

REMAP: An online remote sensing application for land cover classification and monitoring

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Abstract

1. Recent assessments of progress towards global conservation targets have revealed a paucity of indicators suitable for assessing the changing state of ecosystems. Moreover, land managers and planners are often unable to gain timely access to the maps they need to support their routine decision-making. This deficiency is partly due to a lack of suitable data on ecosystem change, driven mostly by the considerable technical expertise needed to develop ecosystem maps from remote sensing data.
2. We have developed a free and open-access online remote sensing and environmental modelling application, the *Remote Ecosystem Monitoring and Assessment Pipeline* (REMAP; <https://remap-app.org>), that enables volunteers, managers and scientists with little or no experience in remote sensing to generate classifications (maps) of land cover and land use change over time.
3. REMAP utilizes the geospatial data storage and analysis capacity of Google Earth Engine and requires only spatially resolved training data that define map classes of interest (e.g. ecosystem types). The training data, which can be uploaded or annotated interactively within REMAP, are used in a random forest classification of up to 13 publicly available predictor datasets to assign all pixels in a focal region to map classes. Predictor datasets available in REMAP represent topographic (e.g. slope, elevation), spectral (archival Landsat image composites) and climatic variables (precipitation, temperature) that are relevant to the distribution of ecosystems and land cover classes.
4. The ability of REMAP to develop and export high-quality classified maps in a very short (<10 min) time frame represents a considerable advance towards globally accessible and free application of remote sensing technology. By enabling access to data and simplifying remote sensing classifications, REMAP can catalyse the monitoring of land use and change to support environmental conservation, including developing inventories of biodiversity, identifying hotspots of ecosystem diversity, ecosystem-based spatial conservation planning, mapping ecosystem loss at local scales and supporting environmental education initiatives.

KEYWORDS

ecosystem monitoring, Google Earth Engine, image classification, IUCN Red List of Ecosystems, land cover mapping, Landsat Archive, remote sensing, satellite mapping

1 | INTRODUCTION

Maps of land use and land cover change have been a central component of environmental management and conservation planning for decades (Margules & Pressey, 2000). Land cover maps enable the depiction of the distribution of ecosystems and land cover types, assessments of biodiversity and identification of areas undergoing loss, fragmentation or degradation (Haddad et al., 2015; Potapov et al., 2017). As well as supporting spatial conservation planning, including mapping threats to nature, they are often used as surrogates for species distributions. However, existing methods for mapping land cover extent and changes over time are often based on remote sensing and rely on expert implementation and comprehensive knowledge of space borne or airborne sensor data, analytical methods and data uncertainties. This “capacity gap” has been a severe constraint in obtaining information on the status of the world’s natural environment and has hindered environmental conservation programs across a range of spatial scales (Murray et al., 2018; Pereira, Brevik, & Trevisani, 2018).

Recent advances in geospatial data access, storage and analysis have vastly improved our ability to utilize satellite sensor data archives in studies of land cover and land cover change (e.g. Gorelick et al., 2017; Lewis et al., 2016). Moderate (<30 m) resolution remote sensing analyses are now possible at the global extent and have enabled the development of complex remote sensing analyses (Gong et al., 2013; Hansen et al., 2013; Pekel, Cottam, Gorelick, & Belward, 2016). At the same time, increases in satellite revisit frequencies, reductions in the time between data acquisition and delivery to users, and increasing access to data archives have led to the development of near real-time alert systems that can rapidly identify land cover loss and change in areas where no ground observations can be obtained. These systems mainly focus on automatic detection and analysis of land cover change for groups of related biomes (e.g. forests) and have vastly improved the ability of non-specialists, environmental managers and policy makers to access and use remote sensing data (Asner, Knapp, Balaji, & Páez-Acosta, 2009; Hansen et al., 2016; Lucas & Mitchell, 2017).

In this paper, we present a new online geospatial application that enables volunteers, managers, students and scientists with little or no experience in remote sensing to develop classified maps of land cover at the nominal spatial resolution of Landsat data (30 m). The *Remote Ecosystem Monitoring and Assessment Pipeline* (REMAP) utilizes the geospatial data storage and analysis capacity of Google Earth Engine (<https://earthengine.google.com>), a cloud-based analysis platform, to allow users to interactively develop machine learning classifications of land cover within an area of interest anywhere in the world for which there is sufficient archival Landsat data. The

REMAP application additionally allows monitoring and analysis of land cover change by enabling users to map ecosystem distributions at two points in time (2003 and 2017), quantify area change in each map class, and report the standard distribution size metrics used by the International Union for the Conservation of Nature (IUCN) Red List of Ecosystems (Keith et al., 2013).

REMAP was developed to complement a range of other applications that support the conservation of biodiversity, including GeoCAT (Bachman, Moat, Hill, de la Torre, & Scott, 2011), Global Forest Watch (www.globalforestwatch.org), the Map of Life (www.mol.org) and R packages such as “REDLISTR” (Lee & Murray, 2017) and “rCAT” (Moat & Bachman, 2017). Potential uses of REMAP include mapping the distributions of ecosystem types (Murray et al., 2018), developing land cover maps for protected areas (Lucas et al., 2015), assessing the performance of protected areas over multi-decadal time frames (Green et al., 2013; Murray & Fuller, 2015), and identifying areas where degradation or loss of ecosystems has occurred (Bhagwat et al., 2017). REMAP was also developed to support the global effort to assess the status of all ecosystem types on earth under the IUCN Red List of Ecosystems criteria (Keith et al., 2015; Rodríguez et al., 2015) and can contribute to monitoring progress towards addressing the 2020 Convention on Biological Diversity Aichi Targets (CBD 2014). We describe here the rationale for design, methodological considerations and analytical framework of REMAP, and demonstrate its utility and limitations with three case studies (see Case Studies).

