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Land Cover and Forest Formation Distributions for St. Kitts, Nevis, St. Eustatius, Grenada and Barbados from Decision Tree Classification of Cloud-Cleared Satellite Imagery

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ABSTRACT.—**Satellite image-based mapping of tropical forests is vital to conservation planning. Standard methods for automated image classification, however, limit classification detail in complex tropical landscapes. In this study, we test an approach to Landsat image interpretation on four islands of the Lesser Antilles, including Grenada and St. Kitts, Nevis and St. Eustatius, testing a more detailed classification than earlier work in the latter three islands. Secondly, we estimate the extents of land cover and protected forest by formation for five islands and ask how land cover has changed over the second half of the 20th century. The image interpretation approach combines image mosaics and ancillary geographic data, classifying the resulting set of raster data with decision tree software. Cloud-free image mosaics for one or two seasons were created by applying regression tree normalization to scene dates that could fill cloudy areas in a base scene. Such mosaics are also known as cloud-filled, cloud-minimized or cloud-cleared imagery, mosaics, or composites. The approach accurately distinguished several classes that more standard methods would confuse; the seamless mosaics aided reference data collection; and the multiseason imagery allowed us to separate drought deciduous forests and woodlands from semi-deciduous ones. Cultivated land areas declined 60 to 100 percent from about 1945 to 2000 on several islands. Meanwhile, forest cover has increased 50 to 950%. This trend will likely continue where sugar cane cultivation has dominated. Like the island of Puerto Rico, most higher-elevation forest formations are protected in formal or informal reserves. Also similarly, lowland forests, which are drier forest types on these islands, are not well represented in reserves. Former cultivated lands in lowland areas could provide lands for new reserves of drier forest types. The land-use history of these islands may provide insight for planners in countries currently considering lowland forest clearing for agriculture.**

KEYWORDS.—**vegetation map, land-use change, Landsat, Caribbean, forest conservation, machine learning, multidate**

INTRODUCTION

Gaps in the global network of conservation reserves are mostly in montane and insular tropical landscapes, where species endemism is high (Rodrigues et al. 2004). The need to expand reserve networks on tropical islands is particularly urgent (Myers et al. 2000; Rodrigues et al. 2004). Habitat losses are often extensive, and land development pressures can be large. Conservation planning often starts by mapping habitats with Landsat satellite imagery (Scott et al. 1993). These maps can then support simple to complex assessments of reserve networks. Simple "representativeness" assessments, for example, estimate the extent of each forest formation or ecological zone that is under protection. Such initial assessments have provided timely data to planners on whether conservation reserve networks may under represent some ecosystems (Powell et al. 2000; Helmer et al. 2002; Helmer 2004). Data for these simple assessments, however, are often unavailable or outdated. One reason is that standard methods for automated satellite image interpretation are not effective for detailed mapping of land cover and forest formations in montane and insular tropical landscapes. Complications include steep environmental gradients, spectral confusion between land-cover classes, and persistent cloud cover. Consequently, mapping these complex landscapes with satellite imagery is a subject of research. Methods that work well in one landscape may not distinguish classes that are important in another one.

The first objective of this study is to test an approach to mapping forest formations and land cover with satellite imagery over two study areas in the Caribbean. The first study area is Grenada, where the approach has not been tested. The second area is St. Kitts, Nevis and St. Eustatius, where Helmer and Ruefenacht (2007) test a simpler set of classes than we test here when comparing methods to fill cloud gaps in Landsat imagery. The approach can be described as decision tree classification of cloud-cleared Landsat imagery and ancillary data, and it may include cloud-cleared image mosaics from more than one season. Earlier work outlines three main advantages of this overall approach for complex Caribbean landscapes (Helmer and Ruefenacht 2007; Kennaway and Helmer 2007): 1) decision tree classifications digest ancillary geospatial data that can resolve spectral confusion between classes; 2) fairly seamless image mosaics speed training data collection; and 3) when available, multiseason imagery reveals extents of drought deciduous woody vegetation, which also improves training data. Many recent studies show the advantages of image classification with decision trees, and decision tree classification is almost becoming common in remote sensing (Hansen et al. 1996; Friedl and Brodley 1997; Lawrence and Wright 2001; Vogelmann et al. 2001; Homer et al. 2004; Carreiras et al. 2006; Ruefenacht et al. In Press). However, only two examples classify Landsat imagery with decision trees in a tropical island setting (Helmer and Ruefenacht 2007; Kennaway and Helmer 2007). Kennaway and Helmer (2007) map forest formations and land cover with decision trees over the Caribbean islands of Puerto Rico, Vieques and Culebra. The land-cover types and forest formations that we map in this study include ones that earlier work collapses, delineates by hand, ignores, or does not encounter.

The second objective of this study is to better understand the extent to which the reserve systems or informal reserves of the above four islands, as well as the informal reserves of Barbados, represent different forest formations. We also ask whether land cover has changed on these islands over the last half-century. Earlier work on the Caribbean island of Puerto Rico shows that the extents of protected lowland forest formations can be small (Helmer et al. 2002). Cultivated land area has declined in Puerto Rico, which may mean that more land is available for setting aside conservation reserves in lowland areas. These same areas, however, are where most of the land-cover change to urban or built-up land occurs (Helmer 2004). The trends in Puerto Rico could also occur on the islands in this study. However, recent and detailed land-cover data have not been available to quantify the extent to which reserves include different forest formations.

Materials and Methods

Overview

To accomplish our first goal, we used decision tree software to classify Landsat image mosaics over two study areas: one area included St. Kitts, Nevis and St. Eustatius, and the other area was the island of Grenada. In the classifications, we combined ancillary raster data, like topographic variables, with the Landsat image bands.

The Landsat imagery included one image mosaic and one image for Grenada, and two image mosaics for the St. Kitts study area. The image mosaics were developed by applying regression trees to normalize images from other dates to fill the cloudy areas present in the base scene for each mosaic. We then assessed accuracy of the Landsat image classifications with 1-m pan-sharpened, false color IKONOS imagery dated from 2000-2003. For a few remaining cloudy areas, we manually interpreted forest formations and land cover from the IKONOS imagery.

