Remote Sensing in Ecology and Conservation
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INTERDISCIPLINARY PERSPECTIVES

A simple remote sensing based information system for monitoring sites of conservation importance

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Abstract

Monitoring is essential for conservation of sites, but capacity to undertake it in the field is often limited. Data collected by remote sensing has been identified as a partial solution to this problem, and is becoming a feasible option, since increasing quantities of satellite data in particular are becoming available to conservationists. When suitably classified, satellite imagery can be used to delineate land cover types such as forest, and to identify any changes over time. However, the conservation community lacks (a) a simple tool appropriate to the needs for monitoring change in all types of land cover (e.g. not just forest), and (b) an easily accessible information system which allows for simple land cover change analysis and data sharing to reduce duplication of effort. To meet these needs, we developed a web-based information system which allows users to assess land cover dynamics in and around protected areas (or other sites of conservation importance) from multi-temporal medium resolution satellite imagery. The system is based around an open access toolbox that pre-processes and classifies Landsat-type imagery, and then allows users to interactively verify the classification. These data are then open for others to utilize through the online information system. We first explain imagery processing and data accessibility features, and then demonstrate the toolbox and the value of user verification using a case study on Nakuru National Park, Kenya. Monitoring and detection of disturbances can support implementation of effective protection, assist the work of park managers and conservation scientists, and thus contribute to conservation planning, priority assessment and potentially to meeting monitoring needs for Aichi target 11.

Introduction

The protected area network is the cornerstone of site-based conservation, and it is specifically named in Aichi Target 11 of the CBD, which requires world governments to conserve 17% of land through “protected areas and other effective area-based conservation measures” (CBD, 2010). Target 11 also calls for these sites to be effectively and equitably managed (CBD, 2010). Site managers need to know what is happening on sites if they are to respond to current or potential threats to sites. There are standardized methods for *in situ* monitoring of sites, including management effectiveness – PAME (Coad et al. 2013) and Important Bird and Biodiversity Area monitoring (BirdLife International, 2006; Mwangi et al. 2010). However, accepted methods for monitoring land cover and assessing park integrity are lacking for many areas of the globe. Standardization of monitoring would allow data to be collated at national, regional and international levels, allowing progress toward targets, such as CDB Target 11, to be monitored globally.

The loss of natural habitat, especially deforestation and conversion for agriculture, are perhaps the largest threats to biodiversity (Pimm et al. 1995, 2014), so solutions need to be found that allow for easy monitoring of habitat loss across conservation sites. Remote sensing, and satellite data in particular, has been identified as a useful tool for conservation in tracking land cover (e.g. Turner et al. 2003; Buchanan et al. 2009; Leidner et al. 2013). However, classifying and processing the data can be complex, and the need for a simple solution for protected area monitoring was highlighted recently by Rose et al. (2015).

There are already a number of tools and data sources that are available to the conservation community for making assessments of land cover. Indeed, several global products related to land cover state and change, developed by using medium spatial resolution satellite imagery, have been published (e.g. Global Forest Cover (Hansen et al. 2013), Global Land cover (Gong et al. 2012), CLASlite – (http://claslite.carnegiescience.edu/en/) and the Protected Area Archive (http://asterweb.jpl.nasa.gov/paa/). However, these products either focus on one land cover type or they cover limited time periods. In other cases, accuracies are not always acceptable or consistent with other studies (Achard et al. 2014). CLASlite and Global Forest Cover help to lower the entry barrier for mapping and assessing vegetation from satellite imagery, but they focus exclusively on loss and regrowth of tree cover. The conservation and biodiversity community requires accurate data on the dynamics of all vegetation types (grassland, herbaceous vegetation, shrubs, etc.) (Rose et al. 2015), and not just forest. Consequently, the toolbox we present here is a step forward in conservation monitoring.