2 | REMAP: REMOTE ECOSYSTEM MONITORING & ASSESSMENT PIPELINE

REMAP (<https://remap-app.org>) is a free and open-source web application that classifies land cover according to user-supplied training data and a set of globally available remote sensing datasets as predictor variables (Figure 1). We followed six design principles to develop REMAP:

1. *Provide the ability to develop high quality maps from remote sensing data in a short time frame and without the need for high performance computers.* Maps can be developed in REMAP within a few minutes and, because REMAP completes classifications online by accessing Earth Engine, the only prerequisites are an internet connection and web browser.
2. *Reduce the need to download, pre-process and process remote sensing data for use in environmental mapping.* The system offers access to 13 publicly available geospatial predictors that represent spectral, topographic and climatic variables that may influence the

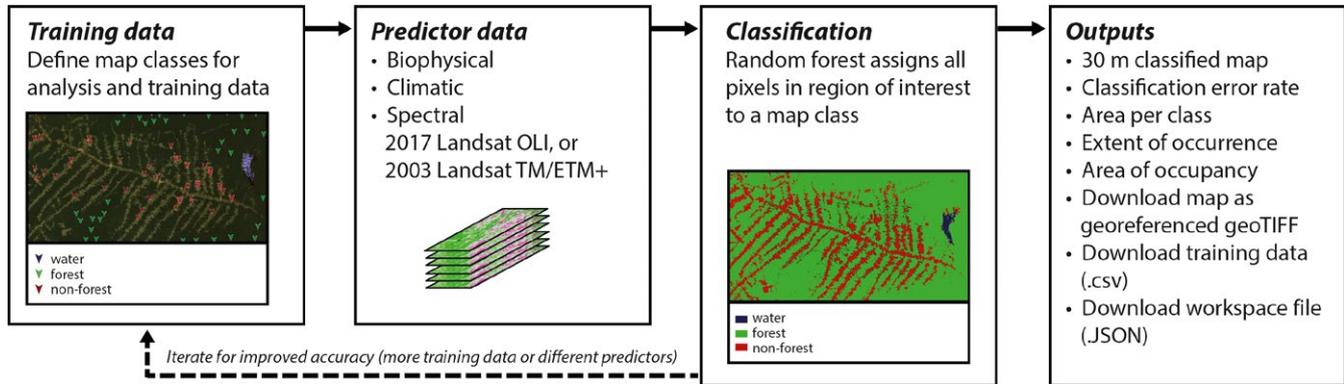


FIGURE 1 Simplified process chart of REMAP: the remote ecosystem monitoring and assessment pipeline. REMAP requires spatially resolved training data, and estimates class membership of all pixels in a region of interest using global remote sensing predictor layers and the random forests classification algorithm. To facilitate observations of land cover change, classifications in REMAP can be implemented on Landsat data obtained in the year 2003 or data obtained in the year 2017

distribution of different land cover types. Default predictors were selected to enable the development of high quality maps of the widest range of land cover types possible, and users are provided with options to explore different combinations of predictors in the production of their classified map.

3. *Simplify implementation of machine learning classification approaches.* REMAP conducts its classifications using the random forest algorithm (Breiman, 2001) with a single execute button. This approach allows users to implement a widely used machine learning method known to achieve high classification accuracy from large numbers of potentially correlated predictor variables (Rodriguez-Galiano, Ghimire, Rogan, Chica-Olmo, & Rigol-Sanchez, 2012).
4. *Permit the production of maps for at least two time periods to enable the quantification of any detectable spatial change.* REMAP can be used to measure the impacts of, for example, deforestation (Hansen & Loveland, 2012), coastal reclamation (Murray, Clemens, Phinn, Possingham, & Fuller, 2014) and many other ecological changes that can be reliably observed with Landsat sensors.
5. *Enable estimation of standard spatial metrics used for assessing the status of ecosystems.* Metrics that are useful for environmental conservation, including area, change in area, extent of occurrence (EOO) and area of occupancy (AOO), can be calculated by users to assess ecosystem change and contribute to global efforts to assess the status of ecosystems.
6. *Implement free and open access software design principles.* Source code for REMAP is available and we will maintain open access to the application (see *Data Accessibility*).

2.1 | Data

The 13 publicly available gridded datasets that were selected for inclusion in REMAP (Table 1) met the requirement of (1) full global extent, (2) free availability with sufficient open access to be included in the

Earth Engine public data archive, and (3) sufficiently high spatial resolution to permit identification of ecosystem distributions and common land cover classes. The final set of predictors includes spectral variables and derived indices from archival Landsat sensor data for two time periods, climate data (mean annual rainfall and mean annual temperature; Hijmans, Cameron, Parra, Jones, & Jarvis, 2005) and topographic data (derived from Shuttle Radar Topography Mission data).

To obtain the required global coverage of cloud-free Landsat sensor data for two periods, referred to here as “past” (1999–2003) and “present” (2014–2017), we developed two global Landsat image composites from Landsat Archive at-surface reflectance products (Table 1). We produced image stacks of all Landsat scenes for each period ($N_{1999-2003} = 340,658$ images; $N_{2014-2017} = 375,674$ images) and applied the Earth Engine implementation of the FMASK cloud masking algorithm (Gorelick et al., 2017). From these, the median pixel of Landsat Enhanced Thematic Mapper (ETM+; bands 2–5) bands 2–5 (visible blue to shortwave infrared) and Operational Land Imager (OLI; bands 1–4) was used to generate the two 4-band global image composites. From these composites, Normalized Differenced Vegetation Index (Pettorelli, 2013), Normalized Difference Water Index (McFeeters, 1996) and several other index layers were generated for use as spectral predictors (Table 1). The provision of spectral data for two time periods facilitates the estimation of change in land cover extent, which is important for monitoring the impact of threatening processes such as deforestation (Hansen et al., 2013), fragmentation (Haddad et al., 2015), coastal reclamation (Murray et al., 2014), aquaculture (Thomas et al., 2017) and water extraction (Tao et al., 2015). Future versions of REMAP will allow users to choose any point in time between the launch of Landsat 5 and the present day to develop their classifications.

