**Earth observation archives for plant conservation: 50 years monitoring of Itigi-Sumbu thicket**

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**Abstract**

Itigi thicket is a spatially restricted ecosystem only present in Zambia and Tanzania. It is thought to be highly threatened and therefore we need to urgently assess the threats to this ecosystem as well as extent and rates of change to derive its true conservation status. In this study we focus on the Itigi-Sumbu thicket surrounding Lake Mweru Wantipa in Zambia, which occurs both inside and outside a National Park (IUCN category II). Earth observation data archives provide the means to assist the conservation assessment process by allowing the monitoring of the ecosystem over time. In particular, the Landsat archive offers over 40 years of imagery at a resolution suited to the distribution of this ecosystem. In this study we exploit this archive and extend it back 50 years using historical aerial photography. The remote-sensing data were classified according to presence of thicket at five dates across a 50-year period and these outputs were combined to produce a deforestation map. Crucially, this map was assessed for accuracy using a novel approach to expert knowledge, which shows that the resultant map is highly accurate (93% overall accuracy). A confusion matrix was used to provide a confidence interval to the deforestation figures. Results indicate that 64% of the Itigi-Sumbu thicket around Lake Mweru Wantipa has been cleared over the last 50 years and that the largest area of remaining thicket is currently situated within the Mweru Wantipa National Park. This deforestation figure provides the means to assess the conservation status of Itigi-Sumbu thicket as part of the Red List of Ecosystem as Endangered (EN).

**Introduction**

Itigi thicket is a low, dry forest consisting of a closed stand of bushes and climbers between 3 and 7 m tall (White 1983) and is found only in two small areas in Zambia and Tanzania. This dry, primarily deciduous and almost impenetrable vegetation type is unique in its species composition, featuring nearly one hundred woody plant species, many of them endemic (White 1983; WWF 2014). The entire ecosystem is believed to be threatened, with reported clearance of 50% in the Tanzanian portion (Kideghesho 2001) and as much as 71% in Zambia (Almond 2000). These statistics, however, are not verified and thus the conservation status and level of threat of the ecosystem remain unclear (WWF 2014).

In Zambia, this vegetation type (termed Itigi-Sumbu thicket) is highly sensitive to disturbance and this regression appears to be irreversible (Trapnell 1943; Fanshawe 1971); once the thicket has been cleared it does not regenerate and is replaced by a fire climax wooded grassland, Lake Basin chipya (Trapnell 1943; WWF 2014). The main threat to the Itigi-Sumbu thicket comes from rapid population growth resulting in an increasing demand for land and resources. This results in traditional, shifting ‘citemene’ slash and burn agriculture in which the thicket is cut down, and its branches piled up and burnt to produce ash which fertilizes the crop. Cassava is the main staple grown in the poor, sandy soils of the area and, after only a few years, the soils are quickly exhausted and the farmer moves on (Trapnell 1943). In addition, the
The close proximity of thicket to Lakes Mweru Wantipa and Tanganyika means that the thicket has come under ever increasing pressure due to immigration associated with the fishing industry on these lakes (NORAD 1989).

The need to conserve the thicket has already been recognized. In 1972 the area along the western shore of Lake Mweru Wantipa, which contained large expanses of thicket, was declared a National Park (IUCN category II). When it was established, the national park had wildlife populations of lion, elephant and the black rhinoceros, all of these species benefiting from the cover provided by the thicket. However, the park’s wildlife population has since been much reduced and black rhinoceros have disappeared as a direct consequence of the clearing of the thicket (Almond 2000). It is clear that the need to provide robust data (in terms of quantities and spatial distributions) on the loss of the thicket is pressing. The Red list of Ecosystems provides a scientific tool to document the conservation status of terrestrial ecosystems (http://iucnrle.org/). Five risk assessment criteria have been developed to form the basis of the analysis, one of them being “Decline in Distribution” (Criterion A). This criterion allows for an ecosystem to be assessed (along with other criteria to be fulfilled) based on the reduction in geographic distribution over the past 50 years (Rodriguez et al. 2015).