Here, we introduce and demonstrate an open access, remote sensing based toolbox for site monitoring and a biodiversity and protected areas information system. The toolbox meets many of the needs identified by conservationists (Buchanan et al. 2015; Rose et al. 2015), and allows individuals with little experience of the use of remote sensing to undertake dedicated assessments of land cover and use, and their change, at the site scale. The use of a standardized assessment of land cover/use and type allows data to be collated to produce comparable estimates of change across sites. This allows analysis of the effectiveness of actions, but more importantly, allows consistent statistics to be calculated at the local and regional scales. The toolbox, which can be used offline, requires little capacity or training to pre-process and classify satellite imagery and validate the thematic map results, and is designed specifically for non-(geospatial)-expert conservationists, and PA managers. The biodiversity and protected areas information system integrates various protected area and biodiversity data including the toolbox's thematic land cover/use maps, using open source web services. We illustrate the use of the toolbox with a case study on Lake Nakuru National Park, Kenya before aggregating the results from 10 protected areas in East Africa in order to describe broad patterns of land cover change and show the accessibility of the processed data through the information system.

Materials and Methods

Toolbox – data, pre-processing and image classification

The satellite IMagery ProCessing Toolbox (v1.2b), IMPACT (http://forobs.jrc.ec.europa.eu/products/software/) was developed with pre and post image processing capabilities and combines automated processing chains with minimal user interaction (Fig. 1). The toolbox utilizes data from the USGS Landsat program which, by stretching back to the 1980s (Turner et al. 2013, 2015), provides a readily accessible retrospective baseline land cover.

In the toolbox, an automated pre-processing chain converts digital numbers to top-of-atmosphere reflectance, undertakes clouds and cloud shadows masking, and performs image normalization. The next step is an automated unsupervised classification, using an empirical knowledge-based decision tree approach based on spectral band reflectance characteristics and spectral indices as described in Szantoi and Simonetti (2013) (Fig. 1). The procedure is based on a minimal mapping unit (MMU) of 5 ha, and multi-date image segmentation that assigns individual pixels into objects for each year for which an image has been selected. These objects are then automatically classified using an automated knowledge-based classification algorithm, where the algorithm groups individual pixels within a segment (by year) into a land cover class based on their occurrence frequencies.

Six major land cover types are mapped and an additional 'cloud/shadow' class is used. The applicable land cover classes are: tree cover (over 70% canopy cover and tree height over 5 m), tree cover mosaic (between 30% and 70% canopy and tree height over 5 m), other wooded land (less than 30% of canopy cover, less than 5 m of canopy height, shrubs included), other land cover (non-woody land cover, includes herbaceous vegetation and grass), bare and burnt (a mostly temporary class, depends on seasonality) and permanent water.

We pre-defined the land cover classes based on previous large-scale land cover monitoring studies such as Achard et al. (2014) so that it would fit the various geographical locations to be mapped. The use of a stan-

