**Does REDD+ have a chance? Implications from Pemba Tanzania**

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Supplementary material 1 HIMA: Funding period and debates over carbon density.

The project “Hifadhi ya Misitu ya Asili (HIMA) – Piloting REDD+ in Zanzibar through Community Forest Management” was designed and implemented between April 2010 and December 2014 by CARE International, the Department of Forestry and Non-Renewable Natural Resources (DFNRNR), the US-based company Terra Global, and the local community forestry NGO (JUMIJAZA). It received a no-cost extension until August 2015.

Here we respond to a recent claim that Zanzibar’s forests have a comparatively low carbon density value (Ravikumar et al. 2017), thereby rendering Zanzibar a poor model from which to generate insights for REDD+ more generally. We contest this suggestion for two reasons. First, there are conflicting calculations about the precise carbon density of Zanzibar, resulting from the fact that multiple Woody Biomass Surveys exist that use different methodologies for counting trees and calculating carbon density. Updated calculations are currently being performed by Terra Global Capital, which will become the official statistics used for the REDD+ project. Second, the presumption that low-density projects will fail due to their low supply of carbon credits neglects market dynamics. The market price of carbon credits varies across projects in accordance with the various attributes that include poverty reduction, preservation of biodiversity, the extent to which the project assures “no harm” and “permanence”, as well as perhaps its international recognition. Therefore, by selling high quality credits, projects can partially abate the problem of a low total tonnage through higher prices. Additionally, we would argue that by focusing only on forests with high carbon density, other valuable, unique and threatened forests with lower carbon density, such as some parts of East African coastal forests (Siex, 2011), could become marginalized from conservation.

Supplementary material 2 Methods for calculating forest cover change per year per ward

Satellite imagery

In order to quantify forest cover within each ward with a Community Forest Management Agreement (CoFMA, see main paper) and the degree of loss or gain in forest cover over the last two decades, we analysed a collection of Landsat 5, Landsat 7 and Landsat 8 satellite images. Landsat imagery was chosen as it is open source, spans the entire temporal period of the study, and has a high spatial resolution of 30 m2 and bi-weekly data availability (Cohen & Goward, 2004). A two-year composite image was produced to represent three time periods of interest; 2001 (May 2000–May 2002) and 2010 (October 2009–October 2011) from a combination of Landsat 5 and 7 ETM+, and 2018 (January 2017–January 2019) from Landsat 8 OLI. All images were top-of-atmosphere reflectance, ortho-rectified, and had cloud, water and cloud shadow pixels removed via the mask CFMASK in Google Earth Engine (GEE) version 7.3.2 (Foga et al., 2017; Gorelick et al., 2017). Each pixel in the resulting composite image represented the median value for visible, NIR and Normalized Difference Vegetation Index (Near Infrared and Red) bands computed from the input imagery.

Training data

Eight land cover classifications were initially identified in Pemba; mangrove forest, natural high forest, agriculture, urban development, bare land, coral rag shrub, coral rag forest and agroforestry. We collected > 400 waypoints via a handheld GPS device (Garmin eTrex 20 GPS handheld unit) within a subset of wards on the island during a field survey in June–July 2015 and inspected the waypoints on Google Earth imagery for 2015. To obtain training points across the entire island, we then created training data locations by purposefully selecting 440 coordinates throughout the island and assigning each coordinate a land cover class via visual inspection from Google Earth 2001, 2010 and 2018 imagery. After preliminary analysis, and in line with the objectives of our study, the number of classifications was reduced to forest (mangrove, coral rag forest and natural high forest) and non-forest (agriculture, urban development, bare land, coral rag shrub, agroforestry).

Land cover classification

Images were classified as forest or non-forest for 2001, 2010 and 2018 using a ‘Random Forest’ supervised classification in Google Earth Engine. Seventy percent of the training data locations were randomly assigned to train the Landsat 7 and Landsat 8 composite data and the remaining 30 percent used for post-classification accuracy assessment (Hijmans & van Etten, 2012; Stehman, 1997). The resulting classified images’ overall accuracy from the confusion matrix was >90% for all images and demonstrated excellent agreement with the kappa coefficient (Supplementary Table 1). Potential sources of error in classifications may be attributed to initial training data collection on Pemba, cloud cover distorting satellite imagery and a Scan Line Corrector error on Landsat 7.

The classified images were clipped to the 18 wards that held a Community Forest Management Agreement (CoFMA) as of 2015. Shapefiles of ward areas were obtained from *Global Administration Areas 3.6* (GADM, 2018). Shapefiles of government forest protected areas were obtained from the National Bureau of Statistics (United Republic of Tanzania). Government forest protected areas that lie within the study region were excluded from spatial analysis. Within each CoFMA, total area (m2) of forest and non-forest were then quantified for the three years of interest (2001, 2010, 2018) by zonal statistics in *QGIS* (QGIS Development Team, 2018). Due to the number of cloudy pixels differing for each year of imagery, forest area (m2) was divided by total forest area (m2) (forest + non-forest) to obtain a percent of the CoFMA that was forest for each year (Supplementary Table 2).

