Habitat Mapping in a Subtropical Environment using Remote Sensing

Rusmini, M.[a], Hughes, J.[b], Poli, S.[a], Bertolè, L.[a]

[a] ERM Italy Srl, Impact Assessment and Planning, via San Gregorio 38, 20124 Milan, Italy.
[b] ERM Southern Africa (Pty) Ltd, Impact Assessment and Planning, Great Westerford 240, Main Road Rondebosch 7700 Cape Town, South Africa.

Abstract: The collection of information regarding biodiversity and habitat mapping for IA studies on large projects is more and more demanding, especially in the context of remote areas. Remote Sensing can assist Impact Assessment (IA) in extracting useful information by providing a synoptic view of habitats distribution in space and time. Remote sensing was applied to map land cover and habitats in a remote area of Subtropical Africa to inform a study of Biodiversity and Ecosystem Services. The habitat mapping was based on a supervised classification of multi-temporal Landsat imagery for an overall area of about 20,000km^2. The classification was driven and validated through ground truths collected by ecologists. The overall accuracy was determined to be more than 80%. The resulting habitat map played an important role throughout the study, including mapping of habitat status and sensitivity (based on IFC categories of modified, natural and critical), demonstrating differential rates of habitat change over time prior to project development, and providing a basis for discussion with engineers on assessment of alternatives. This study demonstrated the value of a combination of fieldwork and Remote Sensing as a reliable and cost-effective approach in representing habitat type and status for a large area that couldn't be adequately surveyed by field effort alone.

1 Introduction

In the framework of Environmental Impact Assessment studies, the need for synoptic, harmonized, and cost-effective baseline data has been all along a crucial issue. Fieldwork campaigns cannot always provide complete information due to sampling extension, HS, time and costing [1]. Remote Sensing is increasingly recognized as a reliable and cost-effective tool for environmental baseline data collection [2]. In this paper we describe an approach based on the synergic use of field surveys and Remote Sensing analysis in a study on Biodiversity and Ecosystem Services (BES) for a proposed linear infrastructure of about 250km in Africa. The overall study was required in compliance with IFC Performance Standards 6 [3].

The project area occupies a strip of coast of about 20,000km^2 characterized by a typical subtropical climate with wet and dry seasons. Frequent and widespread floods in the wet season and poor road network restricted access to roughly 50% of its extent. A Land Cover classification map was extracted from multitemporal Landsat data and field ground truths. This map drove the two fieldwork campaign performed. The collected ground truths were successively used to refine the classification. The study aimed at creating a Habitat Map in compliance with IFC Standards as well as providing information concerning Habitat changes and potential Alternative Assessment.

2 Ground Data Collection

Prior to fieldworks we performed a desktop study in order to find available ground truths for habitat mapping belonging to former conservation projects*. A preliminary aerial survey was performed on November 2013 to provide an overview of the study area. A 13 days wet season survey was undertaken by the ecology team on February 2014. The survey was affected by significant detour requirements around flooded areas. The dry season survey took place at the beginning of September 2014. Overall, the 20-25% of the proposed infrastructure layout was not surveyed. Rapid habitat assessment and vegetation

* Due to confidentiality reasons the information sources cannot be cited herewith.

type identification were performed at 142 locations (63 locations in the wet season and 79 in the dry season).

Detailed plot sampling was performed in representative habitats, providing 49 sampling locations (33 in the wet season and 7 in the dry season). 42 threatened species were recorded based on IUCN Red List [4]. 22 species resulted *Vulnerable*, 10 *Endangered*, and 2 *Critically Endangered*. Nearly all threatened species resulted to belong to *Coastal Dry Forest (CDF)* habitat.

Ecologists performed Large Mammals, Birds, Herpetofauna, Aquatic, and Ecosystem Services surveys during both the campaigns. Based on recorded data, ecologists characterized the habitat prioritization according the IFC Standards.