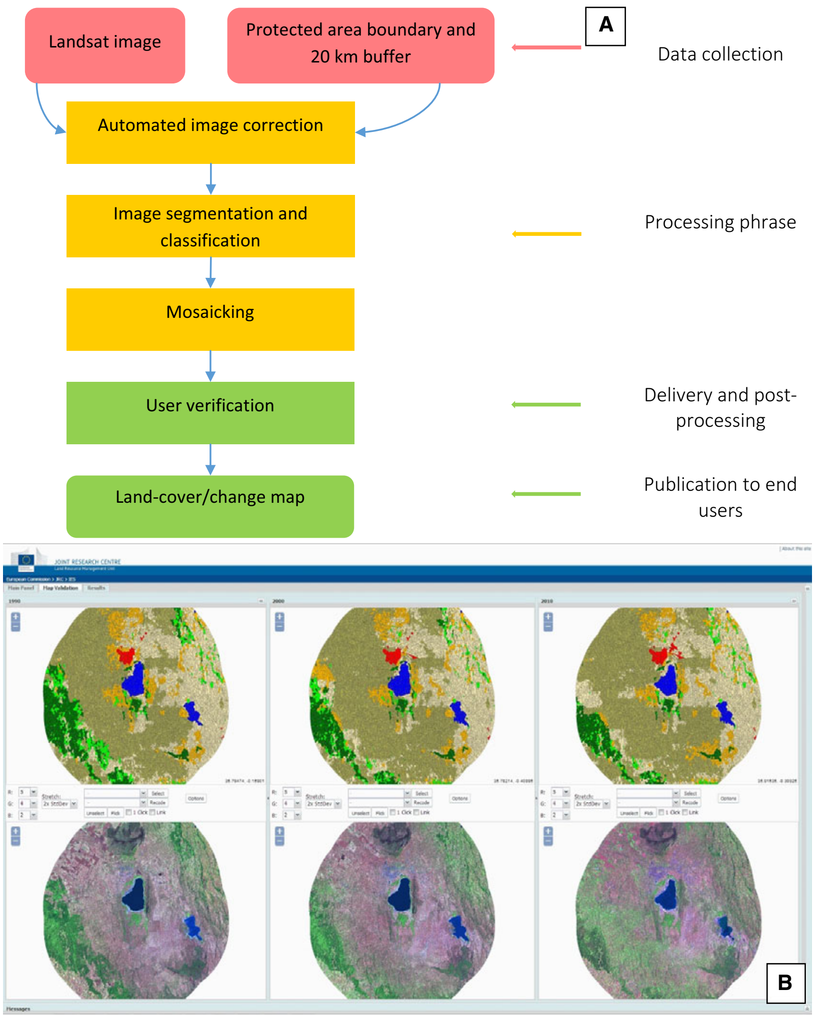

Figure 1. Schematic representation of the data processing flow in IMPACT. Pink layers represent inputs, orange are the automated steps and green indicates steps where user input is needed (A). The interface of the map refinement and verification tool (B).

dard algorithm means the land cover classes should be comparable between sites, allowing amalgamation of results for national and regional scale analyses. These land cover types are broad, but they are appropriate to capture the dynamics which have been identified as being the major land cover related threats to biodiversity, namely conversion and degradation of natural areas (i.e. forest loss) and expansion of agriculture.

Land use classes, most importantly agriculture and human settlements/urban, are not included in the automatic classification since based on their spectral signatures they are generally part of the 'other land cover' and the 'bare and burnt' land cover classes. Inclusion of these land uses in the image classification algorithm would be inaccurate due to the spectral similarities. However, if the user is interested in discriminating such land use classes, there is a 'verification' option within the toolbox where refinement and verification of the automated classification output is possible (Figs. 1 and 2). This map refinement and verification procedure allows users to derive reliable and highly accurate maps and land cover change statistics, and to include agriculture and human settlement classes.

The user input (verification) phase allows the user to (a) review the land cover maps generated by the automated system and (b) revise and modify (correct) them interactively if mis-classification errors are present using higher spatial resolution imagery (Fig. 1) through various other data sources (e.g. Google Earth™ (https://earthgoogle.org), OpenNebula (http://opennebula.org/) or Global Risk Assessment Services (https://www.gras-system.org). The unverified maps must be used with caution as temporal seasonality effects are present in many cases. These could lead to misclassification errors, and hence to inaccurate land cover maps and change statistics.

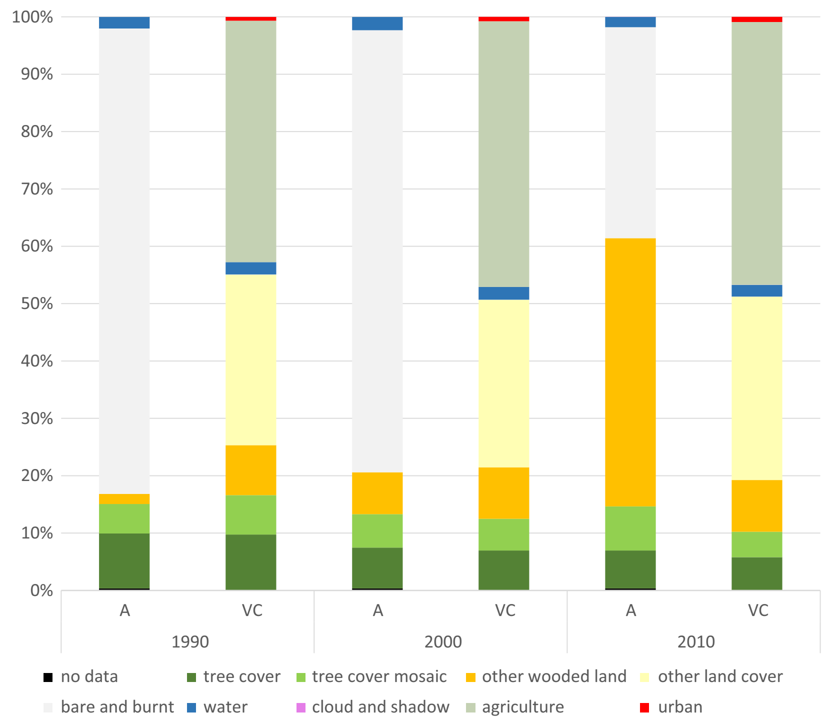

Figure 2. Land cover and land use statistics for Nakuru National Park (and 20 km buffer zone) before and after map refinement and verification. (A – automated, VC – verified and refined).