One approach to deriving data on thicket loss retrospectively is to mine the Earth Observation data (i.e. acquired via remotely sensing) archives. Earth Observation data provide a powerful way to directly observe large-scale ecosystems, consistently across time and space (Boyd 2009), particularly for biodiversity monitoring (Turner et al. 2015). Specifically, these data can contribute to monitoring protected areas and their geographical proximities (Rose et al. 2015). An area can be studied over a period of time using a time series of images with the same coverage acquired at dates of interest (epochs). Here, in this study, the Landsat series of satellites offer the most suitable approach to monitoring Itigi-Sumbu thicket cover over time. They provide repetitive, global coverage, multi-spectral imagery at a spatial scale where natural and human-induced changes can be detected and monitored over time (Markham et al. 2008; Skidmore et al. 2015). The Landsat archive offers over 40 years of imagery (since 1972) freely available to any user (Woodcock et al. 2008) and it will grow in the future given commitments to Landsat-type sensing systems (Committee on Implementation of a Sustained Land Imaging Program 2013). Often a time series of interest can be further extended back in time if complementary remotely sensed data are available. In this study we exploit the fact that
there were aerial photographs captured in this area in 1964 which afforded the extension of the time series of Earth observation data to the ideal of 50 years. Areas where aerial photographs are not available or difficult to obtain could take advantage of the opening up of declassified Corona data (Song et al. 2015) with worldwide spatial coverage and principal focus in Eastern Europe and Asia. This circa 2.5-m spatial resolution dataset would provide a suitable alternative to the aerial photographs used in this study for other areas and ecosystems globally.

It is a key time for the use of remotely sensed data for conservation (Pettorelli et al. 2015), where there is a realization of the intrinsic value of the archive of these data. However, correct practices must be employed in their use and the role of the conservationist is integral to this. The commonly accepted approach to monitoring land cover over time is via a supervised spectral classification which, among other steps, requires an accuracy assessment to be conducted. The remote-sensing science and application communities have developed increasingly reliable, consistent and robust approaches for doing this (Olofsson et al. 2013, 2014) and this ensures integrity in any statistics produced (i.e. for considering the conservation status of an ecosystem) and if used correctly can be extremely informative in ensuring the optimal value of remotely sensed data (Foody 2015). In this study we determine the extent and rates of change in Itigi-Sumbu thicket around Lake Mweru Wantipa, Zambia, over the last 50 years using historical aerial photography in combination with archived Landsat data and expert knowledge.

Materials and Methods

Study site

Itigi-Sumbu thicket occurs in patches that are immediately adjacent the shores of Lake Mweru Wantipa in Northern Zambia, close to the international borders of the Democratic Republic of Congo and Tanzania (Fig. 1). This comprises an area of 5,000 km² in total, with a land cover which is a mosaic of Miombo woodland, Chipya, edaphic grasslands and Itigi-Sumbu thicket. Within the study area is the Mweru Wantipa National Park, comprising a 3134 km² area to the west of the lake (Fig. 2). The National Park contains the largest known block of protected Itigi-Sumbu thicket around Lake Mweru Wantipa providing a “best-case” scenario in terms of loss compared with the thicket beyond its protective borders. Expert knowledge alongside remotely sensed data (in particular historical aerial photography) was available in this study area. This was not the case for the other portion of

Figure 2. Study area (black box) immediately adjacent the shores of Lake Mweru Wantipa comprising known patches of Itigi-Sumbu thicket in Zambia. The red polygon shows the extent of Mweru Wantipa National Park. Overlapping areas contain the largest block of protected Itigi-Sumbu thicket. Black and White mosaic denotes the extent of aerial photography.
protected thicket in Zambia, within Nsumbu National Park and the unprotected thicket in Tanzania (Fig. 1). Therefore, both of these areas of thicket were outside the scope of this study.

