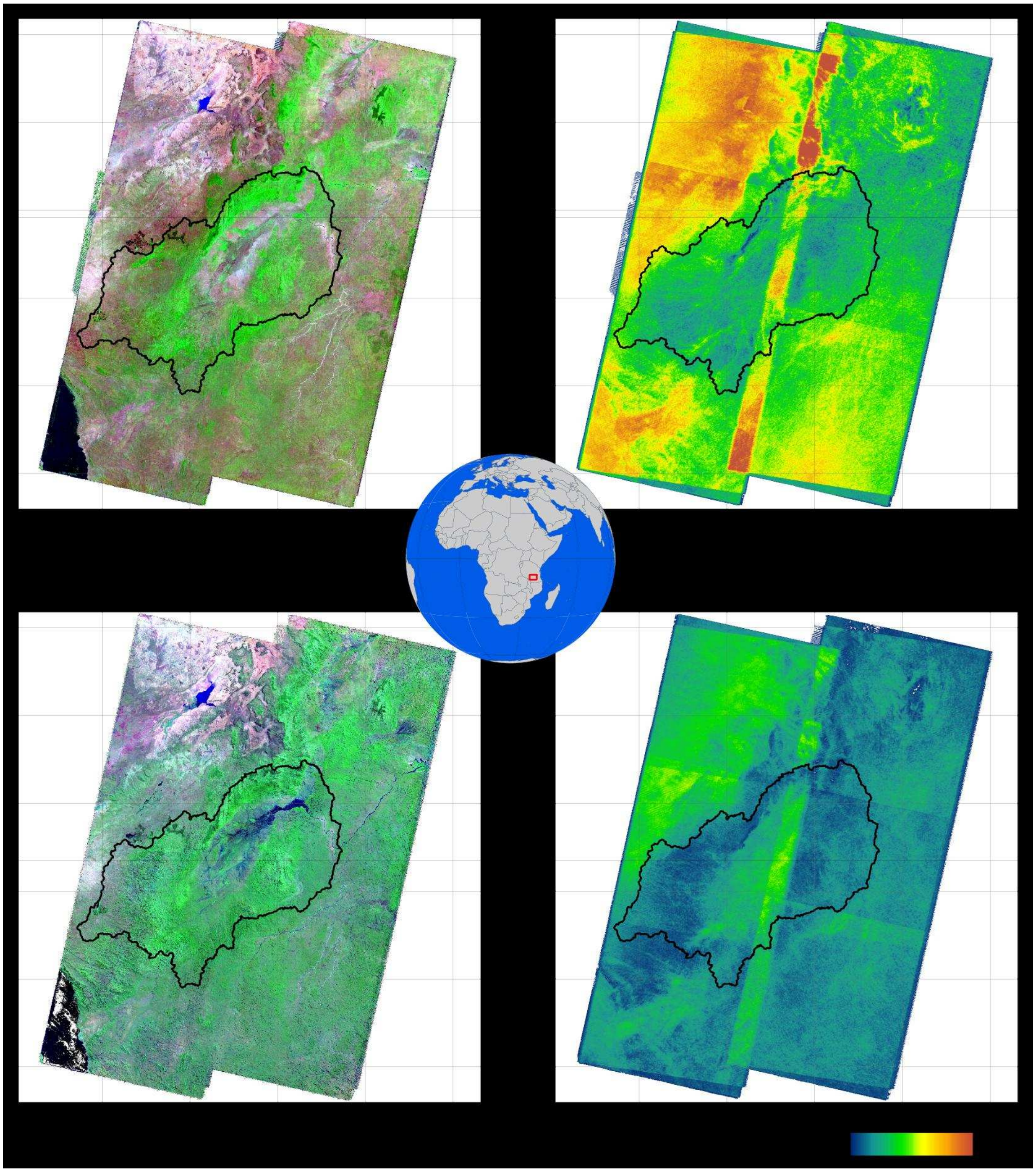


Figure 2: Dry season composite (RGB = 7 – 4 – 2) 2013-2015 (a), number of cloud free dry season observations 2013-2015 (b), rainy season composite (RGB = 7 – 4 – 2) 2013-2015 (c), and number of cloud free rainy season observations 2013-2015, the maximum number does not exceed 38 (d).