2.2 | User input

Users of REMAP generally follow an eight-step procedure to map, assess and monitor ecosystem types or land cover classes (Table 2).

TABLE 1 List of predictor layers available for use in land cover classifications using REMAP

Long name	Short name	REMAP default	Earth Engine ID
Topographic			
Shuttle radar topography mission (SRTM) elevation	Elevation	●	USGS/SRTMGL1_003
SRTM slope	Slope	●	USGS/SRTMGL1_003
Climatic			
Mean annual temperature	Mean Annual Temperature		WORLDCLIM/V1/BIO
Annual precipitation	Annual Precipitation		WORLDCLIM/V1/BIO
Spectral			
Normalised difference vegetation index (NDVI)	NDVI	●	LANDSAT/LC8_SR
Normalised difference water index (NDWI)	NDWI	●	LANDSAT/LC8_SR
Water band index (WBI)	WBI		LANDSAT/LC8_SR
Blue band minus Red band (BR)	BR		LANDSAT/LC8_SR
Normalised difference blue green (BG)	BG	●	LANDSAT/LC8_SR
Blue band	Blue	●	LANDSAT/LC8_SR
Green band	Green	●	LANDSAT/LC8_SR
Red band	Red	●	LANDSAT/LC8_SR
Near infrared band (NIR)	NIR	●	LANDSAT/LC8_SR

Short name refers to the name given to each layer in the REMAP user interface. REMAP default indicates whether the predictor is used in a default classification. Raw data and metadata information for all predictors used in REMAP are available for download from Google Earth Engine.

Initially, users must decide whether to produce a map using the Landsat mosaics produced from the “past” (1999–2003) or “present” (2014–2017). Users are then required to define their region of interest interactively (focus region) or to upload a vector file (.kml). This enables REMAP to clip input data to a region of interest and limit the extent of the classification. The maximum size of the region of interest is presently 100,000 km² due to limitations applied to users of Earth Engine (Gorelick et al., 2017). Future versions of REMAP may increase this size limit, although for larger regions or more complex map classifications, we recommend users directly utilise Earth Engine (<https://earthengine.google.com>).

Spatially resolved training data that define map classes of interest are used to assign a class membership to all pixels within a focal region. Map classes can represent any land cover type, such as ecosystems (e.g. mangrove), land uses (e.g. agriculture), areas of change (e.g. deforestation) or artificial surfaces (e.g. urban areas). When developing land cover maps, we recommend that users adopt land cover classification taxonomies that are internationally recognized and conform to International Organisation for Standards (ISO) such as the Food and Agricultural Organisation’s (FAO) Land Cover Classification System (LCCS). Training data can be acquired interactively by adding training points via the user interface with reference to the predictor layers or base imagery. External data which identify the location of observation points and their class membership (.csv file) can also be uploaded. Training points may be sourced externally from field observations, external data archives, expert opinion, literature or existing maps. In general, classifications with larger numbers of training points will achieve higher class accuracies. We recommend users supply a minimum of 50

points per class to develop an initial map. REMAP will provide a warning if users initiate the classifier with less than 20 training points in any class.

2.3 | Classification approach

REMAP uses a random forest classifier to assign pixels to user-defined map classes (Breiman, 2001). With sufficient training data that are representative of the classes of interest, REMAP implements the classification on the predictor data and returns a classified image where all pixels are assigned to a map class. In many cases, use of the default predictors (Table 2) has been shown to yield classification accuracies that are acceptable to many users. To allow users to assess classification accuracy, REMAP reports the classification error rate (James, Witten, Hastie, & Tibshirani, 2013), which is the percentage of all of the training points that were incorrectly classified by the model that was trained with all of the training data. Users can tune their classifications to minimise the error rate, either overall or for the class(es) of interest, by providing more training data for the classifier or by selecting a custom set of predictors (Table 2). For any map products produced with REMAP, we suggest an accuracy assessment is conducted on independent validation data such as ground-truth data (Congalton & Green, 2008).

2.4 | Ecosystem monitoring and assessment

Once a classified map of acceptable accuracy has been produced, REMAP can conduct the spatial analyses required to assess Criteria A (change in distribution size) and B (range size) of the IUCN Red List of Ecosystems (Bland, Keith, Miller, Murray, & Rodríguez, 2017; Keith

et al., 2013). To assess Criterion A, REMAP computes the area of each class by summing the number of pixels in each class. Criterion A requires assessors to estimate change in area over time, which can be achieved by repeating the workflow for the second time period. To account for potential changes in land cover between the two time periods, users should develop a new training set or modify the existing set to ensure accurate representation of land cover in the second time period. Once area estimates are completed for two time periods, assessors can follow the IUCN Red List of Ecosystems guidelines to estimate area change manually (Bland et al., 2017), using GIS software, or with the recently developed “REDLISTR” R package (Lee & Murray, 2017). To assess Criterion B of the IUCN Red List of Ecosystems, REMAP applies a minimum convex polygon to a class of interest and reports its area, representing the Extent of Occurrence (EOO) of the map class. Finally, the Area of Occupancy (AOO) of a map class is calculated by applying a 10 × 10 km grid and counting the number of grid cells occupied by the map class (Bland et al., 2017; Murray et al., 2017).

To support further analyses of the classified map data, users can export each classified map as a georeferenced raster file (.tif) for use in GIS software. Furthermore, training data can be exported as a.csv file with fields “latitude”, “longitude” and “class” suitable for import into a GPS unit or other analysis software. Training data can also be saved as a JSON file, which is analogous to a ‘save workspace’ function, allowing users to return to their analysis at a later time by uploading the JSON file (see Supporting Information Appendix 1 for examples).