The study area lies typically between 950 and 1200 m above sea level in a relatively flat terrain. The climate for this area can be divided into three distinct seasons: the cool dry season running from May to August, the hot dry season from August to November and the rainy season from November to April. Rainfall is variable in both amount and distribution over time and location, year-to-year variation being as great as 50%. Itigi-Sumbu thicket is linked to soil type. The soils are typically grey-toned pinkish brown and pinkish buff sandy loams, with a higher clayey content in the subsoil and low humic content (Trapnell 1943). Itigi-Sumbu soils often show impeded drainage and, in some cases, a cement-like duricrust may be present (pers. obs Smith; Trapnell 1943; White 1983). As this unique soil structure is broken down by cultivation (p. Smith, unpubl. data), this is the most likely reason why the thicket does not regenerate after clearance, even if it is protected from fire (Fig. 3).

Physiognomically, the thicket is a two-storeyed forest (Fig. 3) with an open overwood of emergent trees, 6–12 m high over a dense thicket underwood (Fanshawe 1971). The understorey is so dense that very little light penetrates to the ground layer, with the result that ground vegetation is sparse, being confined to a few small herbs and grasses (White 1983). Fanshawe (1971) lists 92 woody species in Zambian Itigi, and notes that it shares only a quarter of its floristic composition with the Tanzanian type. The close proximity of the Zambian thicket to the Mbala local centre of plant endemism, and the lack of botanical exploration carried out in this vegetation type, suggests that Itigi-Sumbu thicket contains many undescribed and undocumented species.

Data

The monitoring of Itigi-Sumbu thicket was carried out using a combination of Landsat images and aerial photography to cover the study area on a frequent basis and over a time period of 50 years. Landsat images are provided as part of the GLS (Global Land Survey) dataset, a collection of images optimally selected for land-cover

Table 1. Listing of all data sets, including landsat images and aerial photography used in this study.

| Collection          | Path/row | Acquisition date | Instrument          | Sensor                              | Spatial resolution* | Spectral resolution* |
|---------------------|----------|------------------|---------------------|-------------------------------------|---------------------|----------------------|
| Royal Air Force     | V1/543A/512 | June 1964       | Aerial Photography  | PAN camera recorded on film         | 3 m                 | PAN                  |
|                     | V2/543A/512 |               |                     |                                     |                     |                      |
| GLS1990             | 172/66   | 2nd June 1989   | Landsat 5           | Thematic mapper                     | 30 m                | MS: 6 bands          |
| GLS2000             | 172/66   | 13th May 2002   | Landsat 7           | Enhanced Thematic Mapper(ETM+)      | 15 m                | PAN                  |
| GLS2010             | 172/66   | 24th May 2009   | Landsat 5           | Thematic Mapper                     | 30 m                | MS: 6 bands          |
| USGS                | 172/66   | 10th June 2015  | Landsat 8           | Operational Land Imager (OLI)       | 15 m                | PAN                  |

*Only those bands used in the analysis.
change studies (Gutman et al. 2008, 2013). The global GLS dataset has been created using the primary Landsat sensor of the time. The earliest GLS of 1975 acquired by the multispectral scanner did not allow for sufficient discrimination (i.e. to distinguish thicket from non-thicket in the supervised classification process) for this study (due to its limited spectral and spatial resolution). Therefore, only images from GLS1990 to 2010 (individual scene dates may range +/− 3 years) were selected. Specifically for this study we used images collected in 1989, 2002 and 2009. In addition, to bring the monitoring up to date one of the latest Landsat 8 images collected in 2015 was added to the dataset (the latter image was downloaded from the USGS).