mountainous areas whereas during the dry season this pattern is less clear. Fig. 3 shows the classification results for the rainy season. The figure shows preliminary results where the dry and rainy season results of level 1 are not combined as introduced above. As a result some areas in particular in the west of the catchment have been misclassified. The statistics of the accuracy assessment with independent validation data that has not been used for the classification reveals good classifier performance. But training and validation data are concentrated on the east of the catchment since this is of major interest for the GlobE project. This imbalance leads to unreasonable results in the western part of the catchment. However, the classification performance in the eastern part is good resulting in reasonable patterns. As known from other studies [9], teak plantations are mainly concentrated south of the Kilombero river. This can be confirmed from Fig. 2b.

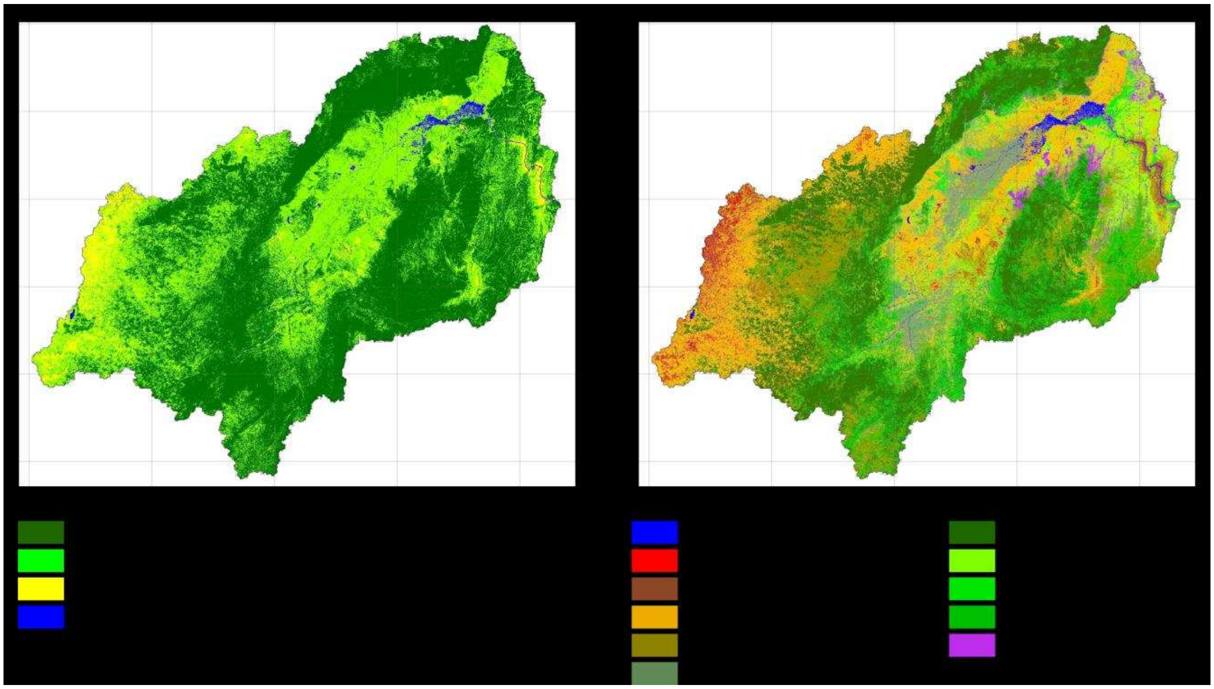


Figure 3: Level 1 (a), and Level 2 (b) classification of rainy season 2013-2015.

Other forest classes such as the mountain forest and degraded mountain forest (i.e., mountain forest that experiences human impact through fire or logging) are also well captured. Gallery forests are detected along the Kilombero river.

5. DISCUSSION AND CONCLUSION

We showed that the creation of cloudfree composites for dry and rainy seasons is feasible for the Kilombero catchment. Combining classification results of both seasons allows to derive stable and dynamic classes. From those, more detailed information can be derived in a second level. An optimal selection of multitemporal metrics and better understanding of their interpretation is needed, however, to fully use the potential of the data.

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