3 | CASE STUDIES

Classifications of remote sensing data enable the measurement and monitoring of a wide range of environmentally relevant variables. To

demonstrate the practical uses of REMAP, we developed case studies for (1) mapping a single ecosystem type (e.g. Murray, Phinn, Clemens, Roelfsema, & Fuller, 2012; Nascimento, Souza-Filho, Proisy, Lucas, & Rosenqvist, 2013), (2) generating a comprehensive land cover map for a region of interest (e.g. Connette, Oswald, Songer, & Leimgruber, 2016; Malatesta et al., 2013), and (3) quantifying land cover change between two periods (e.g. Olofsson, Holden, Bullock, & Woodcock, 2016; Sexton, Urban, Donohue, & Song, 2013; Thomas et al., 2017). All training data (.csv), REMAP workspace files (.JSON) and settings (Supporting Information Table S1) used to reproduce these case studies are available in supplementary material (Supporting Information Appendix 1) and can be used in association with tutorials available on the REMAP website (<https://remap-app.org/tutorials>).

1. *Mapping single land cover types or ecosystem types.* Mapping the distribution and change in mangrove ecosystems has been an important focus of ecosystem monitoring programs for decades due to their provision of ecosystem services (Mumby et al., 2004; Spalding et al., 2014) and susceptibility to a wide range of threats (Asbridge, Lucas, Ticehurst, & Bunting, 2016; Cavanaugh et al., 2014; Duke et al., 2017). In this case study, we developed a simple classification of mangroves and non-mangrove from a set of 150 training points for a small focal region (8301 ha) in the Gulf of Carpentaria, Australia (Figure 2). Comparison against base imagery suggests the development of an acceptable map of mangroves (Figure 2), confirmed by a classification error rate of <1% (Supporting Information Table S1)
2. *Comprehensive classification of land cover for a focal region.* Production of land cover maps, which represent all land types in a region, is a common objective of remote sensing programs (Lucas & Mitchell, 2017). We used REMAP to develop a land cover

TABLE 2 Descriptions of major analysis steps required to develop classified maps in REMAP. Analysis step refers to button in the sidebar of the REMAP user interface

Analysis steps	Purpose	Options
1 Past-present	Select the period for which the classification is conducted	Run the classification on either the 2017 (present) or 2003 (past) Landsat image mosaic
2 Focus region	Define the boundary of the analysis (region of interest)	Move vertices or supply by.kml file
3 Build training set	Define the map classes to be used in the classification and provide georeferenced locations for each class	Uploading a training set (.csv,.kml or.JSON) or train interactively using Landsat image mosaics and predictor base layers
4 Select predictors	Select predictor layers to be used in the classification	Custom selection or use default settings (Table 1)
5 Classify	Run the random forest classification and return the classified map	REMAP will provide a warning if the classifier is initiated with <20 points in any class
6 Results	Obtain map accuracy statistics and area of each map class in hectares	
7 Assessment	Obtain area, AOO and EOO estimates for a single map class	
8 Export data	Export training data or the classified image	Export training data as a.csv (for mapping or using in a GPS), a.JSON file (for saving the current workspace). To download the georeferenced.tif file for further analysis, use direct download or download to Google drive

map with classes *semi-deciduous vine forest*, *eucalypt woodland* and *human settlement* for a focal region in the dry tropics of Northern Australia (Figure 3; Supporting Information Figure S1). A visual comparison with ecosystem maps produced by the state-wide regional ecosystem mapping program, which develops regulatory land cover maps through manual interpretation of aerial photography and Landsat TM and SPOT satellite imagery, indicated good agreement between the two mapping methods (Figure 3; Neldner, Wilson, Dillewaard, Ryan, & Butler, 2017; Queensland Department of Natural Resources and Mines 2017). We provide a second land cover example that covers a larger area with more land-cover classes in the Supplementary

Material (Munaung Island, Myanmar, Supporting Information Figure S2).

3. *Quantifying land cover change.* To demonstrate capacity to detect changes in land and water, REMAP was applied to the two Landsat composite images available (2003) and OLS (2017) data acquired over Dubai, United Arab Emirates. The resulting maps provide quantitative information on the extent of marine ecosystem loss as a result of large-scale coastal reclamation projects (Figure 4). REMAP's use for change mapping is also demonstrated with a deforestation example at Roraima, Brazil (Figure 1, Supporting Information Figure S3, Supporting Information Appendix A).