For the second goal, we first mapped forest formations and land cover for Barbados by manually interpreting 1-m pan-sharpened, true color IKONOS imagery, circa 2000. Much of Barbados was cloud-obscured in all available Landsat imagery. Also, because we did not have multiseason imagery for Barbados, some forest formations were generalized. Secondly, we quantified the extents of protected forest by formation for all five of the islands. For Grenada, Barbados and St. Eustatius, we used a protected area database for the insular Caribbean produced by The Nature Conservancy. The primary source for protected areas was the World Database on Protected Areas (WDPA-Consortium 2003), which was enhanced using country-scale protected area information (TNC 2007). All of the Barbados protected areas in the database are only informally protected. A 1000-ft contour provided boundaries for protected lands on Nevis, because development is prohibited above that elevation. Boundaries for the new central forest reserve on St. Kitts, which include most lands above 1000 ft elevation, came from the St. Kitts Physical Planning Division. We manually digitized boundaries for Brimstone Hill National Park, in St. Kitts. Finally, we assessed whether changes in cultivated land or forest areas have occurred over the last half-century by comparing areas of cultivated lands and other land-cover types from the maps with area estimates from a table published in Beard (1949). Beard (1949) extensively surveyed several islands of the Lesser Antilles from 1942 to 1946. He inventoried the species composition of and mapped forest types, and he estimated the areas of different forest types, pasture and grazed woodlands, cultivated lands and "other uncultivated" lands (towns, villages, sand dunes, salt flats). We only present comparisons based on the tabular results in that publication. As we discuss later, the scale of the maps published in Beard (1949) is too coarse for change detection within a geographic information system.

Study areas

The Caribbean Leeward islands of St. Kitts, Nevis, and St. Eustatius, and the Windward islands of Grenada and Barbados, are part of the Lesser Antilles. The climate and woody vegetation formations on the islands are subtropical or tropical, and they range from xeric forests and shrublands to semi-deciduous, seasonal evergreen or evergreen forests including cloud forests. Volcanic geology dominates four of the islands, which each have one or more mountains of volcanic origin. Elevations on the volcanic islands range from just below sea level in some wetlands to 600 m on St. Eustatius, 1156 m on St. Kitts, 985 m on Nevis, and 840 m on Grenada. Karst substrates dominate most of Barbados, which has elevations that range to 336 m and a more restricted range of vegetation formations.

Classification scheme

As in Helmer et al. (2002), the forest and shrubland classes are designated to the formation level (Table 1). Formations are adapted from Areces-Malea et al. (1999), who classify Caribbean vegetation according to standards of the US Federal Geographic Data Committee (FGDC 1997). Mapping forests to the formation level is practical for satellite image classification in these landscapes when plot-level floristic data are not available (Helmer et al. 2002). Image spectra or geospatial environmental data can usually distinguish woody formations because environmental and physiognomic factors, like leaf phenology, largely define them.

TABLE 1. Woody vegetation formations mapped in this study. Formation groups or subgroups are shown in bold typeface. All formation groups are tropical or subtropical and broadleaved unless otherwise noted.

Woody vegetation Formation **This study (adapted from Areces-Malea, 1999 and USFGDC, 1997)**	**Plant Community Formation** **Beard, 1949**
Drought Deciduous and Semi-Deciduous Forest, Forest/Shrub, Shrubland or Woodland (Dry, Dry-Moist), Lowland or Submontane	***Seasonal Formations—Dry Scrub Woodlands***
Deciduous, Evergreen Coastal and Mixed Forest or Shrubland, with or without Succulents (on Limestone or other substrates)	Dry Evergreen Formations[1]
	Dry evergreen forest
	Littoral woodland
	Evergreen bushland
	Secondary and Sub-Climax Dry Evergreen Communities
	Thorny thickets
	Vegetation of sand-dunes and rocky slopes
	Secondary and Sub-Climax Seasonal Communities
	Cactus bush
Drought Deciduous Woodland (grazing or fire ongoing)	Rough grazing[2]
	Secondary Seasonal Communities
	Logwood thicket (*Haematoxylum campechianum*)
	Logwood-Acacia bush
	Thorn savanna (*Prosopis pallida* savanna)
	Leucaena thicket (*Leucaena leucocephala*)
	Croton thicket (*Croton spp.*)
Drought Deciduous Forest/Shrub (grazed in past)	Secondary Seasonal Communities
	Logwood thicket (*Haematoxylum campechianum*)
	Logwood-Acacia bush
	Leucaena thicket (*Leucaena leucocephala*)
	Croton thicket
Semi-Deciduous and Drought Deciduous Forest on Limestone (includes Semi-Evergreen Forest)	Seasonal Formations
	Semi-Evergreen Seasonal Forest
Semi-Deciduous Forest (includes Semi-Evergreen Forest)	Deciduous Seasonal Forest

TABLE 1. Continued

Woody vegetation Formation This study (adapted from Areces-Malea, 1999 and USFGDC, 1997)	Plant Community Formation Beard, 1949
Seasonal Evergreen and Evergreen Forest or Forest/Shrub (Moist, Moist-Wet, Wet, Rain), Lowland or Submontane	***Seasonal Formations—Evergreen Seasonal Forest Optimal Formation—Rain forest***
Seasonal Evergreen Forest with Coconut Palm	—
Seasonal Evergreen Forest	Seasonal Formations—Evergreen Seasonal Forest
	Optimal Formation—Rain forest
	Secondary and Sub-climax Communities
	Pioneer forest
	Tree-fern brake
Evergreen Forest[3]	*Miconia* thicket
Evergreen Forest—Cloud Forest (Moist-Wet, Wet, Rain), Lower Montane	***Montane Formations***
Sierra Palm, Transitional and Tall Cloud Forest	Lower Montane Rain forest
	Montane thicket
	Secondary and Sub-climax Communities
	Palm brake
	Miconia thicket
Elfin and Sierra Palm Cloud Forest[4]	Elfin Woodland
	Secondary and Sub-climax Communities[4]
	Palm brake
	Pioneer communities of volcanic ejecta
	Fumarole vegetation
Forested Wetlands	***Edaphic Formations***
Mangrove	Mangrove Woodland
Seasonally Flooded Savannas and Woodlands	Seasonal-Swamp Formations—Savanna

[1]Other Dry Evergreen Communities of Beard: Fire grasslands (occurs in St. Kitts and mapped as pasture/grass).
[2]Not part of dry scrub woodlands in Beard
[3]Sierra Palm present in some areas, like Steep Non-Forest Vegetation.
[4]Montane Non-Forest Vegetation includes Montane herbaceous vegetation, Fumarole vegetation and Miconia thicket.

In the FGDC standards for subtropical or tropical woody vegetation, *drought deciduous* refers to woody vegetation formations in which at least 75% of woody canopy species are deciduous. *Semi-deciduous* means that most upper canopy trees are drought deciduous and many understory trees and shrubs are evergreen, but the evergreen and deciduous woody plants are not always separated by layers. This definition overlaps with the FGDC definition for *semi-evergreen*, in which 25 to 75% of canopy tree species are deciduous. To avoid confusion, we use only the term *semi-deciduous* (after Areces-Mallea et al. 1999), and we use it for stands with 25 to 75% of deciduous woody canopy species. *Mixed* refers to mixed evergreen and deciduous cover that includes trees or shrubs at maturity, as in Areces-Malea et al. (1999). At least 75% of *seasonal evergreen* and *evergreen* canopy species are evergreen. In seasonal evergreen formations, some canopy species drop some leaves during drought.

