Land cover mapping of Babeldaob, Republic of Palau

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GIS data accompany this report at https://www.fs.usda.gov/Internet/FSE_DOCUMENTS/fseprd835201.zip

Forest Service

Land cover on Babeldaob, Republic of Palau, was mapped from satellite imagery and related data using a combination of computer modeling and visual interpretation. The map classifies land cover on the island into six types representing conditions as they were in 2014. No accuracy assessment has been conducted yet; while field-classified ground points were available, they were not suitable for map validation because they were used to inform the modeling.

Land cover was classified into classes following broad categories used by Cole et al. (1987)[1]:

- Forest: upland areas dominated by trees other than mangrove species **(Fig. 1)**.
- Mangroves: low-lying areas dominated by mangrove tree species **(Fig. 1)**.
- Grassland/savanna: areas of grass, herbaceous ground cover, bare soils, and/or bauxite; may include shrubs or trees scattered or in small patches **(Fig. 1)**.
- Marsh: low-lying; dominated by grasses, sedges, and herbs in standing water **(Fig. 1)**.
- Built-up: artificial structures including buildings and roads; may include dirt roads and bare areas around buildings.
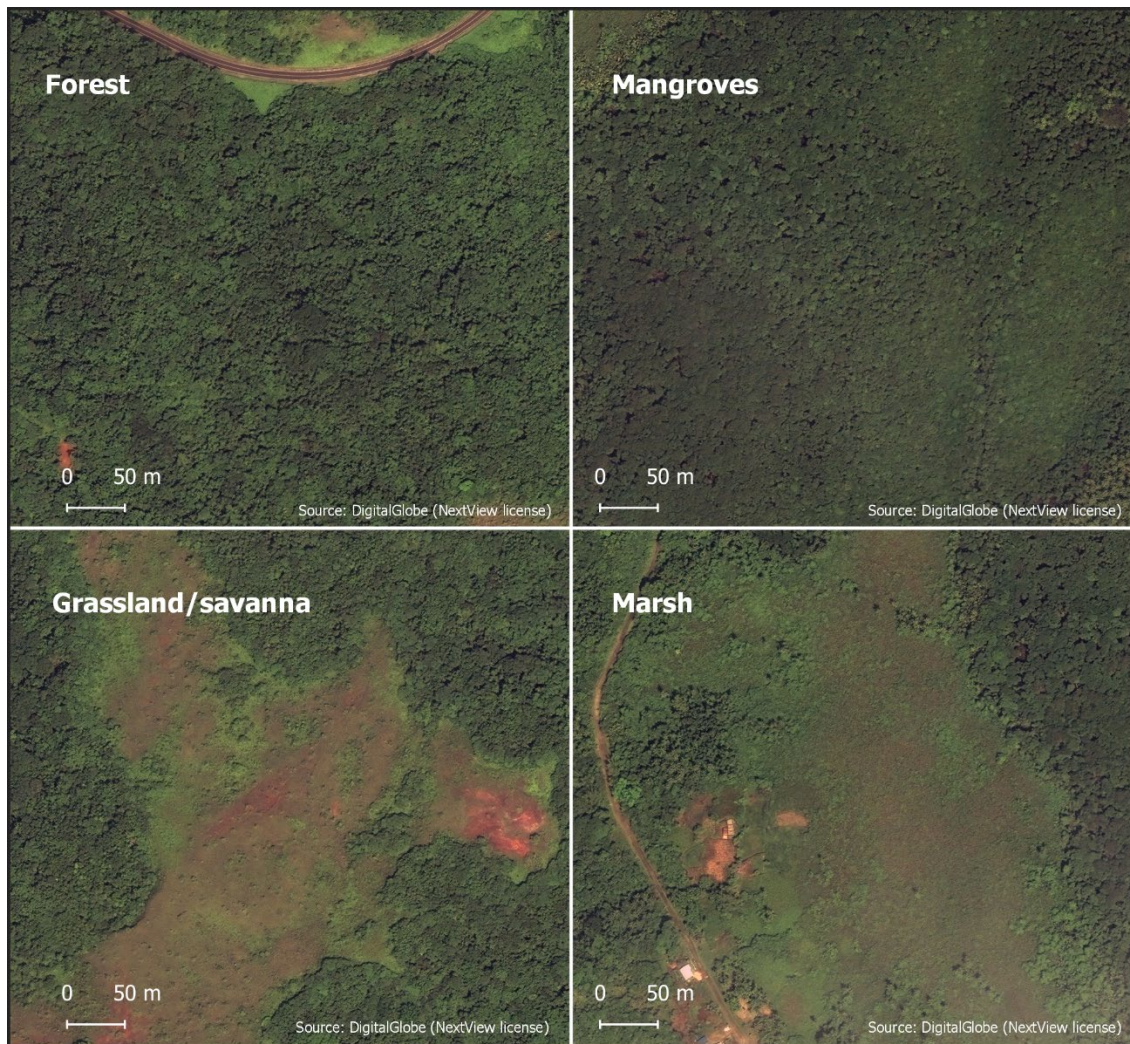- Water: both coastal and inland.