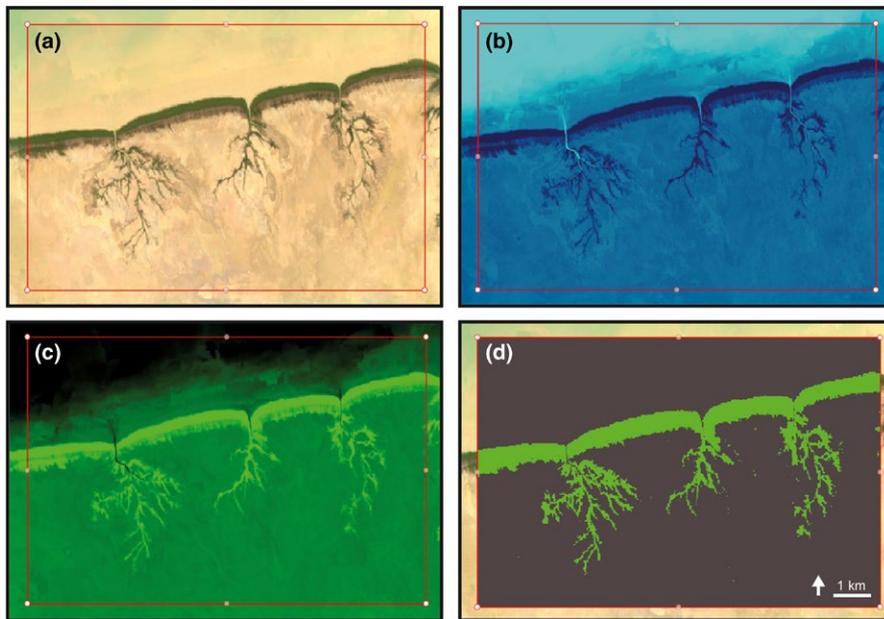


FIGURE 2 Workflow demonstrating the use of REMAP to map of a single ecosystem type, mangroves of the Gulf of Carpentaria, Australia. The panels show (a) the Landsat 8 OLI 3-year composite base layer from which all Landsat indices available in REMAP are calculated, (b) the Normalized Differenced Water Index (NDWI), (c) the Normalized Differenced Vegetation Index (NDVI) and (d) the final classified map of the distribution of mangroves in the region of interest (red box)

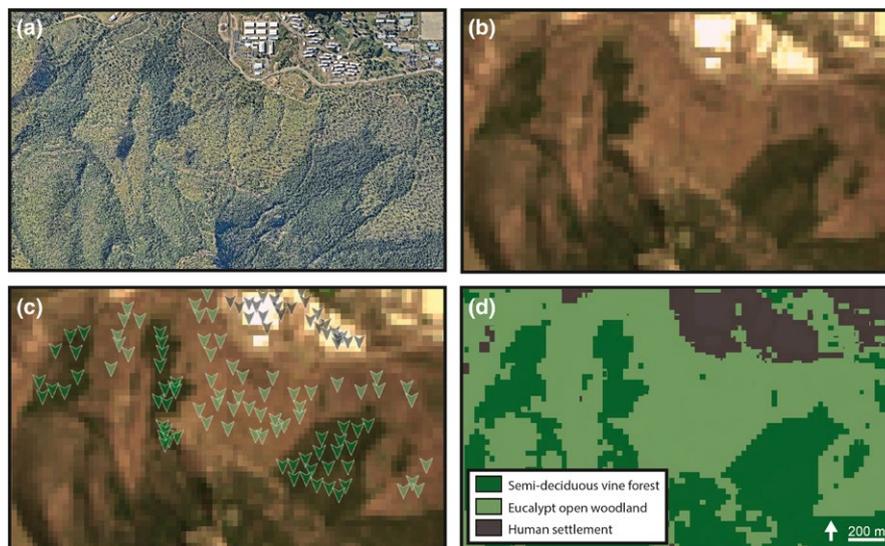


FIGURE 3 Demonstration of the use of REMAP to classify ecosystem types, Mount Stuart, Queensland, Australia. (a) High resolution aerial photograph, (b) the 2017 Landsat OLI image composite, (c) training data used to produce the final 3-class map, and (d) the final classified map of the distribution of ecosystems in the focal region. Aerial photography in panel (a) copyright 2017 Nearmap Australia Pty Ltd

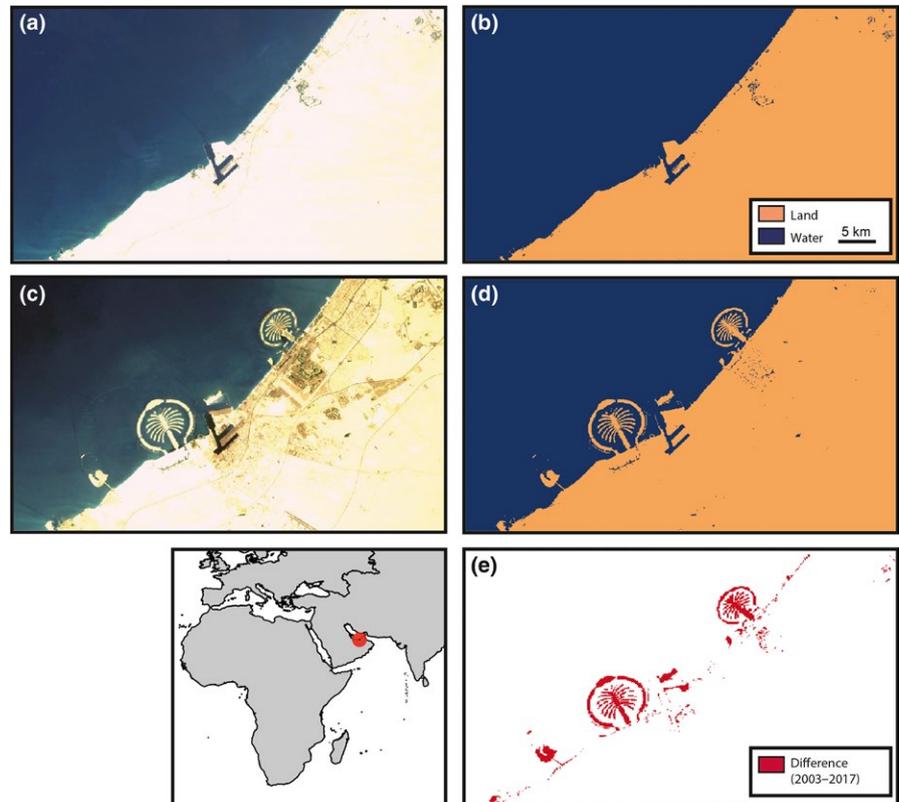


FIGURE 4 The use of REMAP to identify cover change between 2003 and 2017, Dubai. The classified land-water maps developed from (a) the 2003 global Landsat mosaic and (b) 2003 land-water classification (c) 2017 global Landsat mosaic and (d) 2017 land-water classification. (e) image differencing allows areas of coastal reclamation to be mapped and quantified. Refer to Figure 1 and Supporting Information Appendix A for a deforestation example. Image differencing was performed by subtracting (b) from (d) in QGIS (QGIS Development Team 2018)