Forest includes lands with at least 25% tree or tree plus shrub cover, combining the two forest successional stages of Helmer et al (2002). The one case in which we distinguish the younger *forest/shrub* class is where young stands are drought deciduous but adjacent older forest is semi-deciduous (*forest/shrub* includes lands with 25-60% tree plus shrub cover, or ≥60% cover of uniformly young seedlings or saplings that may include shrubs). This definition of forest differs from the FGDC standards and Areces-Malea et al. (1999), which call lands with 25-60% tree cover woodlands. As in Helmer et al. (2002), we reserve the term woodland for lands with >25% canopy cover of drought deciduous shrubs or trees, which are often leguminous and thorny, and a clear understory that fire and grazing maintain and that may include grasses or forbs. If these disturbances cease, drought deciduous woodlands may succeed to drought deciduous forest/shrub, which legumes often also dominate, and they may eventually succeed to semi-deciduous or mixed formations. In the map legends we generalized the driest coastal forest and shrubland formations into one class. With the exception of large patches of *Coccoloba uvifera* on St. Kitts, most patches of coastal evergreen forest were too small to be distinct from the matrix of drought deciduous and mixed formations. In addition, in Barbados, the class deciduous, evergreen coastal and mixed forest or shrubland (with or without succulents), also includes a mosaic of drought deciduous, semi-deciduous and seasonal evergreen forest/shrub below and to the northeast of Mt. Hillaby.

Landsat imagery

Even the clearest Landsat images for each study area still had many clouds obstructing land. Consequently, we used a regression tree method (Helmer and Ruefenacht 2005) to make nearly cloud-free image mosaics. Such mosaics are also known as cloud- filled, cloud-minimized or cloud-cleared imagery, mosaics, or composites. The base or *reference* image for each mosaic is usually the clearest one available for the season of interest. The *subject* images are other image dates that are cloud-free where the reference image is cloudy. The regression tree method normalizes subject images to the reference image for each mosaic. The normalization minimizes atmospheric, phenological and illumination differences between the various image dates that form each mosaic. Because the new subject image data are calibrated to the reference image for each mosaic with regression tree models, they more seamlessly fill cloudy areas in the reference image. Details on the method are available in Helmer and Ruefenacht (2005). Most of the Landsat scenes were terrain-corrected, Landsat 7 Enhanced Thematic Mapper (ETM+) images (Table 2). We also used two ETM+ images over the St. Kitts area and one Landsat 5 image over Grenada that were not terrain-corrected. All images were co-registered, to within <1 pixel root mean square error, to the clearest terrain-corrected image for each study area.

We made two image mosaics for the St. Kitts study area (Helmer and Ruefenacht 2007), including one mosaic for each of two stages of phenology for drought deciduous woody vegetation (Table 2). Drought de-

TABLE 2. Landsat image mosaics in this study, including the base, or reference image for each image mosaic and the dates and overlay orders of images that filled clouds in each reference image.

Phenology of drought deciduous woody vegetation[1]	Landsat image dates for reference image in each mosaic	Overlay order of subject images for image mosaics (2^{nd}-below-top to bottom)	Cloud-obscured land cover in reference image (%)	Cloud-obscured land cover in image mosaic (%)
Grenada, WRS Path/row 001/052				
Leaf-on	11 Nov 01	24 Mar 86-30 Sept 00	2.2	0.6
St. Kitts, Nevis and St. Eustatius Path/row 002/048				
Leaf-on	12 Dec 99	5 Sept 00-2 Feb 03-11 Sept 02	9.1	2.2
Leaf-off	11 Sept 02	2 Feb 03-5 Sept 00-12 Dec 99	20.7	2.2

[1]Drought deciduous formations include drought deciduous woodlands, drought deciduous forest and drought deciduous forest/shrub.

ciduous woody vegetation was "leaf-on" in the base scene for the mosaic from the beginning of the dry season. Drought deciduous woody vegetation was in a "leaf-off" state in the base image for the other. For Grenada, we made one image mosaic and used a Landsat 5 scene as a leaf-off image in the classification.

Landsat image classifications

We evaluated whether the decision tree software See5 (http://www.rulequest.com) could effectively classify cloud-cleared Landsat imagery 1) in Grenada, and 2) for a more detailed set of classes than previous work in the St. Kitts study area. Reference, or *training* data for each classification consisted of 25 to >100 multipixel patches distributed throughout the extent of each class, resulting in a dense training dataset of thousands of pixels per class. The data included field-based data for St. Kitts, Nevis, and Grenada that was collected between January and June 2003. Field data collection relied on simultaneously observing land cover and forest formation both in satellite imagery and in the field. In the field we integrated a Global Positioning System (GPS) receiver with a laptop computer (with a daylight-viewable image display) running the ERDAS Imagine GPS tool (Leica-Geosystems, 2003).

To distribute training data throughout the extent of each class, we then supplemented these field data by visually interpreting pan-sharpened, 1-m false color or true color IKONOS images. The IKONOS imagery was from the years 2000-2001 for St. Kitts and Nevis, and from 2003 for Grenada. The images were dated between October and February, when drought deciduous woody vegetation was in a leaf-on stage. Field work in St. Kitts and Nevis included traversing eight elevation gradients on windward and leeward sides of these islands. This extensive training data allowed us to estimate the elevations where seasonal evergreen forest changed to evergreen forest for different windward and leeward slopes, even though these two forest types were not visually distinct in the IKONOS imagery. The training data for sugar cane included subclasses that differed by field maturity. Most drought deciduous vegetation was in a leaf-off stage in the leaf-off image mosaic; however, we also included a separate training class for some patches of drought deciduous woodlands that were greened up in the leaf-off imagery. The training data also initially combined the signatures for large patches of coastal evergreen forest or shrubland in St. Kitts with seasonal evergreen forest for later editing. Spectral signatures for all barren lands were also combined, and barren lands were later manually separated into different classes (e.g. quarry, sand, bare ground) after decision tree classification. In mountainous areas, we collected a shadowed and sunlit version of each class (Helmer et al. 2000). In Grenada, training data for herbaceous agriculture were joined with training data for pasture, and herbaceous agriculture was manually recoded from pasture.