3 Remote Sensing Data Collection and Preprocessing

Given the dimension of the study area (~20,000km^2) and the scope of work, Landsat data were selected: six to eight multispectral bands among Visible, Near Infrared, and Short Wave Infrared wavelengths with 30m pixel size and an overall image coverage of 32,400km^2. Landsat archive offers a global time series of about 40 years, and each image is available free of cost. To entirely cover the study area, two satellite frames were required. Five suitable image pairs were collected from the USGS archive between 1999 and 2013. We collected an adjunctive image from 2008 to evaluate flood extent of the main river system (Table 1). The images were converted into *Top-of-Atmosphere Radiance* [5] and mosaicked. Each image pair was recorded consecutively along the same flight line with a delay of few seconds. No major radiometric differences were detected within each pair; hence the mosaicking procedure did not require advanced radiometric calibration.

Table 1 – Selected Landsat imagery from sensors 5, 7 and 8 (SLC off: after L7 Scan Line Corrector failure).

Acquisition Date	Sensor	Season	Cloud Coverage
1999/12/07	L7	Dry season	25%
2003/04/22	L7	Wet Season	5%
2006/06/25	L5	Wet season	2.5%
2013/05/25	L8	Wet season	20%
2013/08/31	L8	Dry season	15%
2008/02/25	L7 (SLC off)	Wet Season	10