4 | DISCUSSION

REMAP is a fast, user-friendly approach to developing land cover maps from freely available remote sensing data and its outcomes can be accepted if the accuracies of classifications meet the expectations of the users. Our case studies indicate that such accuracies can be achieved in REMAP but these depend upon the accuracy and amount of training data, and on the a priori decisions made for the mapping process (e.g. the number and diversity of classes to be mapped). By utilizing the geospatial storage and analysis capacity of Earth Engine, REMAP allows users with no prior knowledge in remote sensing and analysis to develop maps directly within a web-browser. This enables mapping to be undertaken in regions by locally responsible individuals and organisations where computing infrastructure is scarce or the quality of Internet connections do not allow the download of remote sensing data for local analyses. Indeed, REMAP is particularly useful for participatory mapping projects, expert elicitation and engagement with a wide-range of environmental stakeholders. As with all software, the responsible use of REMAP is a matter for each user; we strongly recommend reporting independent assessments of map accuracy for all products developed in REMAP prior to their use for decision-making, navigation, environmental reporting or any other purpose (Congalton & Green, 2008).

We acknowledge that REMAP has several limitations. Most notably, the ability of REMAP to produce accurate maps is limited by the quality of the training data, the accuracy of the predictors and the suitability of the predictor set for distinguishing land cover classes. Further

development of the REMAP application will therefore include a greater number of relevant predictor data layers, such as climate maxima and minima. Future work will also focus on (1) extending the temporal length and density of the global image composites to allow for monitoring of land use and cover change at higher temporal resolution and for users to select of specific time periods for their maps, (2) utilizing additional sources of available satellite imagery (e.g. Sentinel 2), (3) enhancing analytical capabilities by introducing new analysis tools (e.g. image differencing), and (4) adapting the application for use in collecting field data and producing maps in mobile devices.

In conclusion, we have developed REMAP to make remote sensing accessible to a very wide audience with the aim of broadening the use of classified maps in ecosystem monitoring and conservation programs, and to help support the conservation of natural environments. We expect REMAP to extend the ability of volunteers, students, scientists and managers to assess the extent of land cover changes and implement conservation actions to reduce the loss of natural ecosystems.

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AUTHORS' CONTRIBUTIONS

N.J.M., D.A.K. and R.M.L. conceived the project. N.J.M. and J.H.W. developed the remote sensing classification approach. J.H.W., D.S. and N.J.M. wrote the application code and website. N.J.M. wrote the manuscript with input from all coauthors.

DATA ACCESSIBILITY

REMAP: the remote ecosystem monitoring and assessment pipeline is a freely accessible and open-source web application available at: <https://remap-app.org>. Data used to develop the figures in this manuscript are available at figshare (Murray, Keith, Simpson, Wilshire, & Richard, 2018a) (<https://doi.org/10.6084/m9.figshare.5579620>). A snapshot of the remap source code is available at zenodo (Murray, Keith, Simpson, Wilshire, & Richard, 2018b) (<https://doi.org/10.5281/zenodo.1045576>). Nearmap aerial imagery courtesy of Nearmap Pty. Ltd. (© 2017 Nearmap Australia Pty. Ltd.).