Due to technological advances over the past 40 years of Landsat missions, the images used were from different sensors; Thematic Mapper (TM), Enhanced Thematic Mapper (ETM) and the Operational Land Imager (OLI). All images had the same spatial resolution (30 m). The accuracy of GLS 2000 data can be expected to be better than 25 m RMSE for most of its constituent scenes (Rengarajan et al. 2015). The GLS 2000 dataset is the geographic reference for the Landsat Data Continuity Mission (LDCM) and the rest of the GLS data products which have been registered to within one pixel geolocation accuracy (Tucker et al. 2004; Gutman et al. 2008). This geometric accuracy ensures any temporal change observed by the time series is a result of land-cover change rather than image rectification issues.

All Landsat images in the time series were acquired during the dry season (May and June), to minimize cloud cover but also changes due to phenological differences. To take the time series of remotely sensed data 50 years back from the present day (2015), a set of aerial photography was acquired. This was captured by the UK’s Royal Air Force in June 1964 (series V1/543A/512 and V2/543A/512) by a panchromatic camera and recorded on film. A set of 26 frames divided into five flight line passes were acquired to cover the area. A summary of the full time series of remotely sensed data used is provided in Table 1.

Field data on the species composition and soils of the Itigi-Sumbu thicket were collected in June 1998 and in May 2012 by one of the authors of this study (Smith). GPS data from herbarium collections and soil sample sites were also used as reference data in this study.

**Data processing and mapping of Itigi-Sumbu thicket**

Change detection commonly uses a time series of remotely sensed data, applying different techniques depending on the nature of the dataset (Singh 1989; Coppin et al. 2004; Lu et al. 2004). For this study, dataset was uncalibrated (i.e. still at digital numbers) and with different spectral and spatial resolution at each time epoch (Thenkabail 2015). In such cases as this, post-classification comparison is the most practical approach as individual images are processed and classified independently based upon each scene’s characteristics. Change is then considered at a later stage as the comparative analysis of the output at each time period (Singh 1989). Thus, the remotely sensed data at each epoch were processed and analysed independently to produce a map of Itigi-Sumbu thicket extent. Individual maps were subsequently combined to quantify the loss of Itigi-Sumbu thicket in the study area over the 50 years of study.

**Aerial photography**

The first step in using the aerial photography captured in 1964 was to apply a geometric correction so that these data could form the base of the time series. This was challenging, due to variation in pixel size across the set of photographs, the presence of strong geometric distortions introduced by the camera and the lack of photogrammetric information on the camera model. The aerial photographs were therefore registered to the 2002 Landsat 7 panchromatic image (spatial resolution of 15 m) using 16 ground control points selected from temporally stable ground features and adjusted using a third-level polynomial transformation. This was the polynomial function that yielded the lowest RMSE of the many tested using a set of eight check points to assess the accuracy of the geometric registration. The RMSE obtained was 30 m which was deemed suitable to be used in a time series with the Landsat multispectral data which has a spatial resolution of 30 m.

The panchromatic aerial photographs (Fig. 3) provide limited spectral information to use in the automated mapping of the thicket. This restriction was further exacerbated by the poor quality of the available frames with obvious vignetting on mosaicking of the data to produce a continuous layer. Therefore, the aerial photography (scanned at 3-m resolution) was visually interpreted and digitized after gaining knowledge of the area from ground surveys of the Itigi-Sumbu thicket in 1998 and 2012. The result of this interpretation and digitizing process was a layer which delimited the extent of the thicket in 1964. This layer was then rasterized and resampled to 30-m resolution (to match Landsat imagery) using a majority filter to produce a map of the extent of Itigi-Sumbu thicket in 1964 that could form the basis of the time series.
Landsat multispectral images

The most notable characteristic of Itigi-Sumbu thicket is its dense, mixed evergreen and deciduous composition (Wild and Fernandes 1967; White 1983) which contrasts strongly with the other vegetation types in the area (i.e. Lake Basin Chipya and Miombo woodland) which are deciduous and have a less dense canopy. This feature was key when spectrally discriminating Itigi-Sumbu thicket in the Landsat imagery as the evergreen component of the Itigi-Sumbu thicket remains active in the dry season and thus stands out in its spectral response against the rest of the vegetation in the study area. This enabled successful mapping of the thicket when employing a spectral classifier in a supervised classification (i.e. an automated method of mapping thicket extent from each image at each date).