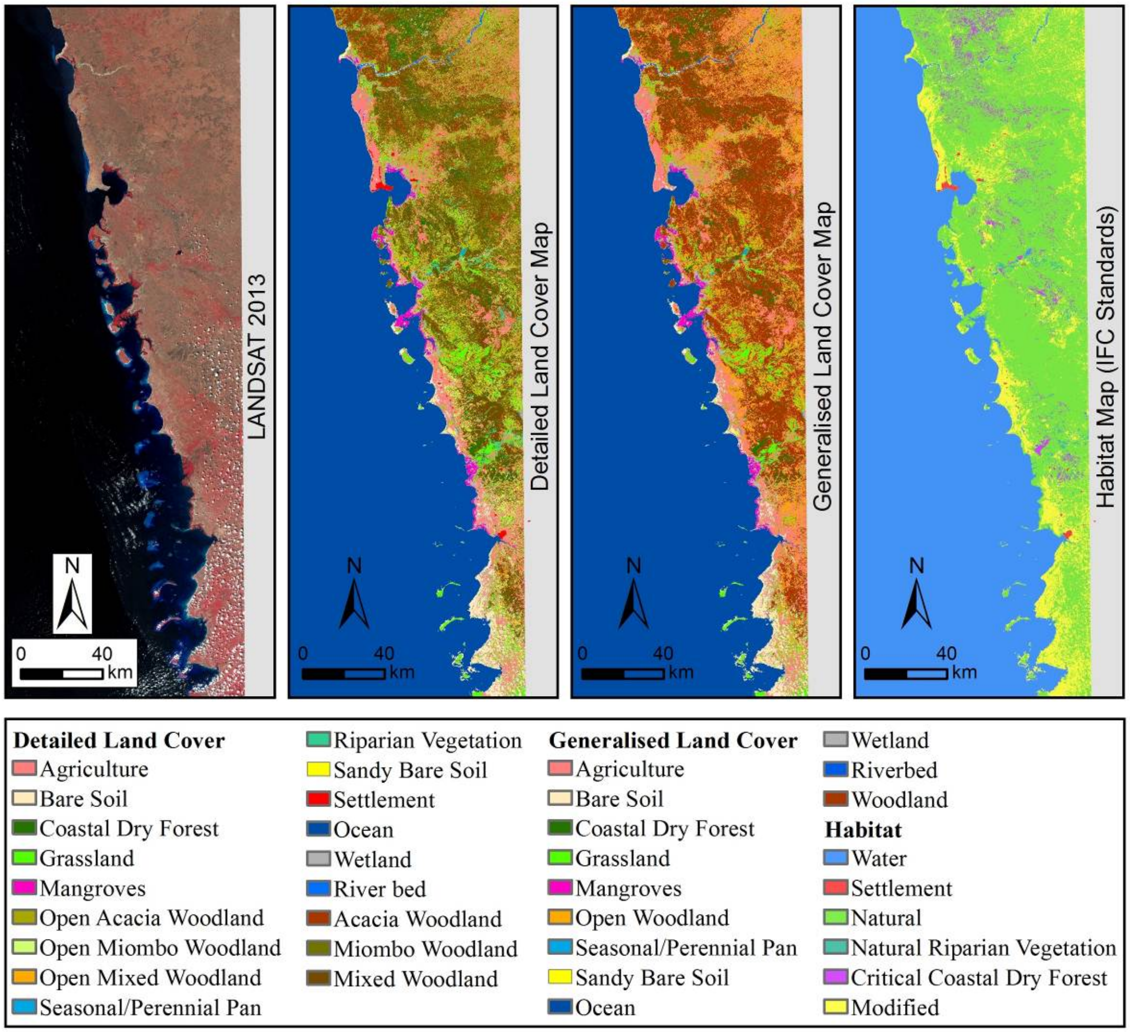
4 Remote Sensing Analysis

For the image classification, we adopted the *Maximum Likelihood* algorithm, one of the most robust parametric methods for supervised classification. It calculates a-priori probability function of membership based on variance and covariance values extracted from the training samples provided by the user, and assumed to be normally distributed. This function is then used to classify each pixel in the image [6,7].

Prior to fieldworks, we performed a first classification run using existing information on habitat distribution and ground truths from previous conservation projects after the validation of the ecology team. A total of 18 land cover classes were derived (Figure 1 – Detailed Land Cover). The classification followed a step-wise process in order to extract all the target classes. The first step was performed on the images recorded during wet season. The L8 image from 2013 was used as basis, while the other two images (L5 from 2006 and L7 from 2003) were used to overcome the presence of clouds in the L8 frame. During the first step we ignored a few classes identified by ecologists, such as *Riparian Vegetation*, and the different *Woodland* and *Open* Woodland types.

Secondly, we attempted to differentiate *Woodland* and *Open Woodland* into Miombo, Acacia, and Mixed by exploiting the higher plant vigor in the dry season of Miombo compared to Acacia [8]. Agricultural land was extracted from all five images, and then merged together, assuming that there was no agriculture loss in time. This procedure avoided the misclassification between vegetated crops and other vegetated classes like *Grassland*. *Riparian Vegetation* was extracted from the 2013 dry season image using NDVI (Normalized Difference Vegetation Index – ratio between the difference and the sum of Near Infrared and Red bands) [9]. This approach exploited the considerably higher chlorophyll content of this class in dry season due to the presence of adjacent water bodies. Pans/lakes were detected using an NDWI (Normalized Difference Water Index), calculated as per the NDVI with the Green band replacing the Red one [9]. An existing detailed GIS polygon layer was used to map settlements. Within each polygon, every pixel not assigned to non-vegetated class was flagged as "*Settlement*". This map was mainly used for identifying field survey locations.