Figure 1. Principal vegetation types used in the classification, as imaged by the WorldView-2 satellite.

Three satellite image mosaics, and four topographic models derived from satellite imagery, were used in the mapping:

- An eight band, 2.4-m resolution mosaic of WorldView-2[2] imagery collected during 2014.
- A three band, 50-cm resolution mosaic of WorldView-2 imagery collected during 2014.
- A digital surface model, digital terrain model, and satellite image mosaic from Vricon[3], at 50-cm resolution, derived from satellite imagery collected during 2014–2016.
- A canopy height model and a slope model, at 50-cm resolution, derived from the Vricon digital surface model and digital terrain model.

The imagery and digital elevation models were acquired by the USDA National Resources Conservation Service and shared with the USDA Forest Service; the WorldView-2 mosaics were acquired from DigitalGlobe[5] under the U.S. Government's EnhancedView Program and the Vricon products were purchased from Vricon.

The computer modeling involved object-based image analysis, in which an image is "segmented" into polygon segments (the "objects") comprised of pixels with similar characteristics and intended to represent contiguous areas of the same land cover type. Summaries of each object's characteristics (e.g., the average amount of blue light reflected by the pixels it encloses), referred to as object "features", are calculated, and the values of the objects' features are used in a machine learning classifier algorithm to estimate the land cover type that each object represents. The classifier algorithm is "trained" using sample objects that have had their land cover type labeled by the operator, from which it "learns" how objects representing different land cover types differ in their feature values; it then uses the feature values of the remaining (unlabeled) objects to predict the land cover type that each represents. Various methods are then used to correct incorrect predictions made by the classifier.

The object-based image analysis relied principally on the eight band, 2.4-m resolution WorldView-2 mosaic. Segmentation was conducted in eCognition Developer 9.2[4] using the multi-resolution segmentation function, resulting in approximately 800,000 objects. Several thousand of these objects were classified and labeled by visual interpretation for use as training samples, and features that distinguished sample objects of each given class from those of other classes were selected by exploratory analysis. Features selected included the average and standard deviation, among pixels within sample objects, of (a) the amount of light reflected within different spectral bands, (b) vegetation and water indices (NDVI and NDWI) derived from spectral reflectances, (c) ground elevation and slope angle, and (d) canopy height. The training samples and selected features were used in neural network models within the R Language and Environment[5] to classify remaining objects into land cover types. **Figure 2** illustrates a small subset of the initial unclassified objects and their subsequent classifications.