As Itigi-Sumbu thicket is the priority habitat and the other vegetation types were secondary to the study, there was no need to accurately map all vegetation types. Thus, the supervised classification approach adopted here focussed effort principally on the class of interest, Itigi-Sumbu thicket, at all stages in the classification process (i.e. class training, class allocation and accuracy assessment). Support vector machine (SVM)-based classifications have been demonstrated to be especially suitable for mapping priority habitats as the focus of the classification process is on the vegetation type of interest; resulting in a reduction in the number of training sites required (Sanchez-Hernandez et al. 2007a,b; Li et al. 2011; Stenzel et al. 2014).

Each Landsat image in the time series (i.e. 1989, 2001, 2009 and 2015) was classified to produce a map of thicket extent. The first step in any supervised classification is the training process, in which a dataset that spectrally describes each class to be mapped is produced for machine learning (i.e. the SVM). The challenge here was that coincident information on the thicket for each date of mapping was not available. However, as Itigi-Sumbu thicket has a relict ecology in that once cleared it does not regenerate, the training process exploited this as a rule; if the thicket was present in the study area in 2015 it must have been present throughout the time series, and this was confirmed on the base data of the aerial photography. Thus, a set of 150 training pixel locations for the thicket class was generated from high-resolution imagery (via the Google Earth platform) that was temporally coincident with the 2015 Landsat image.

The Google Earth high-resolution imagery has a horizontal positional accuracy that is sufficient for assessing moderate-resolution remote-sensing data such as those from Landsat (Potere 2008) and thus suitable here. Consequently, the 150 locations were applied to the 1989, 2001, 2009 and 2015 images to form unique spectral training sets for each image to be used by the SVM classifier. For non-thicket areas, comprising all remaining vegetation types and land covers, 150 training sites were randomly selected from the beginning of the time series with the assumption that they remained non-thicket throughout. A SVM supervised classification was performed on each image at each date to produce a thematic map with the extent of Itigi-Sumbu thicket.

The final step in a land-cover classification is to provide an accuracy assessment of a thematic map produced. As contemporary testing data (at each epoch) were not available and could not employ the same rule as used in the training step, it was accuracy of the final thicket deforestation map that was assessed (see below).

Post-classification change detection and thicket deforestation map

The resultant maps showing the extent of Itigi-Sumbu thicket at each date were combined to produce a map of deforestation of Itigi-Sumbu thicket throughout the 50 years (Fig. 4). This produced a final map which has five

![Figure 4. Work flow. Deforestation mapping procedure showing each step of the analysis and the generated final products.](image)
classes, each one providing information about where and what period the Itigi-Sumbu thicket was lost. As stated earlier, it was this final map that was assessed for accuracy. A fundamental recommendation of good practice when assessing the accuracy of change maps is that the dataset used for validation is of higher quality change information than that used for training the classification (Olofsson et al. 2014). For change maps going back in time the main issue is the lack of sources for contemporary validation data; Google Earth provides an extremely useful source of high-resolution data suitable for validation (Knorn et al. 2009; Schneider et al. 2010; Giri et al. 2011), but when the time span of the study goes back beyond the era of high-resolution commercial satellites Google Earth is no longer an option. In those cases historical aerial photography is often used for validation (Lunetta et al. 2006), but for this study,
the only existing set of aerial photography was used as part of the time series.