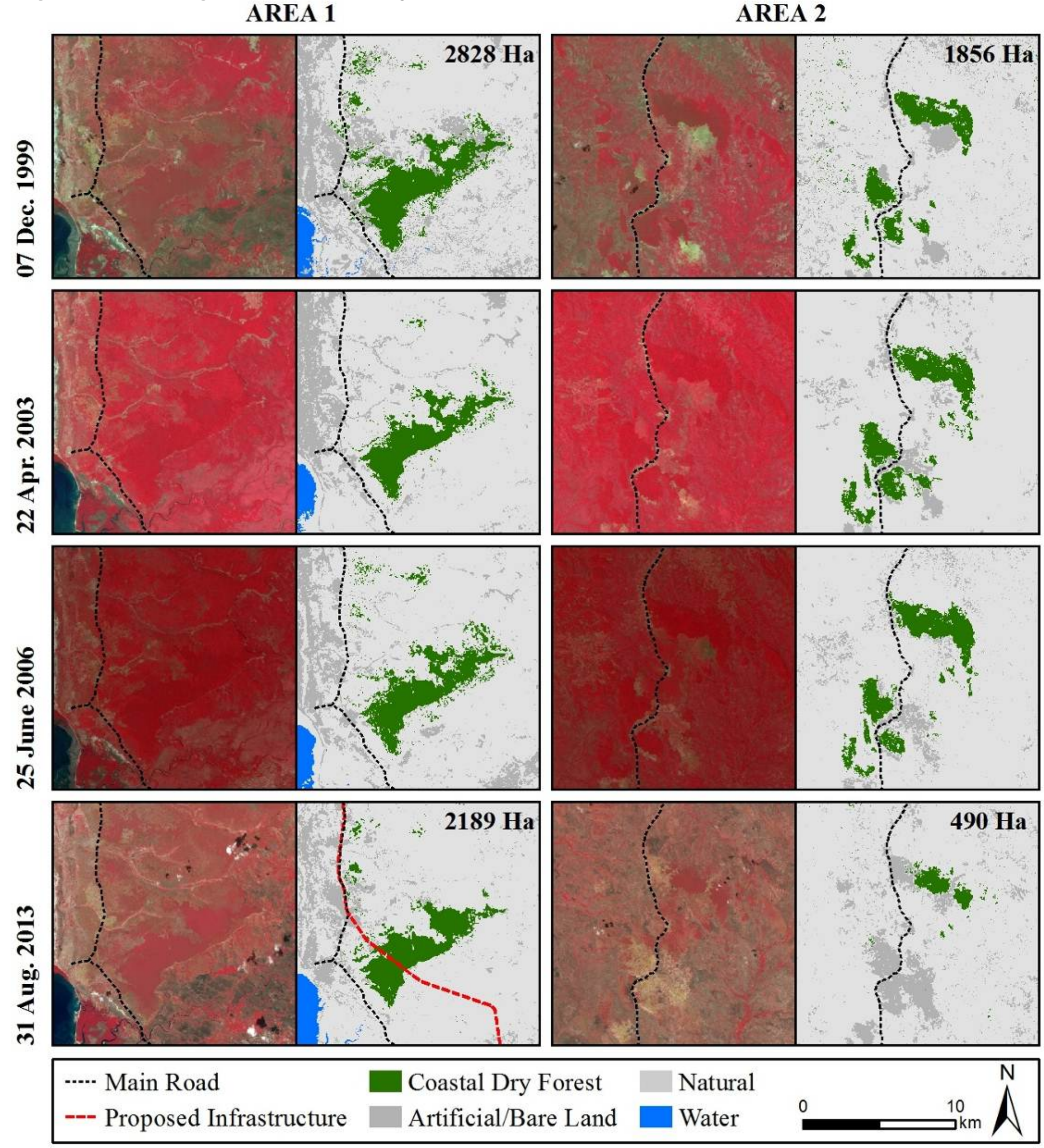
Figure 1 – Overall extent of the study area, intermediate and final products of Remote Sensing analysis.



After field surveys, we performed a second round of classification, using the 142 ground truths from the rapid habitat assessment. The same step-wise approach described above was applied, except for the subdivision of *Woodland* and *Open Woodland* into Miombo, Acacia and Mixed subclasses. Being available sufficient and up-to-date ground truths for each species, these classes were directly detected in the supervised classification. The resulting land cover map was then refined with GPS records of all pans and lakes encountered during the fieldworks. The resulting classification is shown in Figure 1 (Detailed Land Cover). According to plot samplings and preliminary results from land cover mapping, the Miombo-Acacia variability resulted too high to be depicted in a 30x30m pixel. *Woodland* and *Open Woodland* comprised a mosaic of mixed deciduous trees that could not be easily differentiated from interseasonal imagery. The classification was reduced to 12 classes as shown in Figure 1 (Generalized Land Cover).

To understand recent habitat changes in the study area, we mapped the extent of change in the sensitive *CDF* habitat through multi-temporal images. The Infrastructure crosses two main areas of *CDF* (Figure 2). Due to the wide difference in vegetation between dry and wet season images, automatic change detection methods didn't work; therefore the *CDF* extent for each image was estimated trough the same classification algorithm used before and the results were compared. Overall, while in the Area 1 *CDF* loss was about 20% in 14 years, in Area 2 the total habitat loss was around 75%, mainly in the last five years.

Figure 2 – Change Detection Analysis.



Remote sensing was also used to evaluate the potential flood hazard in the area. Available online databases were consulted to find flood events records occurred in the study area. The research indicated a 100years return period flood occurred between January and February 2008. From the Landsat7 image recorded in 2008 February 25th the flood footprint was extracted by exploiting the NDWI. The extension was slightly underestimated due to the delay of the image from the main flood wave.