Following classification of all objects, automated "knowledge based" rules were used to correct the classifications of objects that the neural network classifiers had mislabeled. For example, visual examination revealed that the classifier tended to label portions of mangrove forests as marsh; given that marsh does not occur within mangrove forests, all objects or contiguous clusters of objects labeled as marsh that were completely surrounded by objects labeled as mangroves were relabeled as mangroves. Further such "knowledge based" rules were implemented, such as pertaining to grassland/savanna objects surrounded by mangrove or marsh objects, mangrove objects surrounded by forest or grassland/savanna objects, etc.
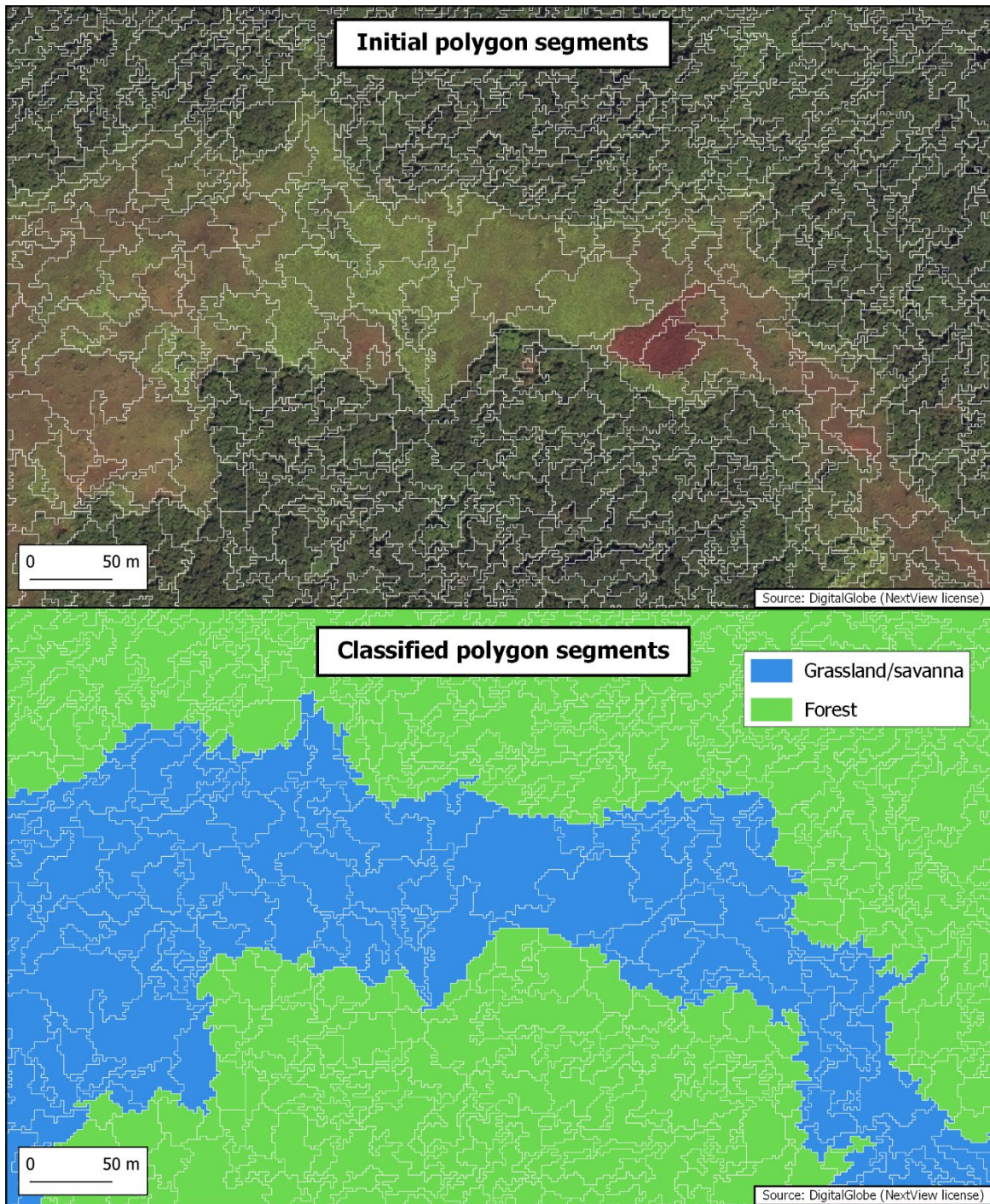
Figure 2. Example of polygon segments, before and after classification, generated from satellite imagery.

Finally, visual inspection and manual correction of misclassified objects were conducted using the 50-cm resolution three band WorldView-2 mosaic and the 50-cm resolution Vricon image mosaic. The higher resolution of these image products improved visual interpretation of land cover; they were useful as well for revising land cover in areas obscured by clouds or shadows in the eight-band image mosaic used for segmentation and the automated classification.

The final map appears in **Figure 3**, at the end of this report.

Possible avenues for future mapping efforts

Two avenues for further mapping of land cover on Babeldaob, by any interested party, seem potentially fruitful. Field validation of land cover in select areas of the island could be conducted and used to assess the accuracy of the map, and the accuracy could be improved by further visual interpretation and manual correction of incorrectly classified objects. Efforts could further be made to classify existing classes into subclasses, to the extent that this would be useful; for example, attempts could be made to delineate agroforest from within the existing "forest" class if, say, estimating the area of forest used for food production would be valuable. Finally, an updated map representing current land cover, as opposed to land cover in 2014, could be produced – suitable WorldView-2 images covering Babeldaob, collected in August/September 2020, are now available. More advanced methods than those described here have become easier to use, in particular deep learning via convoluted neural network models.

References

1. Cole, Thomas G.; Falanruw, Marjorie C.; MacLean, Colin D.; Whitesell, Craig D.; Ambacher, Alan H. 1987. Vegetation survey of the Republic of Palau. Resource Bulletin PSW-22, Pacific Southwest Forest and Range Experiment Station, USDA Forest Service.