For each study area, the Landsat image bands were joined with ancillary geographic data layers into a many-layer set, or *stack,* of raster data. When using decision trees to classify raster data stacks, the decision tree software determines which of several image bands and ancillary layers most accurately distinguish classes based on the training data. The values of the spectral and ancillary predictor variables in the training data pixels parameterize the decision tree model. The spatial distribution of different forest types classified by the decision tree is on a per-pixel basis. Decision trees quickly identify complex relationships between variables and apply them in a classification model. They are useful for both description and prediction. This study applies them for prediction, the primary goal of which is accuracy (De'ath and Fabricius 2000). Consequently, ancillary data can include correlated variables. Although the resulting models can be complex, complex models are appropriate when the goal of a classification is accuracy rather than to characterize the relationships between the classes and the spectral or ancillary data.

Landsat image bands in the stacks included bands 1-5, 7, and two band indices: the normalized difference vegetation index (NDVI) and the band 4:5 ratio. For the St. Kitts study area, we also included variance over 3x3 windows of the 15-m pan band from the leaf-on image mosaic that we then resampled to a 30-m cell size. The NDVI gauges vegetation greenness, and the band 4:5 ratio is sensitive to forest structure and successional stage in tropical landscapes (Fiorella and Ripple 1993; Helmer et al. 2000). The ancillary data included distance to primary road, distance to coast, distance to ravine, and topographic variables from Shuttle Radar Topography mission digital elevation data (Farr and Kobrick 2000). Topographic variables included elevation, slope, slope position, aspect, and topographic shading based on the sun elevation and azimuth of each image date (or reference image date in the case of image mosaics) (Leica-Geosystems 2003). The locations of each pixel in the training data were used to extract corresponding values of the image bands and ancillary data from the stack of raster data for each classification. These data were then input into the See5 software to create a classification model which we then applied to classify the raster data stack.

We used the default values in See5 for classification with *pruning.* Decision tree pruning deters trees from so closely fitting one particular set of training data that they *over fit* training data, meaning that the accuracy of classifying new cases begins to decline. Pruning in See5 removes parts of the decision tree with high predicted error rates. We also included the *boosting* option with 10 trials; each trial results in a new tree. In boosting, See5 constructs many decision trees, in this case 10, in which construction of each successive tree focuses on misclassified cases in the previous tree. In final classification, each pixel is classified with each of the 10 trees and the most commonly predicted class is assigned to that pixel. The final classification, then, is the outcome of a vote by 10 different decision trees. Finally, we applied larger misclassification costs for the most common misclassifications from initial runs of the program. The classification model was then applied to the stack of raster data with the Classification and Regression Tree (CART) tool for ERDAS Imagine (Leica-Geosystems, 2003) from the U.S. Geological Survey (ftp://edcftp.cr.usgs.gov/pub/edcuser/dewitz/NLCD_mapping_tool).

Accuracy assessments

For the study areas that underwent decision tree classification, stratified random samples, of about 50 pixels per class, provided data for estimating classification accuracies. The accuracy assessments excluded classes or areas that were entirely visually-interpreted: forested and nonforested wetlands in the St. Kitts study area, herbaceous agriculture in Grenada and the remaining cloudy areas. Barren classes were also combined for the assessment. We differentiated the barren pixels by visual "heads-up" digitization over the IKONOS imagery. With evergreen and seasonal evergreen forest formations not being distinct in the IKONOS imagery, we combined them in the accuracy assessment. These accuracy assessment observations fill error matrices from which we then calculated overall percentage of correctly classified pixels (those data in the main diagonal of a matrix divided by the total number of observations), producer's and user's accuracies, and the Kappa coefficient of agreement (Cohen 1960; Congalton 1991). Producer's accuracy is the proportion of reference observations for a given class that were classified correctly, indicating how well the classification model identifies known cases. It is related to omission errors (Omission error = 1 – Producer's accuracy). User's accuracy is also a class-level measure of accuracy and is the proportion of observations classified to a given class that actually were that class. It indicates the likelihood that a given location is classified correctly, and it is related to commission error (Commission error = 1 – User's accuracy). The Kappa coefficient is a statistic that measures overall agreement after adjusting for chance agreement. It was developed to compare agreement between raters in social science studies, but remote sensing studies commonly use it to assess classification error. Because forest formations and land cover for Barbados were for the most part manually delineated, we did not perform an accuracy assessment for that map. Very fine resolution imagery was not available for St. Eustatius at the time of the accuracy assessment. However, we verified and manually edited the classification for St. Eustatius based on the high resolution imagery that is now viewable on Google Earth (http://earth.google.com/).

RESULTS AND DISCUSSION

Landsat image classifications

The Landsat and IKONOS image interpretations produced the first detailed, satellite image-based land-cover and forest formation maps for the islands studied (Figures 2-4, and Table 3). Before manual editing, the overall accuracies for the Landsat image classifications were 69% for the St. Kitts study area and 59% for Grenada. Limited manual editing improved these overall accuracies to 71% and 78%, respec-

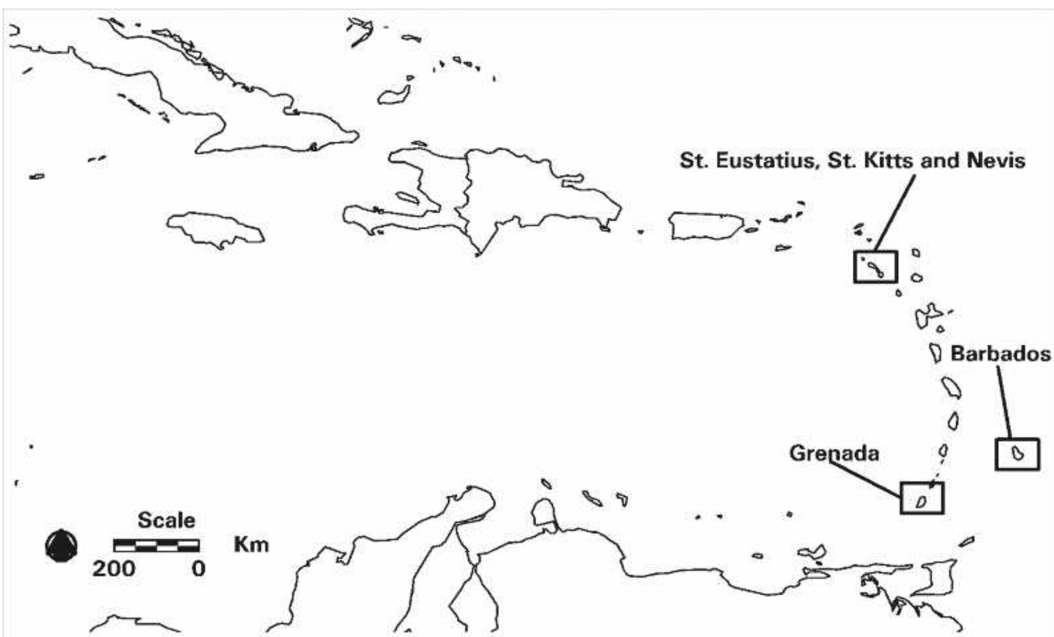

FIG. 1. Study area location.