Monitoring land cover on sites – the protected areas land cover information system

The BIOPAMA Regional Reference Information System (RRIS) is an online biodiversity and protected areas information system hosted by the Joint Research Centre of the European Commission, bringing together relevant information to support decision making for the protection and management of protected areas (http://rris.biopama.org/content/About-RRIS). The protected areas land cover information system represents one module within the RRIS (http://rris.biopama.org/lcc). Processed imagery and validated land cover data are currently available for 772 and 23 protected areas (PAs) in Sub-Saharan Africa, respectively. These protected areas were selected based on their IUCN categories (I–IV) and on some other ranks (e.g. Ramsar wetlands, UNESCO sites). The boundaries were obtained from the World Database on Protected Areas (WDPA) as of March, 2015 (IUCN & UNEP-WCMC, 2015). As the verification is an ongoing procedure, validated land cover data sets are being added to the system in a continuous manner. The protected areas land cover information system under the BIOPAMA RRIS allows users to search any protected area in Sub-Saharan Africa and at a later stage the Caribbean and Pacific regions by name, WDPA ID, and country. In addition, users can select the option to view only validated land cover data or to include unvalidated land cover maps in their selection. Landsat image mosaics for up to three analyzed time periods (currently representing the decades 1990, 2000, 2010) are available for each PA and their 20 km surrounding buffer zones. Users can specify the color band combination using custom Red-Green-Blue values of the multispectral bands or a predefined standard for viewing satellite imagery (false color and natural color) to aid visual interpretation. Users also have the option to toggle auto scaling on the satellite imagery, which attempts to generate a cohesive uniform color pallette for the satellite images that represent the protected area. The resulting maps are displayed simultaneously with synchronized pan and zoom capabilities to allow the user to easily compare differences between decades.

Refinement and verification of the thematic maps

Those protected areas whose land cover maps have been verified are published online and can be viewed, analyzed and downloaded by any registered/anonymous user. The data consists of labeled polygons with a classification and a final category for each year. The unverified data have also been made freely available. However, since the automated classification requires user input in order to verify labels (see Fig. 1), unverified data are not supplied as a true record of land cover – instead it is foreseen that users will download this data to perform their own verifications (e.g. by using the IMPACT Toolbox presented here) and contribute them back to the information system.

Results

Land cover/use change on Lake Nakuru

To demonstrate the use of the toolbox we use Lake Nakuru, Kenya (0°22′0″ S 36°4′60″ E; WDPA ID 762; http://rris.biopama.org/lcc/762) as a case study, not least because this site illustrates the need for the user verification procedure. Following the steps outlined above, and using satellite images from 1990, 2000 and 2010, land cover and land cover change were assessed. The automated image classification algorithm was able to discriminate between most of the major land covers, based on the visual assessment (Fig. 2). Moreover, an accuracy assessment using 429 randomly generated points based on the corrected thematic map (ground truth) and compared to the automated classifier generated thematic map revealed that the overall accuracy of the latter map was over 60% for each investigated year (1990 – 65.73%, 2000 – 60.60% and 2010 – 67.13%).

The verification (and refinement) suggested that the automated algorithm was less able to identify the ‘other wooded land’, ‘other land cover’ and ‘bare and burnt’ mixed classes, confusing these with large agricultural and urban land use classes. Without a refinement and verification step, the agricultural land use would have been classified as simply ‘other land cover’. The decadal land cover maps, subsequent to refinement and verification, show a clear trend in the expansion of agriculture and human settlements (i.e. urban) at the expense of tree cover (close forest) and tree cover mosaic (open forest) over the decades (Fig. 3). A gradual loss of tree cover in the south/southwest area of the study site is apparent, and tree cover/tree cover mosaic were replaced by agriculture. Change can be noticed in the northeastern part, where the transition from tree cover and tree cover mosaic classes to other land, other wooded land and agriculture occurred. The city of Nakuru has expanded at the expense of wooded areas.