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REFERENCES

- Asbridge, E., Lucas, R., Ticehurst, C., & Bunting, P. (2016). Mangrove response to environmental change in Australia's Gulf of Carpentaria. *Ecology and Evolution*, 6, 3523–3539. <https://doi.org/10.1002/ece3.2140>
- Asner, G. P., Knapp, D. E., Balaji, A., & Páez-Acosta, G. (2009). Automated mapping of tropical deforestation and forest degradation: CLASlite. *Journal of Applied Remote Sensing*, 3, 033543. <https://doi.org/10.1117/1.3223675>
- Bachman, S., Moat, J., Hill, A., de la Torre, J., & Scott, B. (2011). Supporting Red List threat assessments with GeoCAT: Geospatial conservation assessment tool. *ZooKeys*, 150, 117–126. <https://doi.org/10.3897/zookeys.150.2109>
- Bhagwat, T., Hess, A., Horning, N., Khaing, T., Thein, Z. M., Aung, K. M., ... Leimgruber, P. (2017). Losing a jewel—Rapid declines in Myanmar's intact forests from 2002–2014. *PLoS ONE*, 12, e0176364. <https://doi.org/10.1371/journal.pone.0176364>
- Bland, L. M., Keith, D. A., Miller, R. M., Murray, N. J., & Rodríguez, J. P. (2017). Guidelines for the application of IUCN Red List of Ecosystems Categories and Criteria, Version 1.1. International Union for the Conservation of Nature, Gland, Switzerland.
- Breiman, L. (2001). Random forests. *Machine Learning*, 45, 5–32. <https://doi.org/10.1023/A:1010933404324>
- Cavanaugh, K. C., Kellner, J. R., Forde, A. J., Gruner, D. S., Parker, J. D., Rodriguez, W., & Feller, I. C. (2014). Poleward expansion of mangroves is a threshold response to decreased frequency of extreme cold events. *Proceedings of the National Academy of Sciences*, 111, 723–727. <https://doi.org/10.1073/pnas.1315800111>
- CBD. (2014). Strategic plan for biodiversity 2011–2020. Secretariat of the Convention on Biological Diversity.
- Congalton, R. G., & Green, K. (2008). *Assessing the accuracy of remotely sensed data: Principles and practices*. Boca Raton, FL: CRC press. <https://doi.org/10.1201/CRCMAPPINSCI>
- Connette, G., Oswald, P., Songer, M., & Leimgruber, P. (2016). Mapping distinct forest types improves overall forest identification based on multi-spectral landsat imagery for Myanmar's Tanintharyi Region. *Remote Sensing*, 8, 882. <https://doi.org/10.3390/rs8110882>
- Duke, N. C., Kovacs, J. M., Griffiths, A. D., Preece, L., Hill, D. J. E., van Oosterzee, P., ... Burrows, D. (2017). Large-scale dieback of mangroves in Australia's Gulf of Carpentaria: A severe ecosystem response, coincidental with an unusually extreme weather event. *Marine and Freshwater Research*, 68, 1816–1829. <https://doi.org/10.1071/MF16322>
- Gong, P., Wang, J., Yu, L., Zhao, Y., Zhao, Y., Liang, L., ... Liu, S. (2013). Finer resolution observation and monitoring of global land cover: First mapping results with Landsat TM and ETM+ data. *International Journal of Remote Sensing*, 34, 2607–2654. <https://doi.org/10.1080/01431161.2012.748992>
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18–27. <https://doi.org/10.1016/j.rse.2017.06.031>
- Green, J. M., Larrosa, C., Burgess, N. D., Balmford, A., Johnston, A., Mbilinyi, B. P., ... Coad, L. (2013). Deforestation in an African biodiversity hotspot: Extent, variation and the effectiveness of protected areas. *Biological Conservation*, 164, 62–72. <https://doi.org/10.1016/j.biocon.2013.04.016>
- Haddad, N. M., Brudvig, L. A., Clobert, J., Davies, K. F., Gonzalez, A., Holt, R. D., ... Townshend, J. R. (2015). Habitat fragmentation and its lasting impact on Earth's ecosystems. *Science Advances*, 1, e1500052.
- Hansen, M. C., Alexander, K., Alexandra, T., Peter, V. P., Svetlana, T., Bryan, Z., ... Rebecca, M. (2016). Humid tropical forest disturbance alerts using Landsat data. *Environmental Research Letters*, 11, 034008. <https://doi.org/10.1088/1748-9326/11/3/034008>
- Hansen, M. C., & Loveland, T. R. (2012). A review of large area monitoring of land cover change using Landsat data. *Remote Sensing of Environment*, 122, 66–74. <https://doi.org/10.1016/j.rse.2011.08.024>
- Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., ... Townshend, J. R. G. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, 342, 850–853. <https://doi.org/10.1126/science.1244693>
- Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., & Jarvis, A. (2005). Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology*, 25, 1965–1978. [https://doi.org/10.1002/\(ISSN\)1097-0088](https://doi.org/10.1002/(ISSN)1097-0088)
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning*. New York, NY: Springer. <https://doi.org/10.1007/978-1-4614-7138-7>
- Keith, D. A., Rodríguez, J. P., Brooks, T. M., Burgman, M. A., Barrow, E. G., Bland, L., ... Spalding, M. D. (2015). The IUCN red list of ecosystems: Motivations, challenges, and applications. *Conservation Letters*, 8, 214–226. <https://doi.org/10.1111/conl.12167>
- Keith, D. A., Rodríguez, J. P., Rodríguez-Clark, K. M., Nicholson, E., Aapala, K., Alonso, A., ... Zambrano-Martínez, S. (2013). Scientific foundations for an IUCN Red List of Ecosystems. *PLoS ONE*, 8, e62111. <https://doi.org/10.1371/journal.pone.0062111>
- Lee, C., & Murray, N. (2017). redlistr: Tools for the IUCN Red List of Ecosystems and Species. R package version 1.0.0. <https://CRAN.R-project.org/package=redlistr>
- Lewis, A., Lymburner, L., Purss, M. B., Brooke, B., Evans, B., Ip, A., ... Mueller, N. (2016). Rapid, high-resolution detection of environmental change over continental scales from satellite data—the Earth Observation Data Cube. *International Journal of Digital Earth*, 9, 106–111. <https://doi.org/10.1080/17538947.2015.1111952>