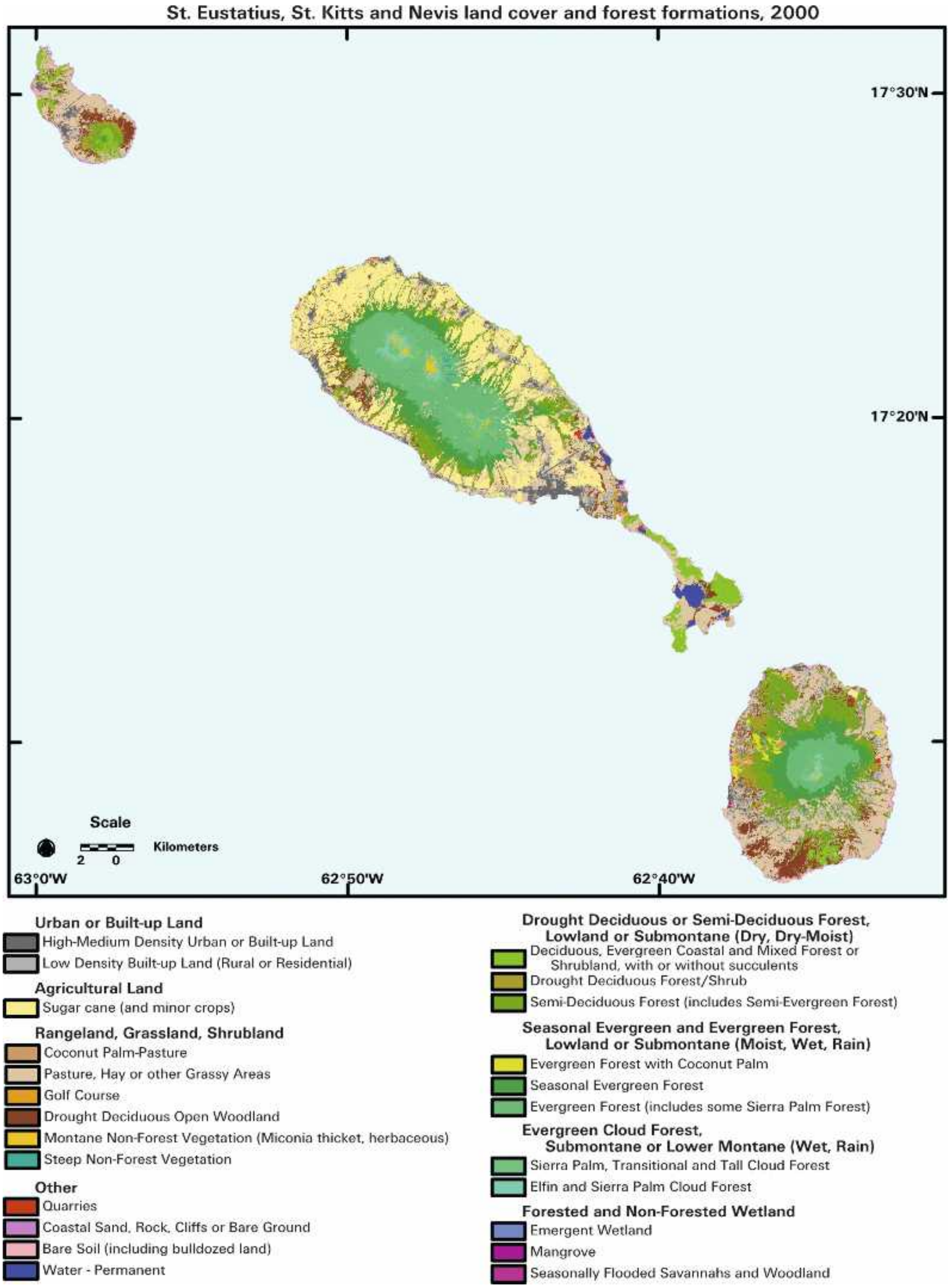

FIG. 2. Map of land cover and forest formations of St. Kitts, Nevis and St. Eustatius circa 2000.