2. See https://www.maxar.com/constellation

3. See https://www.vricon.com/products/vricon-data-suite/

4. See https://geospatial.trimble.com/products-and-solutions/ecognition

5. R Core Team (2020). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL
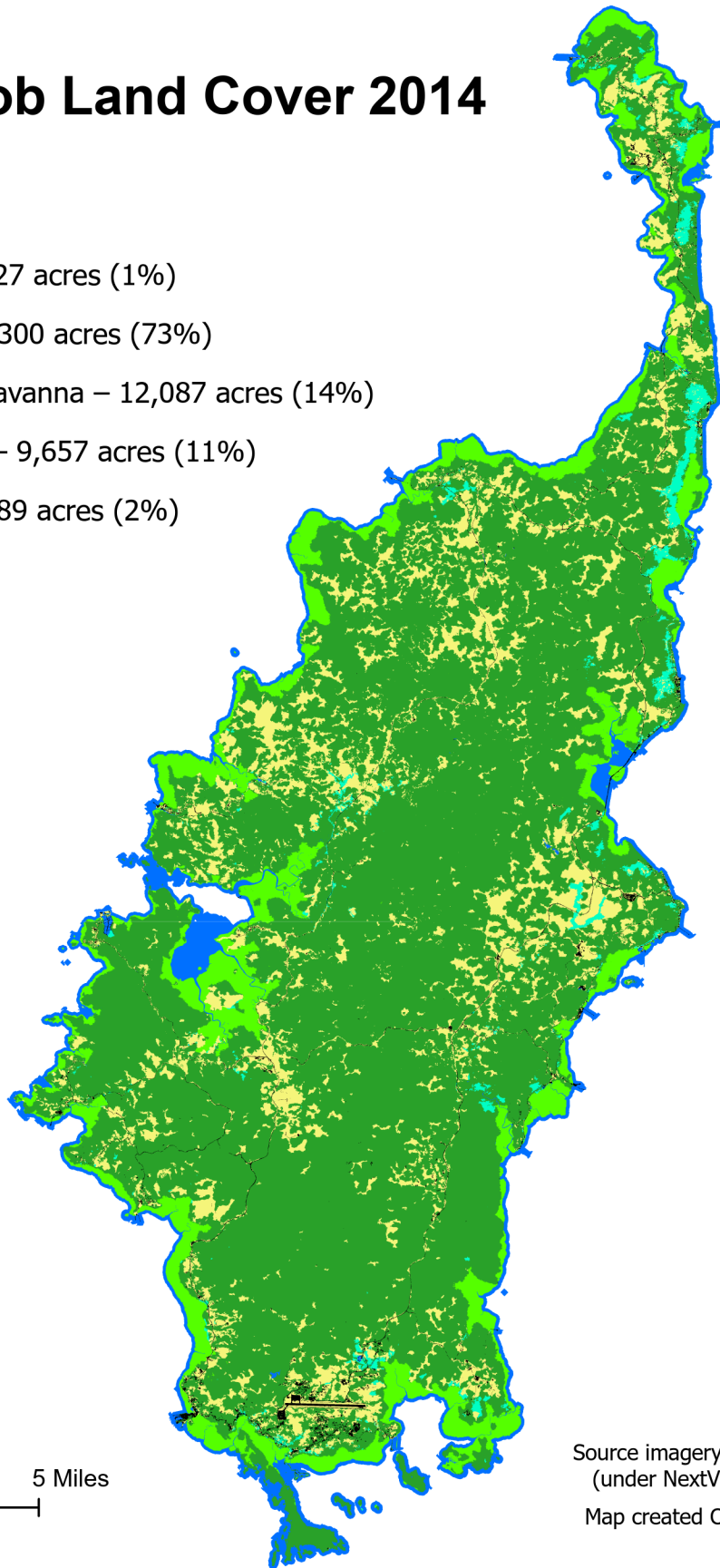
Babeldaob Land Cover 2014

Land cover

- ■ Built-up – 927 acres (1%)
- ■ Forest – 66,300 acres (73%)
- □ Grassland/savanna – 12,087 acres (14%)
- ■ Mangroves – 9,657 acres (11%)
- ■ Marsh – 1,589 acres (2%)
- ■ Water

0   2.5   5 Miles

Source imagery: DigitalGlobe
(under NextView license)

Map created October 2020

Figure 3. Land cover on Babeldaob in 2014.

GIS data available at https://www.fs.usda.gov/Internet/FSE_DOCUMENTS/fseprd835201.zip