To obtain the change in rate of forest loss or gain before (2001–2010) and after (2010–2018) the implementation of COFMAs, first we calculated the annual rate of forest cover change within all CoFMAs for the two time periods using the Compound Interest Law, as per the Food and Agriculture Organization of the United Nations (FAO, 2016). Secondly, the annual rate of forest cover change pre-treatment (2001–2010) was subtracted from the annual rate of forest cover change post-treatment (2010–2018; Supplementary Table 2). Calculations were completed within *RStudio 1.1.3* (RStudio Team, 2015).

Classification results

The results of our analysis are shown in Figure 2 and Supplementary Table 2. We emphasize these results do not substitute for the official analysis to be conducted by Terra Global Capital prior to the official audit of the REDD+ project but are based on our best use of Google Earth Engine and Landsat 5, 7 and 8 imagery. The alternative methodology used by Terra Global Capital for calculating forest cover serves a different purpose of determining the total amount of carbon sequestered for the issuance of carbon credits specified in the HIMA project document.

Although the Zanzibar REDD+ project is designed to determine changes in rates of deforestation from a baseline historical rate at the *archipelago* level (Pemba and Unguja, with the exception of urbanized areas) we focus on forested area *per Pemba ward* as the baseline. We do this for two reasons: first, this is the level at which “motivation payments” (see main text) were distributed during the HIMA project and secondly because the CoFMA groups are organized at the ward level.

Supplementary material 3 Historical continuity in community forest management: Msitu Mkuu and Ras Kiuyu as examples

As noted in the main text, HIMA was built onto a history of decentralized community forest management in Zanzibar (e.g. Pakenham, 1947) that had formal government support, in some case dating back to British colonial conservation policies (Shao, 1992; Benjaminsen, 2014). We briefly overview the history of two forests on Pemba to illustrate this history of community engagement in forest protection to show the complex complementarities in producing conservation goods.

Msitu Mkuu

Msitu Mkuu (188.5 ha) is a relatively undisturbed area of high coral rag forest and low coral rag thicket located on the North-eastern corner of the Pemba Island (Micheweni District) at the margins between the deep soil and coral rag belt of Ras Kiuyu peninsula. The area was recognized by the British as an area of ecological importance and was closed to woodcutting in 1947, and has since 1964 been jointly managed with the Forestry Department with four communities (Mjini Wingwi, Kilindini, Kwale and Chokaaningayo) as, what is now called, a Forest Reserve. Local measures against illegal cutting have been implemented for many years by people living areas around it.

During a visit to Mjini Wingwi in 2015, the villagers reported memories of a strong British effort to protect the forest. They reported their ancestors’ recognition of the importance of the forest, and the assistance they had sought from Mr Parkenham (District Commissioner at the time) for assistance for its protection. The conservation committee also reported a village decision in 1988 to follow up on the mid-century protection strategies, including patrols, with the goal of protecting the forest against threats from local population increase (M. Borgerhoff Mulder, unpublished data, 2015). Villagers and committee members stressed the importance of recognizing the wealth (of an intact Msitu Mkuu) that their fathers had bequeathed them, as well as the presence of sacred sites in the forest, and traditional medicines. In this respect HIMA did not feel like an imposition.

Ras Kiuyu

Ras Kiuyu forest (Micheweni District) is a particularly interesting case, a high coral rag forest with high biological diversity (Siex, 2011) lying in the ward of Kiuyu Mbuyuni. Heavy deforestation occurred in 1972 during a period of severe drought, and as a result of locally elected elders seeking new lands for agricultural production and forest products. However in 1975 local leaders decided to protect the forest. In 1987 it was reportedly gazetted by DFNRNR as a Forest Reserve with a total area of 270 ha, and in 2013 it was included in the HIMA project under the Coastal Forest Conservation Project. Because it joined the programme late, it lacks the formal recognition granted at the August 2015 ceremony (see main text), and does not therefore appear on our map.

Despite being technically managed by the government as a Forest Reserve in planning (Siex 2011), DFNRNR allows the local community to manage the forest autonomously. This is partly a result of initial intimidation (community members threatening outsiders), and partly through compromise. The government authorities recognize that the strongly independently motivated SCC is protecting the second most intact forest on Pemba by prohibiting incursions of agriculture into the forest, and regulating villagers to twice annual highly restricted harvests (beginning and end of Ramadhan). The committee also fines for illegal timber extraction, allowing exceptions for families in emergency. A cursory visit in 2015 revealed no loss of understory, an indicator of banned firewood collection. The committee also has a vigorous and ancient plantation of trees (referred to as “mikongwe”, ancient trees of very hard wood at which “even a chain saw cries”, which they claim dates back to the 1880s; interview notes M. Borgerhoff Mulder, 2015), but this was not visited. The community has marked the forest boundaries with stone markers.