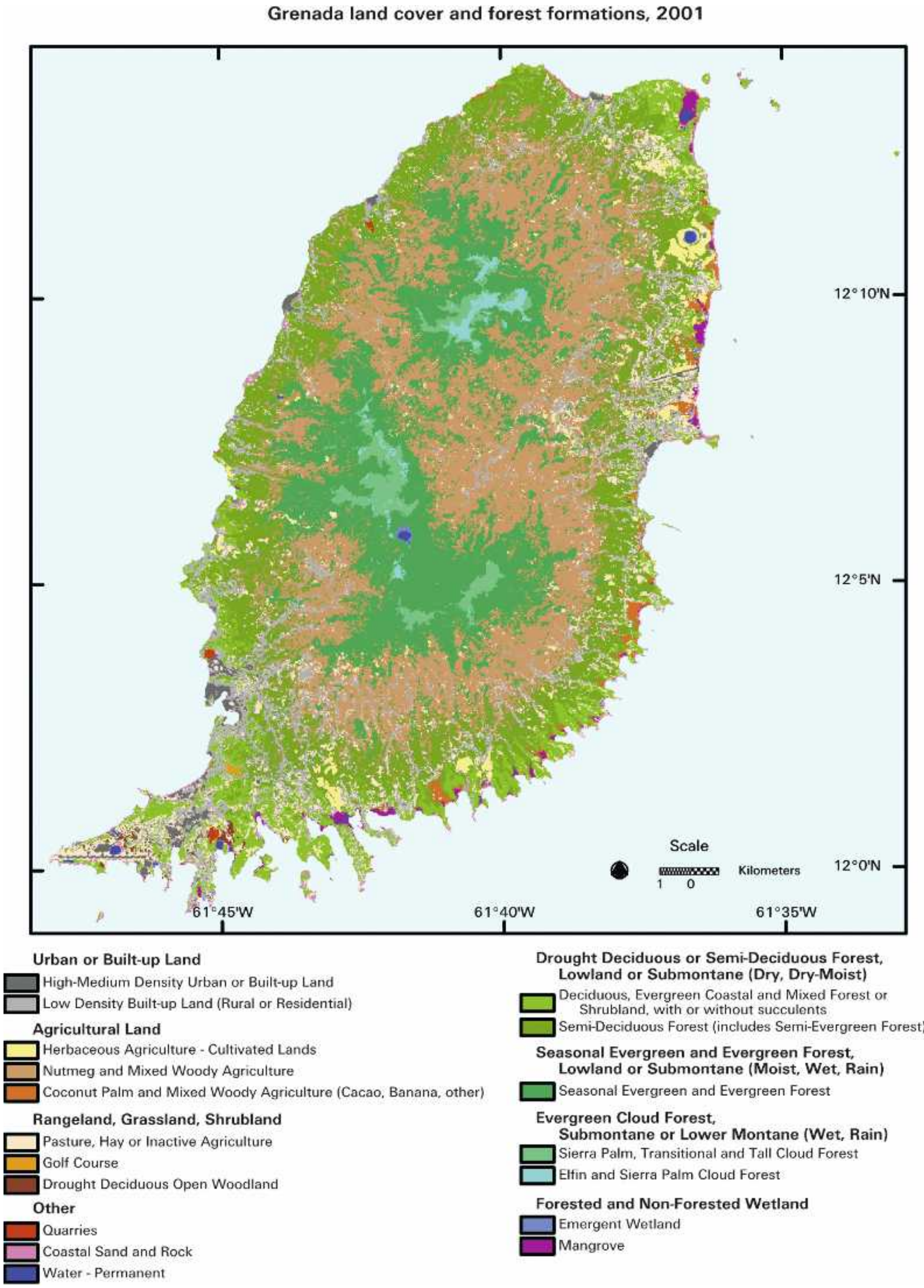

FIG. 3. Map of land cover and forest formations of Grenada circa 2001 (excludes Grenadian islands in the Grenadines).

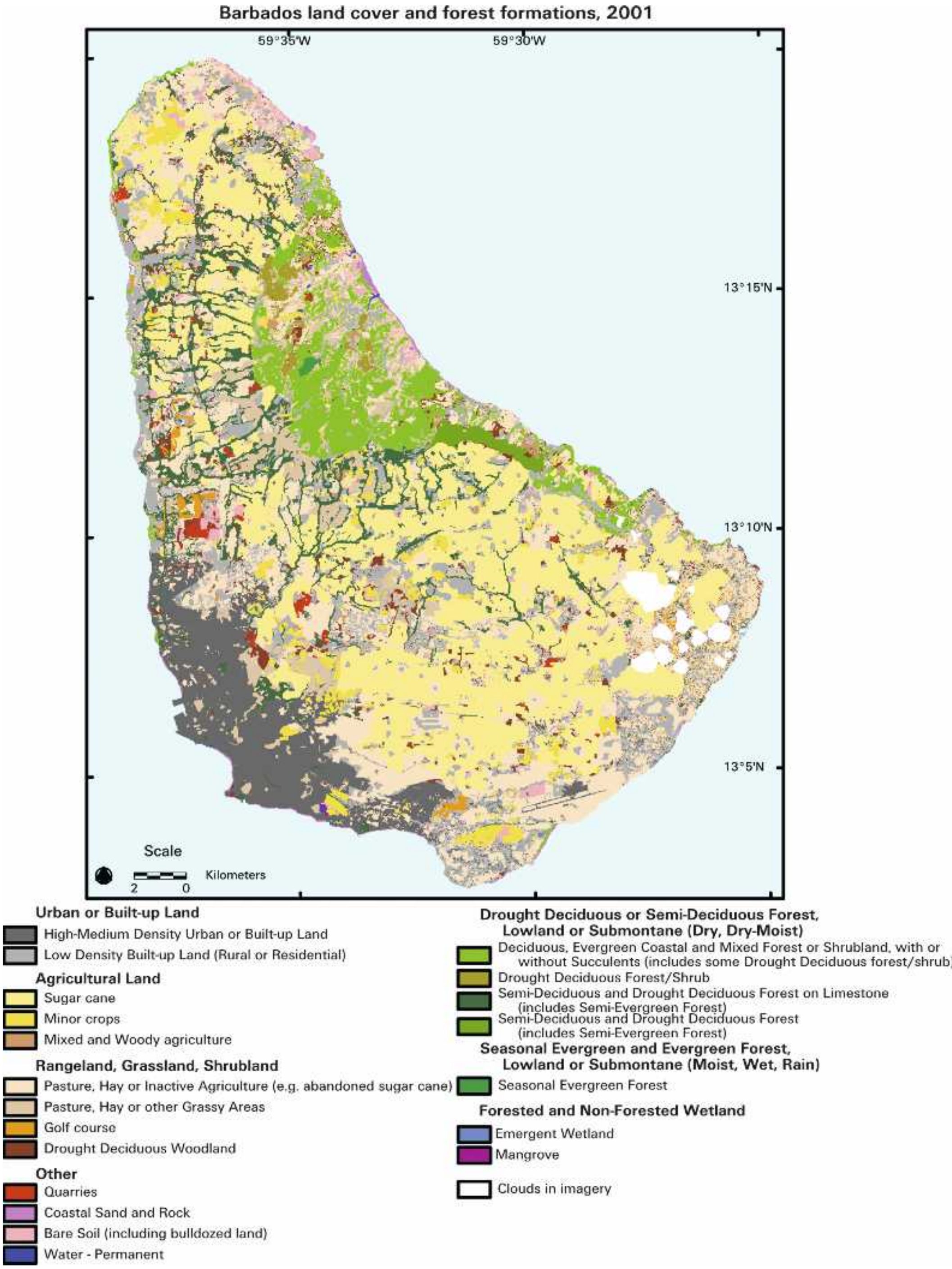

FIG. 4. Map of land cover and forest formations of Barbados, circa 2000.

tively (Appendices A and B). Kappa coefficients of agreement after manual editing were 0.69 ± 0.04 for the St. Kitts study area and 0.76 ± 0.03 for Grenada. Kappa coefficients of agreement between 0.6 and 0.8 are considered "substantial" according to some criteria (Landis and Koch 1977). Kappa coefficients in this range are also considered good in remote sensing studies. In both study areas, the main sources of error were confusion between low density urban lands, herbaceous agriculture, and pasture, as well as confusion between low and high density urban lands. Training pixels for high density urban lands included only pixels with ≥80% manmade structures (from visual interpretation). Those for low density urban lands included both vegetation and about 15 to 80% man-made structures. Both the high and low density urban lands, then, could contain mixed pixels. Landsat image pixels at 30-m resolution that include both man-made structures and vegetation can have spectral signatures like pasture. Imagery with finer spatial resolution would better distinguish man-made structures from vegetation.

As for the woody vegetation classes, most forest types in both study areas were classified with better than 60% accuracy before manual editing. After limited manual editing, most forest types were classified with greater than 70% accuracy. Drought deciduous woodland showed some confusion with pasture, drought deciduous forest or shrubland formations, and semi-deciduous forest. These classes are related, for pasture can have up to 25% cover of the same drought deciduous, leguminous shrubs or trees that dominate in drought deciduous woodland and forest. The two cloud forest types also showed some confusion with each other. They are also closely related, having some tree species in common and overlapping elevation ranges. In Grenada, semi-deciduous forest showed confusion with woody agriculture that included coconut or mixtures of cacao, coconut, banana, and other crops. The high classification accuracy in the error matrix for this class reflects manual editing. Nutmeg plantations in Grenada, which are at middle elevations and have dense evergreen tree cover, are fairly accurately distinguished from evergreen forest by the decision tree classification.