Broader patterns of land cover change

In addition to Lake Nakuru, we assessed land cover change on nine other protected areas in East Africa (Table 1). All showed broadly similar patterns in their land cover change dynamics, with human settlements and agricultural land use increasing in extent in the buffers while the land cover within the protected areas remained stable (Fig. 4). Udzungwa Mountains National Park (19297) was particularly notable for the clear increase in the extent of agriculture and urban (with a concomitant decrease in forest cover). This might indicate that this park is a concern compared to, for example Nechisar National Park (2278) and Mahale Mountains National Park (7521) which remain relatively intact, both within the park and in the buffer surrounding the park.

Discussion and Conclusions

Monitoring is a key part of the conservation process, which allows problems to be identified and solutions developed, and also allows the effectiveness of actions to be assessed. Traditionally, monitoring has been based on *in situ* field assessments, but this can incur considerable costs, especially where sites are remote, inaccessible or extensive. The conservation community has identified an as-yet unmet need to apply remote sensing data in monitoring sites of conservation importance (Buchanan et al. 2015; Rose et al. 2015). Our tool, which can be applied globally, allows assessment of land cover change to be made from anywhere in the world. It meets the criteria that have previously been suggested for a remote sensing based system for monitoring land cover change on sites (Buchanan et al. 2009) in that it is free to use, requiring

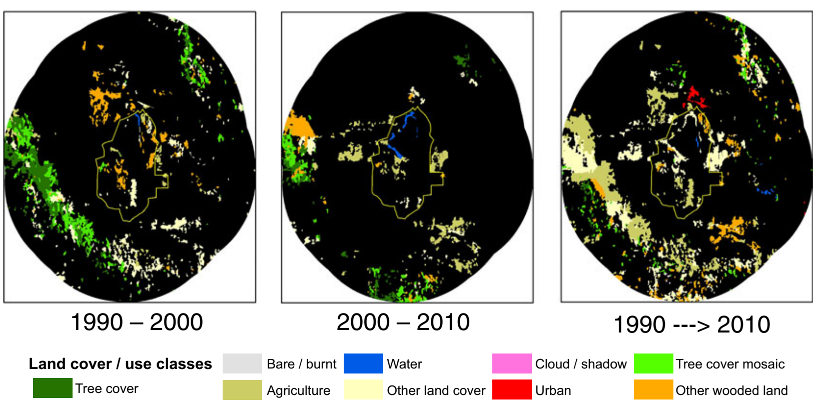

Figure 3. Change detection results of the verified Nakuru National Park and its vicinity (20 km). The change maps for 1990–2000 and 2000–2010 show the original class which has changed during the particular period, whereas 1990→2010 shows the actual (new) land cover class for the year 2010.

Table 1. Protected areas analyzed for land cover/land use change.

WDPA ID	Park name	Country	IUCN category	Centroid (Long/Lat)
653	Simien Mountains National Park	Ethiopia	II	38.17, 13.16
753	Marsabit National Park	Kenya	II	37.95, −2.33
760	Mount Elgon National Park	Kenya	II	34.69, 1.09
762	Lake Nakuru National Park	Kenya	II	36.09, −0.39
764	Ol Donyo Sabuk National Park	Kenya	II	37.26, −1.14
2278	Nechisar National Park	Ethiopia	II	37.89, 5.99
2279	Abijatta-Shalla Lakes National Park	Ethiopia	II	38.52, 7.54
7521	Mahale Mountains National Park	United Republic of Tanzania	II	29.90, −6.21
19297	Udzungwa Mountains National Park	United Republic of Tanzania	II	36.66, −7.79
19726	Malka Mari National Park	Kenya	II	40.76, 4.18

just a login. It utilizes free data (an essential feature if it is to be sustainable) and it requires little expertise in remote sensing, since the built-in logical processing chain utilizes metadata supplied with images to undertake pre-processing. We expect that it will have a major impact in the field of conservation.

This tool adds to an expanding number of methods available to the conservation community for tracking land cover. Many of these tools are simple and easy to use, making them ideal for the conservation community which may have limited remote sensing capacity. However, many of the tools are confined to a consideration of forest (e.g. Global Forest Cover or CLASlite) and not other land cover (habitat) types. Given that the majority of species are dependent on forest, these tools have obvious value for monitoring change in sites of conservation importance, up to a global scale (e.g. Tracewski et al. 2016). However, a consideration of other land cover types is useful for long term monitoring and planning, in order to identify what is replacing the lost forest.