Lastly we converted the Land Cover classes into the Habitat Status defined by the IFC Performance Standards 6. This was based on the characterization by the ecology team of the land cover classes into modified, natural and critical habitats as follows: (Figure 1 – Habitat): *Modified* – Agriculture Bare Soil; *Natural* – Grassland, *Woodland*, *Open Woodland*, Mangroves, Sandy Bare Soil, Wetland; *Natural – Riparian Vegetation*; *Critical – Coastal Dry Forest*. *Water* (Rivers, Pans) and *Settlements* were added for completeness.

5 Results

The classification accuracy assessment was performed using plot samples in 49 locations. The *Overall Accuracy (OA)* and *Cohen's Kappa* were extracted for the two land cover classification levels, together with the *User's* and *Producer's Accuracy* (UA, PA) for *Woodland* and *Open Woodland* classes (Table 2). [10]. *Kappa* and *OA* for the detailed classification were 0.76 and 0.72. While for the generalized classification they reached 0.90 and 0.92, meaning that more than 90% of the classification was correct. These results are affected by the small number validation points. However accuracy assessment estimated with 200 randomly generated points provided results higher than 80%. This proved that most of the uncertainty in the classification was lying in the subdivision between *Miombo* and *Acacia* species.

Table 2 – Producer's and User's Accuracies for Woodland (W) and Open Woodland (OW) classes (left). Overall Accuracy and Cohen's Kappa for Detailed and Generalized classifications (Right).

Class	**PA**	**UA**	**Class**	**PA**	**UA**
OW Acacia	66.7	66.7	Open Woodland	100	78.6
OW Miombo	33.3	50.0			
OW Mixed	66.7	44.4			
W Acacia	50.0	50.0	Woodland	75	100
W Miombo	33.3	50.0			
W Mixed	50.0	60.0			

	Detailed	Generalized
OA	0.76	0.92
Kappa	0.72	0.90

Concerning habitat change detection, the estimation of *CDF* loss demonstrated the effects of fragmentation in critical habitats. Area 2 was already crossed in 1999 by a main road acting as access route to the forest patch. In 14 years *CDF* almost disappeared, with a loss of 75%, to the detriment of modified habitats. Area 1 did not show any fragmentation, and *CDF* loss was 20%. This consideration led the engineers to evaluate other route alternatives.

Table 3 - Alternative Assessment Based on Remote Sensing Analysis (length %)

Habitat Type	**Proposed Layout**	**Alt. 1**	**Alt. 2**	**Alt. 3**	**Alt. 4**
Modified + Settlements	25.3	**41.0**	20.3	*19.4*	33.5
Natural	*51.9*	55.0	68.7	**73.0**	59.1
Natural – Riparian Vegetation	**3.5**	*0.0*	3.1	0.5	2.9
Critical – Coastal Dry Forest	**10.5**	*0.2*	7.7	6.7	1.8
Flood Length 2008	**29.5**	19.0	26.8	23.6	27.3

Table 3 shows the aggregated results of the alternative assessment based on the habitat map (detailed results for each land cover class are available). The flood extent was also considered in the alternative assessment. The original layout resulted to be the most impacting route with 10.5% of its length in *CDF*, and the 3.5 in *Riparian Vegetation*, which are the most critical habitats in the area. Moreover the 29.5% of the entire length was in areas prone to a 100 years return period flooding.

6 Conclusion

Overall, the value of the proposed approach was demonstrated. The study provided harmonized Habitat distribution and characterization data for the entire study area. This approach overcame the normal constraints of time and budget by optimizing fieldwork efforts. We demonstrated a clear example of risks to biodiversity rich forest areas by estimating changes over time of Critical Habitats. Mapping flood extents provided a visually accessible representation of flood hazard, asserting remote sensing as a powerful source of hydrological data in absence of other sources. The main limitation encountered in using remote sensing for habitat mapping was the inability to distinguish woodland types. Overall, the derived habitat mapping over 20,000km^2 provided invaluable input for confirming the project risks and identifying alternative routes to minimize these risks and maintain conservation integrity of the affected project area.

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