The approach in this study, of mapping detailed forest formations and land cover with decision trees and cloud-cleared Landsat imagery, was successful for mapping the 17 classes in the St. Kitts study area and 15 classes in Grenada. Achieving substantial accuracy required only limited manual editing. Based on these results and the other Caribbean island studies mentioned, the approach is apparently robust for these complex tropical landscapes. Helmer and Ruefenacht (2007) and Kennaway and Helmer (2007) discuss some advantages of the overall approach. First, decision trees are nonparametric and handle many different discrete and continuous predictor variables, separating spectrally similar forest types with variables like geology, rainfall or topographic features (Strahler 1981; Skidmore 1989; Friedl and Brodley 1997). The ancillary geospatial data are important to classifying imagery over these landscapes. For a simpler classification set in the St. Kitts study area, Kappa coefficients with no manual editing were 0.3 to 0.6 without ancillary data, suggesting large error. With ancillary data, Kappa coefficients were above 0.6 (Helmer and Ruefenacht 2007). Decision tree classification also avoids unrealistically abrupt borders between forest types that can result from identifying forest type from ecological zone maps (Kennaway and Helmer 2007).

The decision trees themselves are thousands of lines long and too complex to present in detail. However, we summarized the number of times that a variable appears in a tree, and how far down in the tree each variable occurred, with scripts that Ruefenacht et al. (In press) developed. In both classifications, the variables that most commonly appear in the top nodes of the decision trees are spectral, or they are ancillary variables that affect the spectral bands, like image topographic shading based on image sun-target-sensor geometry. The spectral bands and indices among the top nodes of the two decision trees included Landsat image bands 3 (red), 1 or 2 (blue or green), 5 or 7 (shortwave infrared), NDVI, and the

TABLE 3. Areas of land cover and forest formations for St. Kitts, Nevis, St. Eustatius, and Grenada (excluding Grenada Grenadines), from decision tree classification of Landsat imagery, and Barbados (from classification of IKONOS imagery). A "C" indicates a class is present but is collapsed to a more generalized class at a higher level in the hierarchy. A dash indicates that the class was not detectable or not present.

Land-cover or forest formation	Symbol in Appendices	St. Kitts (ha)	Nevis (ha)	St. Eustatius (ha)	Barbados[1] (ha)	Grenada (ha)
Urban or built-up land						
High-Medium Density Urban or Built-up Land	UrbnHi	728	141	100	3,840	308
Low Density Built-up Land (Rural or Residential)	UrbnLo	444	528	42	5,231	2,439
Herbaceous agriculture						
Sugar cane	Cane	4,548	—	—	11,518	
Minor crops (including sugar cane in Grenada)	Crops	—	24	—	1,609	332
Mixed and Woody agriculture						
Nutmeg and Mixed Woody Agriculture	MxdWdAg1	—	—	—	—	8,984
Coconut Palm and Mixed Woody Agriculture (including Cacao, Banana, other)	MxdWdAg2	—	—	—	—	469
Coconut Palm-Pasture	MxdWdAg3	9.3	14	—	248	—
Pasture and Drought Deciduous Woodland						
Pasture, Hay or Inactive Agriculture (e.g. abandoned sugar cane)	PastAg	—	—	—	8,658	2,343
Pasture, Hay or other Grassy Areas	PastGr	2,634	2,724	773	2,459	—
Golf course	Golf	56	49	—	308	12
Drought Deciduous Woodland	DDwoodl	644	981	328	1,081	54
Lower Montane, Non-Forest Vegetation (e.g. *Miconia* thicket)	MontShr	103	12	—	—	—
Steep Non-Forest Vegetation	NonfStp	77	2.8	—	—	—
Drought Deciduous and Semi-Deciduous Forest, Forest/Shrub or Shrubland (Dry, Dry-Moist), Lowland or Submontane						
Deciduous, Evergreen Coastal and Mixed Forest or Shrubland, with or without Succulents, on either Limestone or other substrates[1]	DDMxdForShr	753	210	328	2,913	2,162
Drought Deciduous Forest/Shrub	DDForShr	72	325	89	263	—
Semi-Deciduous and Drought Deciduous Forest on Limestone (includes Semi-Evergreen Forest)		—	—	—	2,864	C
Semi-Deciduous Forest (includes Semi-Evergreen Forest)	SDFor	1,155	1,935	159	277	6,422

TABLE 3. Continued

Land-cover or forest formation	Symbol in Appendices	St. Kitts (ha)	Nevis (ha)	St. Eustatius (ha)	Barbados[1] (ha)	Grenada (ha)
Seasonal Evergreen and Evergreen Forest or Forest/Shrub (Moist, Moist-Wet, Wet, Rain), Lowland or Submontane						
Seasonal Evergreen Forest with Coconut Palm	EVforC	24	158	—	—	C
Seasonal Evergreen Forest	SEfor	1,453	1,031	11	34	C
Evergreen Forest	EVfor	2,726	755	—	—	C
Seasonal Evergreen and Evergreen Forest (combined)	EVSEfor					6,347
Evergreen Forest—Cloud Forest (Moist-Wet, Wet, Rain), Lower Montane						
Sierra Palm, Transitional and Tall Cloud Forest	CLDforTall	575	110	—	—	663
Elfin and Sierra Palm Cloud Forest	CLDforElf	194	45	—	—	198
Forested and Emergent Wetlands						
Mangrove	Mangrove	13	14.5	—	6.9	172
Seasonally Flooded Savannas and Woodland		—	5.4	—	—	—
Emergent Wetland	EmergWetl	1.2	0.8	—	4.0	43
No vegetation						
Quarries	Quarry	15	13	—	201	26
Coastal Sand, Rock and Bare Soil	BareC	107	104	86	172	304
Bare Soil (including bulldozed land)	Bare	104	134	112	1,078	C
Water—Permanent	Watr	260	7.0	—	50	63
Cloud-covered areas in final map		—	—	—	615	—
Total		16,695	9,311	2,029	43,431	31,341

[1]On Barbados, this class includes a mosaic of deciduous and seasonal evergreen forest/shrub northeast of Mt. Hillaby.

band 4:5 ratio. In contrast, the layers that appeared in the "leaves" of the trees were the ancillary ones. The topographic variables were at higher-level nodes than the distance variables (distances to roads, rivers or ravines, or the coast). These results suggest that the decision trees first spectrally segment the images and then use the ancillary variables to separate spectrally similar classes, and that the topographic variables are more generally relevant than the distance variables. This latter result might be expected, because topographic variables probably relate more consistently to forest type than do variables like road distance.