Application of the land cover change tool to monitor Nakuru National Park in Kenya indicated that the land cover within and around the park had stayed relatively stable over the past 30 years. This might indicate that the park was being effective at conserving the natural land cover within its boundaries. The extent of natural land cover in the other parks was broadly stable too, but there was a notable increase in agriculture, and decrease in tree cover, in the 20 km buffers around the parks. Previous studies have found that broadly, protected areas reduce the rate of loss of forest (Geldmann et al. 2013) and all land cover (Beresford et al. 2013). Forest loss and agricultural encroachment are recognized as major threats to biodiversity (Pimm et al. 1995, 2014), and the loss of trees and increase in agricultural land around the parks indicates that pressures on the parks themselves might be increasing. Conservation responses could be informed by these data, allowing the authorities to maintain the integrity of the parks under greatest threat.

The image processing toolbox has evolved from code developed to help in remote sensing assessments of forest loss (Achard et al. 2014). Consequently, as it was originally developed for remote sensing applications, it will also be of use to the remote sensing community. In particular, some of the features which were previously standalone applications (e.g. Baatz's segmentation algorithm http://www.terralib.org/html/v360/TePDIBaatz_8hpp-source.html) are fully integrated in the box's processing chain.

The toolbox is complemented by an information system that allows sharing of results. The toolbox, while requiring some web access, can be used offline and is suitable for situations where remote sensing expertise and capacity to track changes on sites are limited. It can be used to make assessments at the local scale (i.e. by park managers or community site management groups) or for regional level studies, and it covers multiple land cover types.

The toolbox specifically was developed for individuals in the conservation community who have little experience of remote sensing and image pre-processing. The workflow allows such individuals to utilize images which have not had higher levels of processing, opening up a new pool of potential data sources to them.

We presented examples of the toolbox being used with Landsat data, which are available retrospectively, back until the 1980s. This enables conservationists to access a back catalogue of images and make retrospective baselines for monitoring; something not possible from field data. As the imagery selection and pre-processing is highly automated, the inclusion of new medium spatial resolution imagery into the workflow is foreseen, including Landsat 8 OLI and Sentinel 2ab multispectral imagery from 2015 onwards. Continued availability of these data has been highlighted as essential for the continued (and expanded) use of remote sensing by the conservation community (Turner et al. 2015), and will certainly be important for the utility of the RRIS.

At this midpoint in progress toward the 2020 Aichi targets for the CBD (Secades et al. 2014), we envisage that the toolbox could make a contribution toward measuring pro-