- Lucas, R., Blonda, P., Bunting, P., Jones, G., Inglada, J., Arias, M., ... Mairota, P. (2015). The Earth Observation Data for Habitat Monitoring (EODHaM) system. *International Journal of Applied Earth Observation and Geoinformation*, 37, 17–28. <https://doi.org/10.1016/j.jag.2014.10.011>
- Lucas, R., & Mitchell, A. (2017). Integrated land cover and change classifications. In R. Diaz-Delgado, R. Lucas, & C. Hurford (Eds.), *The roles of remote sensing in nature conservation: A practical guide and case studies* (pp. 295–308). Cham, Switzerland: Springer. <https://doi.org/10.1007/978-3-319-64332-8>
- Malatesta, L., Attorre, F., Altobelli, A., Adeeb, A., De Sanctis, M., Taleb, N. M., ... Vitale, M. (2013). Vegetation mapping from high-resolution satellite images in the heterogeneous arid environments of Socotra Island (Yemen). *Journal of Applied Remote Sensing*, 7, 073527. <https://doi.org/10.1117/1.JRS.7.073527>
- Margules, C. R., & Pressey, R. L. (2000). Systematic conservation planning. *Nature*, 405, 243–253. <https://doi.org/10.1038/35012251>
- McFeeters, S.K. (1996). The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features. *International Journal of Remote Sensing*, 17, 1425–1432. <https://doi.org/10.1080/01431169608948714>
- Moat, J., & Bachman, S. (2017). rCAT: Conservation Assessment Tools. R package version 0.1.5. <https://cran.r-project.org/package=rCAT>
- Mumby, P. J., Edwards, A. J., Ernesto Arias-Gonzalez, J., Lindeman, K. C., Blackwell, P. G., Gall, A., ... Llewellyn, G. (2004). Mangroves enhance the biomass of coral reef fish communities in the Caribbean. *Nature*, 427, 533–536. <https://doi.org/10.1038/nature02286>
- Murray, N. J., Clemens, R. S., Phinn, S. R., Possingham, H. P., & Fuller, R. A. (2014). Tracking the rapid loss of tidal wetlands in the Yellow Sea. *Frontiers in Ecology and the Environment*, 12, 267–272. <https://doi.org/10.1890/130260>
- Murray, N. J., & Fuller, R. A. (2015). Protecting stopover habitat for migratory shorebirds in East Asia. *Journal of Ornithology*, 156, 217–225. <https://doi.org/10.1007/s10336-015-1225-2>
- Murray, N. J., Keith, D. A., Bland, L. M., Ferrari, R., Lyons, M. B., Lucas, R., ... Nicholson, E. (2018). The role of satellite remote sensing in structured ecosystem risk assessments. *Science of the Total Environment*, 619–620, 249–257. <https://doi.org/10.1016/j.scitotenv.2017.11.034>
- Murray, N., Keith, D. A., Simpson, D., Wilshire, J. H., & Richard, M. L. (2018a). Supporting information for: REMAP: An online remote sensing application for land cover classification and monitoring. Figshare, <https://doi.org/10.6084/m9.figshare.5579620>
- Murray, N., Keith, D. A., Simpson, D., Wilshire, J. H., & Richard, M. L. (2018b). Code snapshot for: REMAP: An online remote sensing application for land cover classification and monitoring. Zenodo, <http://doi.org/10.5281/zenodo.10455776>
- Murray, N. J., Keith, D. A., Bland, L. M., Nicholson, E., Regan, T. J., Rodríguez, J., & Bedward, M. (2017). The use of range size to assess risks to biodiversity from stochastic threats. *Diversity and Distributions*, 23, 474–483. <https://doi.org/10.1111/ddi.12533>
- Murray, N. J., Phinn, S. R., Clemens, R. S., Roelfsema, C. M., & Fuller, R. A. (2012). Continental scale mapping of tidal flats across East Asia using the Landsat Archive. *Remote Sensing*, 4, 3417–3426. <https://doi.org/10.3390/rs4113417>
- Nascimento, W. R., Souza-Filho, P. W. M., Proisy, C., Lucas, R. M., & Rosenqvist, A. (2013). Mapping changes in the largest continuous Amazonian mangrove belt using object-based classification of multisensor satellite imagery. *Estuarine, Coastal and Shelf Science*, 117, 83–93. <https://doi.org/10.1016/j.ecss.2012.10.005>
- Neldner, V. J., Wilson, B. A., Dillewaard, H. A., Ryan, T. S., & Butler, D. W. (2017). Methodology for survey and mapping of regional ecosystems and vegetation communities in Queensland. Version 4.0. Queensland Herbarium, Queensland Department of Science, Information Technology and Innovation, Brisbane, Brisbane.
- Olofsson, P., Holden, C. E., Bullock, E. L., & Woodcock, C. E. (2016). Time series analysis of satellite data reveals continuous deforestation of New England since the 1980s. *Environmental Research Letters*, 11, 064002. <https://doi.org/10.1088/1748-9326/11/6/064002>
- Pekel, J. F., Cottam, A., Gorelick, N., & Belward, A. S. (2016). High-resolution mapping of global surface water and its long-term changes. *Nature*, 540, 418–422. <https://doi.org/10.1038/nature20584>
- Pereira, P., Brevik, E., & Trevisani, S. (2018). Mapping the environment. *Science of the Total Environment*, 610, 17–23. <https://doi.org/10.1016/j.scitotenv.2017.08.001>
- Pettorelli, N. (2013). The normalized difference vegetation index. Oxford, UK: Oxford University Press.
- Potapov, P., Hansen, M. C., Laestadius, L., Turubanova, S., Yaroshenko, A., Thies, C., ... Minnemeyer, S. (2017). The last frontiers of wilderness: Tracking loss of intact forest landscapes from 2000 to 2013. *Science Advances*, 3, e1600821. <https://doi.org/10.1126/sciadv.1600821>
- QGIS Development Team. (2018). QGIS Geographic Information System. Open Source Geospatial Foundation Project.
- Queensland Department of Natural Resources and Mines. (2017). Regional ecosystem and remnant map version 8.0. Queensland, Australia.
- Rodríguez, J. P., Keith, D. A., Rodríguez-Clark, K. M., Murray, N. J., Nicholson, E., Regan, T. J., ... Wit, P. (2015). A practical guide to the application of the IUCN Red List of Ecosystems criteria. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 370, 20140003.
- Rodríguez-Galiano, V. F., Ghimire, B., Rogan, J., Chica-Olmo, M., & Rigol-Sánchez, J. P. (2012). An assessment of the effectiveness of a random forest classifier for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, 67, 93–104. <https://doi.org/10.1016/j.isprsjprs.2011.11.002>
- Sexton, J. O., Urban, D. L., Donohue, M. J., & Song, C. (2013). Long-term land cover dynamics by multi-temporal classification across the Landsat-5 record. *Remote Sensing of Environment*, 128, 246–258. <https://doi.org/10.1016/j.rse.2012.10.010>
- Spalding, M. D., Ruffo, S., Lacambra, C., Meliane, I., Hale, L. Z., Shepard, C. C., & Beck, M. W. (2014). The role of ecosystems in coastal protection: Adapting to climate change and coastal hazards. *Ocean & Coastal Management*, 90, 50–57. <https://doi.org/10.1016/j.ocecoaman.2013.09.007>
- Tao, S., Fang, J., Zhao, X., Zhao, S., Shen, H., Hu, H., ... Guo, Q. (2015). Rapid loss of lakes on the Mongolian Plateau. *Proceedings of the National Academy of Sciences*, 112, 2281–2286. <https://doi.org/10.1073/pnas.1411748112>
- Thomas, N., Lucas, R., Bunting, P., Hardy, A., Rosenqvist, A., & Simard, M. (2017). Distribution and drivers of global mangrove forest change, 1996–2010. *PLoS ONE*, 12, e0179302. <https://doi.org/10.1371/journal.pone.0179302>

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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