High-quality validation data were obtained from three experts directly assessing the final change map rather than the intermediate products (i.e. the maps of Itigi-Sumbu thicket extent at each date). Images were visually enhanced by pan-sharpening methods (where a panchromatic band was available) and/or contrast-stretching techniques to improve visual interpretation. Following best practice (Olofsson et al. 2013, 2014), a probability sample design, here simple random sampling, was used to select 385 validation locations. The sample size selection was informed using sampling theory (Foody 2009; Fleiss et al. 2013). Specifically, for planning purposes it was assumed that the mapping would have an accuracy of 85%, based on a widely used target in remote sensing, and that the half width of the desired 95% confidence interval should be <3% which indicates at least 306 sites be acquired. Each expert was then provided with a project with all enhanced individual images and the 385 validation locations (displayed with black bulls eye symbols with transparent centre for better visibility) and asked to record for each point the date when thicket cover was lost, starting with the 2015 image and working backwards querying out points that had already been assigned. The working scale was set to 1:30,000 to accommodate for differences in image resolution.

Results showed a small amount of uncertainty in the decisions of the three experts (label disagreements in 34 of the 385 locations). Therefore, a confusion matrix was produced using only those points where all three experts agreed on the label, reporting estimates of overall accuracy, user’s accuracy (commission error) and producer’s accuracy (omission error).

The extent of thicket in each of the epochs was used to calculate the rate of deforestation. This was done temporally, across the 50-year time span, as well as spatially, looking at deforestation rates inside and outside the Mweru Wantipa National Park. The National Park boundaries were downloaded from the World Database on Protected Areas (WDPA) (UNEP-WCMC 2016). Percentage deforestation rates were established by dividing the thicket loss in each epoch \( (A1 - A2) \) by the original extend \( A1 \), and converted into average annual deforestation rates dividing it by the time difference \( (t) \): Average annual deforestation rate (%) \( = \frac{(A1 - A2/A1)}{t} \times 100 \).

## Results

The final map of Itigi-Sumbu thicket deforestation in the study area throughout the 50 years is shown in Figure 5. The accuracy assessment of this map illustrates that the mapping accuracy is extremely high. Taking the error matrix where there is full agreement between each of the three experts (Table 2), it is evident that the overall accuracy of the deforestation map at 93% far exceeds that of the generally accepted accuracy of 85% for landcover classifications (Foody 2002). Of the 351 validation points finally employed (using only those where all three experts agreed on the label) only 24 were allocated to the wrong deforestation class and in almost every case it was confused with the neighbouring date. All classes in the final deforestation map had producer’s accuracies over 89%. Again this exceeded the mapping target.
Employing a rigorous accuracy assessment, as stipulated by Olofsson et al. (2014), allows the adjustment of the amount of thicket mapped at each date. To do so is particularly important here, given the conservation importance of this vegetation. The confusion matrix reports that at the 2015 epoch, of the 351 testing locations 135 had been mapped as remaining thicket by the SVM classifier (i.e. the producer’s accuracy). However, 149 of the 351 testing locations were in fact still thicket and therefore in error by ~4%. This error can be applied to the rest of the mapping for that class (thicket remaining in 2015) to adjust the areal estimate of that class and subsequently the deforestation rates. This calculation of required adjustment was applied using the confusion matrix also to the deforestation estimates at each epoch and used to adjust the thicket deforestation rates.

Figure 6 illustrates the extent of remaining thicket at each date along with deforestation rates. The deforestation map (Fig. 5) indicates that 64.8% of the total thicket area has been cleared over the last 50 years. Most of this area (30.6%) was lost before 1989, but the rate of deforestation rapidly increased between 2002 and 2009 reaching annual deforestation rates of 3.4% during this period. When comparing the deforestation patterns inside and outside the reserve, it is evident that Mweru Wantipa National Park experienced the greatest thicket loss during the first period (1964–1989), when 23% of the original thicket extent was lost. By 2015 it is clear that the largest area of the Itigi-Sumbu thicket remaining in the vicinity of Lake Mweru Wantipa lies within the Mweru Wantipa National Park.