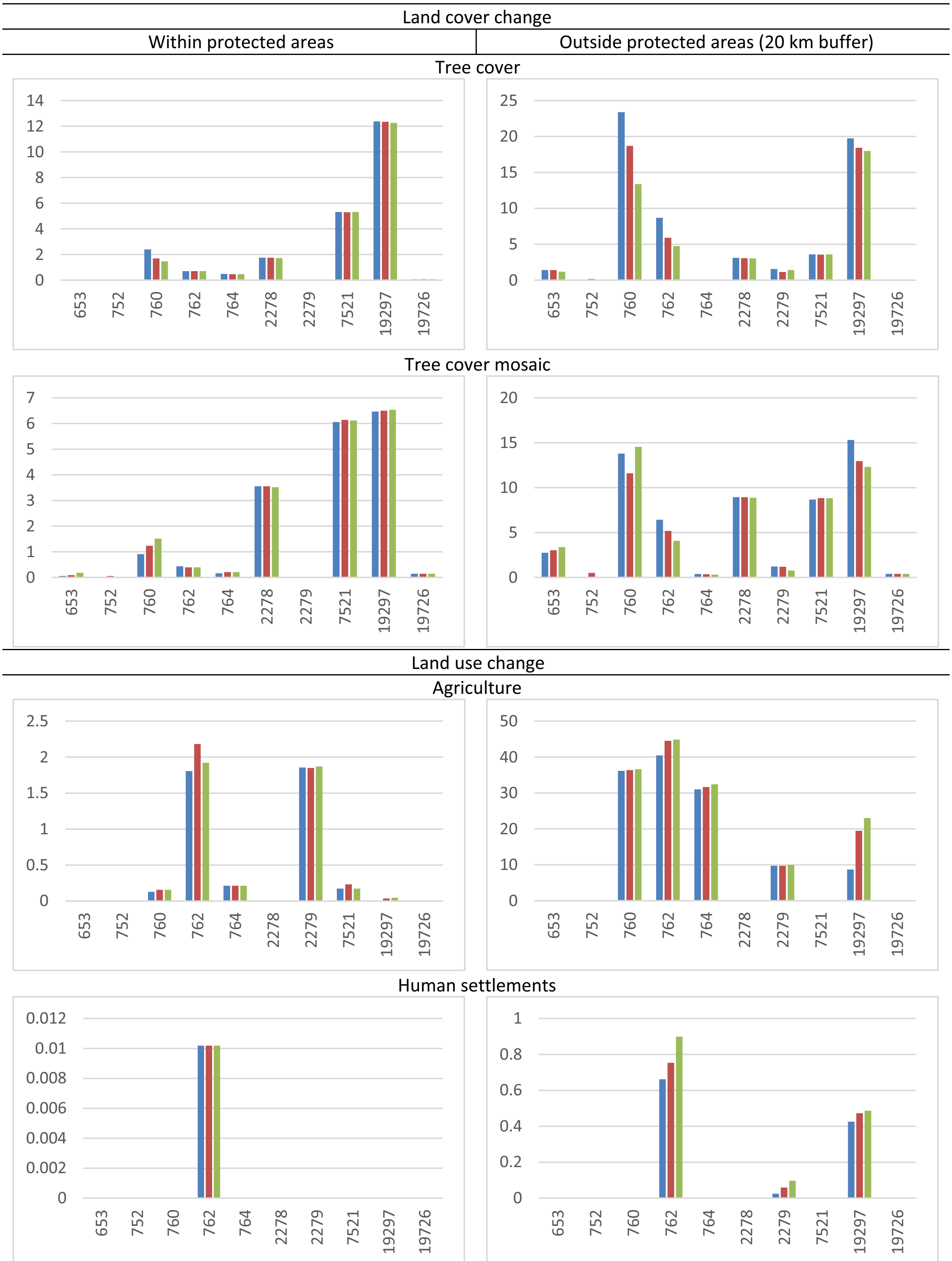

Figure 4. Land cover and land use change dynamics in selected validated protected areas and their buffer zones, expressed in (%) compared to the covered area, in 1990 (blue), 2000 (red) and 2010 (green). Reference numbers (x-axis) are the WDPA IDs for each protected area (see Table 1 for more details).

gress to the 2020 CBD targets (O'Connor et al. 2015). The toolbox could also make a contribution toward measuring the effectiveness of protected areas, something that is needed to measure progress toward Aichi Target 11. Progress toward this target has so far been measured in terms of the extent of coverage of protected areas (e.g. Butchart et al. 2015), rather than effectiveness. The effectiveness of protection in general has been studied (e.g. Geldmann et al. 2013), but the effectiveness at the country level remains unassessed. Analysis of individual protected areas according to a common legend, followed by the upload of these data to a shared web resource will enable collation of data on how effective individual protected areas are at reducing detrimental land cover change, and how effective the entire network of PAs is at halting land cover change, making progress toward measuring Aichi target 11 across all land cover types.

In addition to target 11, the toolbox could contribute directly to target 12, which relates to species conservation. In particular, if species have distributions that are restricted to one or two protected areas or other sites (AZE and IBAs are identified on such criteria), the toolbox could measure change in suitable land cover within these sites as a surrogate for population change for species. Large-scale sampling could also make a contribution toward measuring progress toward target 5 on reduction in the loss of natural habitats. Application of the toolbox for sampling, developing the approach of, for example Brink and Eva (2009) would allow land cover change assessments to be made efficiently across extensive areas which might not otherwise be assessed.

The tool will perhaps be of greatest use in the biodiversity-rich, but conservation-capacity poor, tropics. Analysis could be carried out close to the source of application (i.e. by the staff of a protected area themselves), but given that resources are not available to allow this in every park, analysis could be carried out for multiple parks or sites at a national or regional level. It will always be essential that the data are returned to the point of use, to allow information to be used rapidly by those managing a park on the ground.

Conflict of Interest

The authors declare no conflict of interest.

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