Kiuyu Mbuyuni community members are adamant the forest is theirs, and not that of DFNRNR. When the government also placed beacons to mark the forest boundaries, community members threw these into the sea, and prevented forestry official visits. Generally, the department has granted effective management to the community and its conservation is proceeding well. There is even, in 2019, discussion of a change in protected status, and joint management with DFNRNR, although nothing yet is finalized

Supplementary Table 1 Confusion matrices of the classification map resulting from the Landsat 5 composite image for 2001, Landsat 7 composite for 2010, and Landsat 8 composite for 2018. User and producer accuracy was calculated as per Congalton (1991). Tables show model predictions in columns versus actual classifications in rows.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| 2001 | Non-forest | Forest | Row Total | User Accuracy |
| Non-forest | 86 | 5 | 91 | 94.5% |
| Forest | 3 | 46 | 49 | 93.9% |
| Column Total | 89 | 51 | 140 |  |
| Producer Accuracy | 96.6% | 90.2% |  |  |
| Kappa Coefficient | 0.88 | | | |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| 2010 | Non-forest | Forest | Row Total | User Accuracy |
| Non-forest | 79 | 3 | 82 | 96.3% |
| Forest | 2 | 41 | 43 | 95.4% |
| Column Total | 81 | 44 | 125 |  |
| Producer Accuracy | 97.5% | 93.2% |  |  |
| Kappa Coefficient | 0.91 | | | |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| 2018 | Non-forest | Forest | Row Total | User Accuracy |
| Non-forest | 82 | 0 | 82 | 100.0% |
| Forest | 5 | 38 | 43 | 88.4% |
| Column Total | 87 | 38 | 125 |  |
| Producer Accuracy | 94.3% | 100.0% |  |  |
| Kappa Coefficient | 0.91 | | | |

Supplementary Table 2 Total ward-level percent forest cover for the years 2001, 2010 and 2018, and the annual rate of change in forest cover before (2001–2010) and after (2010–2018) HIMA project implementation. Negative annual rates indicate deforestation and positive annual rates indicate reforestation. Wards that demonstrated an improved rate of annual forest cover change in the second time period as compared to the first are marked with a check box in the final column.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Ward | 2001 forest cover (%) | 2010 forest cover (%) | 2018 forest cover (%) | 2001–2010 mean annual forest cover change (%/yr) | 2010–2018 mean annual forest cover change (%/yr) | Improved annual rate of forest cover change for the second time period: 2010–2018 (Fig. 2) |
| Changaweni | 51.92 | 31.14 | 21.43 | -5.2 | -5.0 |  |
| Fundo | 31.72 | 22.27 | 13.44 | -3.7 | -6.7 |  |
| Gando | 40.37 | 33.17 | 28.92 | -2.0 | -1.9 |  |
| Kambini | 10.64 | 9.78 | 5.93 | -0.9 | -6.7 |  |
| Kangani | 24.46 | 18.23 | 15.53 | -3.0 | -2.2 |  |
| Kifundi | 27.27 | 22.72 | 17.83 | -1.9 | -3.3 |  |
| Kisiwa Panza | 60.89 | 59.45 | 47.88 | -0.3 | -2.9 |  |
| Mgelema | 57.43 | 36.52 | 30.80 | -4.7 | -2.3 |  |
| Mgogoni | 26.73 | 11.63 | 7.12 | -8.4 | -6.5 |  |
| Michenzani | 23.34 | 20.34 | 15.98 | -1.4 | -3.3 |  |
| Mjimbini | 30.32 | 16.37 | 9.53 | -6.3 | -7.2 |  |
| Mjini Wingwi | 26.09 | 21.42 | 14.86 | -2.1 | -4.9 |  |
| Msuka Magharibi | 7.89 | 5.27 | 3.14 | -4.2 | -6.9 |  |
| Mtambwe North | 44.07 | 29.80 | 29.98 | -4.0 | 0.1 |  |
| Mtambwe South | 55.01 | 39.34 | 39.51 | -3.5 | 0.1 |  |
| Shumba Mjini | 52.48 | 44.60 | 35.84 | -1.7 | -3.0 |  |
| Tondooni | 24.76 | 20.99 | 16.08 | -1.7 | -3.6 |  |
| Tumbe Magharibi | 18.47 | 12.64 | 9.58 | -3.9 | -3.7 |  |

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