These deforestation figures can be used as part of the Red List of Ecosystems framework to provide a conservation assessment for the Itigi-Sumbu thicket. Our results show a 64.8% deforestation rate for the last 50 years in Zambia; this along with the 50% deforestation rate reported on the Tanzanian side (Kideghesho 2001) are within the bounds of 50–80%; this gives Itigi-Sumbu thicket a preliminary ecosystem assessment of Endangered (EN) under criterion A1.

Discussion

The results obtained in this study confirm that the Itigi-Sumbu thicket by Lake Mweru Wantipa in Zambia has been declining over the past 50 years and shows that the thicket is highly threatened in this locality. Given that this area is one of just three areas of this thicket worldwide this is a cause for concern. The thicket deforestation figures agree broadly with the findings of Almond (2000); however, we extended the period of study to afford consideration of this vegetation type by conservation initiatives such as the Red List of Ecosystems. Although our findings indicate lower deforestation rates than those previously reported by Almond (2000), it is evident that removal of thicket has been ongoing for a long time on the shores of Lake Mweru Wantipa and current ecological understanding of this thicket suggests that this decline is irreversible. Lake Mweru Wantipa (as well as Lake Tanganyika) attracts immigrants due to their fishing industries (NORAD 1989) and the thicket in the vicinity of the lake is particularly vulnerable because it occurs on accessible, flat land adjacent the lake shore. Clearing takes two forms: (1) slash and burn ‘citemene’ agriculture, primarily for the cultivation of cassava (see Fig. 3C) and (2) selective logging of trees and larger shrubs for firewood and charcoal for cooking and smoking fish (Fig. 3B). The peak in deforestation rates recorded between 2002 and
2009 corresponds with a large influx of refugees in the area from political upheavals in the Democratic Republic of Congo. After the second Congo war finished in 2003, many Congolese became naturalized, settled and started farming in the area (Zytkowski C. pers. comm.).

With respect to spatial patterns, it is evident that the clearance of thicket has been occurring within, as well as outside the boundaries of the Mweru Wantipa National Park. Inside the park, substantial deforestation (23%) occurred between 1964 and 1989, much of it probably before the park was established in 1972. This cannot be confirmed though, as early Landsat data (i.e. in the period 1972–1982) were considered unsuitable for use due to their poorer spectral resolution (the MSS sensor). If these data could be used, then such information would assist in understanding further the patterns of loss immediately prior to and following the establishment of the National Park. More recently, deforestation rates inside the park are substantially lower than those outside, indicating conservation effort is having an effect. The Zambian National Parks and Wildlife Department conducts patrols regularly with the aim of controlling encroachment and illegal farming within the park (Zytkowski C. pers. comm.). A visual inspection of the Landsat images (supported by knowledge of the area) does, however, indicate that inside the park there is substantial degradation of thicket canopy cover, indicating that the selective removal of larger trees is an ongoing problem even if encroachment is under control. This occurrence of degraded thicket could also explain the overestimate in deforestation by the spectral classification approach here (i.e. at ~4%). Notwithstanding this problem, Mweru Wantipa National Park probably represents the best opportunity to conserve the Itigi-Sumbu thicket in the environs of Lake Mweru Wantipa. Remote sensing should be used to continue to monitor the thicket; however, a different approach would be required to ensure that mapping of degraded thicket, in addition to intact thicket, is achieved. This would provide further information with which to target conservation effort.

From this study, the power of the Landsat data archive for conservation efforts is clear. In this case the archive was extended back to an ideal of 50 years (as specified by the Red List of Ecosystems) and the spectral classification approach adopted suited the mapping of Itigi-Sumbu thicket in this landscape. The thicket is spectrally distinctive, which when coupled with its relict ecology (i.e. does not regenerate), allowed the exploitation of the Landsat archive without full reference data (i.e. for training and testing of the land-cover classifications at each time stamp). The achievement of an overall classification accuracy of 93% in the final deforestation map demonstrates just how useful this approach was.

The real benefit here is the combination of expert knowledge with a full understanding of how remotely sensed data can be used; something to be further encouraged (Wang et al. 2010). Of particular note when making proper use of remotely sensed data was the use of the best practice approach to estimating area and assessing accuracy of land change, which often is not conducted (Olofsson et al. 2013, 2014). By employing the implicit information in the confusion matrix an adjustment for error could be applied to the deforestation (thicket cleared) estimates which is particularly important within conservation efforts. The requirement that estimates of land cover (and derived data such as clearance, etc.) should reduce any known uncertainties as much as practicably possible has indeed been noted (e.g. UN-IPCC Good Practice Guidance for Land Use, Land Use Change and Forestry) (Penman et al. 2003); but often this has not been the case (Olofsson et al. 2013).

A number of limitations of this study have been noted. The lack of information on deforestation around the time of establishment of the National Park requires future attention to fully understand the patterns in thicket clearance. Focus here would be on overcoming the lack of spectral detail by improving the spatial resolution of the early Landsat MSS data. Approaches such as super-resolution mapping (SRM) (Muad and Foody 2012) could, for instance, be adopted here. Going forward, however, such limitations occurring as a result of the trade-off between spectral, spatial and temporal resolutions and having in this case to emphasize the temporal detail will start to become less important. This will be of great benefit to conservation efforts. The Landsat archive has already seen improved spectral and radiometric resolution with the launch of Landsat 8 (Irons et al. 2012) and indeed the power of its satellites demonstrated for change detection at a global scale (Hansen et al. 2013) and its application to conservation (Tracewski et al. 2016).

Going forward and looking into future conservation assessments we are on the cusp of the Sentinel era with the recently launched Sentinel 2A awaiting its partner satellite (2B due for launch) and Sentinel 3’s launch imminent. These freely available data via the ESA Copernicus programme are assured for beyond 2030 and available to all via the Scientific Data Hub (European Space Agency 2016). Indeed conservation has been identified as a beneficiary here (Turner et al. 2015). There will still be a need, however, for suitable ground data to support the processing of remotely sensed data, but a growing awareness of the role of remote sensing in conservation should afford targeted ground data efforts. The Web 2.0 era should afford the exchange of such data. We have already seen how the rise of Volunteered Geographic Information (VGI – both formal and informal) (Foody and Boyd...
2013) data exchange platforms such as Google Earth (Google Earth 2016) could benefit conservation.

Overall, this research contributes to the understanding of the conservation status of and level of threat to the Itigi-Sumbu thicket in the vicinity of Lake Mweru Wan-tipa, Zambia. Our deforestation results support the assessment of this ecosystem as Endangered, but it is recommended that the remaining Itigi thicket (both in Zambia and Tanzania) be fully surveyed. Doing so will also confirm whether the Zambian thicket is a separate vegetation type from the Tanzanian type as it has been reported that they share only a quarter of their floristic composition (Fanshawe 1971). If a full survey confirms that this is a shared ecosystem between both countries, a deforestation study should be conducted on the Tanzanian side. This assessment is based on reported figures of 50% deforestation (Kideghesho 2001) for Itigi thicket in Tanzania, as of 2001, and if in the Tanzanian side deforestation rates resemble that of Zambia, then the rate of deforestation is likely to have rapidly increased after 2002. Deforestation rates >80% would place this ecosystem under the critically endangered category. Remote sensing affords such a survey, if suitable expert knowledge or supporting information is available.

Acknowledgements

We would like to thank our colleagues Jonathan Timberlake, Tim Wilkinson and Sara Barrios at Royal Botanic Gardens, Kew and Craig Zytkow, CEO, Conservation Lake Tanganyika, for their invaluable knowledge and input in this study.

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