The second main advantage of the approach is that the fairly seamless cloud-cleared imagery developed with regression trees speeds training data collection. The regression tree normalization more closely matches vegetation phenology between images from different dates than do linear radiometric normalization, linear histogram matching, or atmospheric correction via dark object subtraction (Helmer and Ruefenacht 2007). Ease of training data collection is important. In our preliminary work, these detailed classifications are inaccurate without well-distributed training pixels. Typically, we add to training data after a first round of classification so that the training data identify the correct class of some of the initially wrongly classified pixels. Decision tree classification that combines both spectral data and relevant ancillary data actually can resolve some of the spectral heterogeneity of non-normalized cloud-cleared imagery (Helmer and Ruefenacht 2007). The caveat to this conclusion, however, is that the well-distributed training data available for classification modeling include the cloud-filled areas.

The multiseason imagery is a third main advantage of the approach in this study. Many studies show that multiseason imagery enhances Landsat image classifications in temperate forest landscapes. In this case the differences in display tone (i.e., spectral absorption) between seasons provide additional visual cues to distinguish drought deciduous from semi-deciduous (and semi-evergreen) formations when collecting training data. Helmer et al. (2002) combines these classes. Drought deciduous woody formations are purplish to brown in leaf-off images or image mosaics when displaying Landsat image bands 5 (shortwave-infrared energy), 4 (near-infrared energy) and 3 (red energy) in the red, green, and blue display color guns, respectively. They appear green in "leaf-on" imagery; that is, leaf chlorophyll and water absorb relatively more red and shortwave-infrared radiation. A cautionary note is that tone differences cannot be the only information source when designating training data, because drought deciduous vegetation can be both leaf-off and greened-up in different places in the same scene date. Additional visual cues to distinguish these formations in training data came from the fine spatial resolution IKONOS imagery. Much of the drought deciduous vegetation on these islands has visibly distinct canopies.

Forest protection and land-cover change

In the second half of the 20th century, forest cover has apparently increased on St. Kitts, Nevis, Grenada and Barbados, by about 50 to 950% (Table 4). Pasture, drought deciduous woodlands, and developed or bare lands have also increased. Cultivated lands, meanwhile, have decreased by 59 to 99%. Land cover on these islands has shifted from being dominated by agriculture to having from nearly zero (Nevis) to 30% cultivated land cover (Figure 5). Proportional increases in drier formations at lower elevations, the drought deciduous, mixed and semi-deciduous (including semi-evergreen) forests or shrublands, were larger than those in evergreen formations. Beard (1949) does not detail his methods for mapping or estimating land-cover areas. However, the published estimates of land cover and forest areas are probably the most reliable and consistent ones available from that era. An important note is that the total land areas that Beard reports for each island differ from those in the satellite image-based maps by four to eight percent. As a result, not all of the land area tabulated for 1945 is accounted for in 2000 in Table 4. Still, visual analysis of the

TABLE 4. Land-cover change from about 1945 (Beard, 1949) to about 2000 for St. Kitts, Nevis, Barbados and Grenada. Beard (1949) did not tabulate land-cover areas on St. Eustatius. Net land-cover changes do not sum to zero because total island areas differ by 4% to 8% between the two studies.

Land-cover or forest formation classes (Description in Beard, 1949)	St. Kitts	Nevis	Barbados	Grenada
Urban or built-up land, Golf courses, No vegetation (Other Uncultivated Land[1])				
1945 (ha)	708	40	5,848	202
2000 (ha)	1,714	977	10,885	3,153
Change (%)	*142*	*2,314*	*86*	*1,458*
Herbaceous Agriculture, Mixed and Woody Agriculture (Cultivated Land)				
1945 (ha)	11,223	8,013	33,508	27,661
2000 (ha)	4,557	38	13,375	9,784
Change (%)	*−59*	*−100*	*−60*	*−65*
Pasture, Hay, Inactive Agriculture, other Grassy Areas and Drought Deciduous Woodland (Savannas and Rough Grazing)				
1945 (ha)	344	0	1,922	405
2000 (ha)	3,278	3,705	12,198	2,397
Change (%)	*853*	*3705*	*2,912*	*25*
Drought Deciduous or Semi-Deciduous Forest, Forest/Shrub, and Shrubland (Dry Scrub Woodlands)				
1945 (ha)	809	668	607	1,052
2000 (ha)	1,979	2,469	6,351	8,584
Change (%)	*145*	*73*	*946*	*716*
Evergreen Forest and Forest/Shrub (Seasonal Evergreen, Evergreen, and Cloud Forests) (Rain Forest, Lower Montane Rain Forest, Montane Thicket, Elfin Woodland, Palm Brake and Secondary Rain Forest)				
1945 (ha)	3,946	1,295	20	3,946
2000 (ha)	4,972	2,101	34	7,208
Change (%)	*26*	*62*	*71*	*83*
All forest % Change	*50*	*134*	*948*	*220*

[1]"Towns, villages, military areas, salt ponds, sand dunes, etc."

maps suggests that they are fairly geographically accurate, indicating that they were developed with the aid of topographic maps or aerial photos. Moreover, forest appears in the new maps where it does not appear in the older ones. Finally, new urban developments are visually distinct from older ones in the recent satellite images of the islands. Their presence supports our finding that developed land area has increased. Considering the large land-cover changes, we are confident that the results accurately represent the trends in land-cover change on the islands studied.

Sugar cane cultivation has long been declining in the insular Caribbean, and it continues to do so. For example, sugar production in 2003 declined greatly from previous levels in Jamaica, Trinidad and Tobago, Barbados, and St. Kitts/Nevis (McDonald 2004). In the latter three countries, sugar cane production has become less competitive as growers in other countries, like Brazil and the United States, have mechanized. Meanwhile, land-cover change to urban and built-up lands progresses for housing or tourism. These trends will probably continue, because the European Union has dropped import quotas or price subsidies that gave banana and sugar farmers in some former colonies preferential access to European markets. As a consequence of these factors, the St. Kitts and Nevis government closed the state-run sugar company in 2005. The land-cover changes on St. Kitts, Nevis and Barbados are strikingly similar to those in Puerto Rico, where increases in forest and urban/built-up lands have accompanied an economic shift from agriculture to industry and services (Franco et al. 1997; Rudel et al. 2000; del Mar López et al. 2001; Helmer 2004; Kennaway and Helmer 2007). In Puerto Rico, a recent analysis of land-cover change from 1951 to 2000 showed that agricultural lands in lowland areas, mainly sugar cane cultivation, shift first to pasture or other grassland (abandoned agriculture), and then they reforest or undergo change to urban/built-up lands. In addition, urban development also

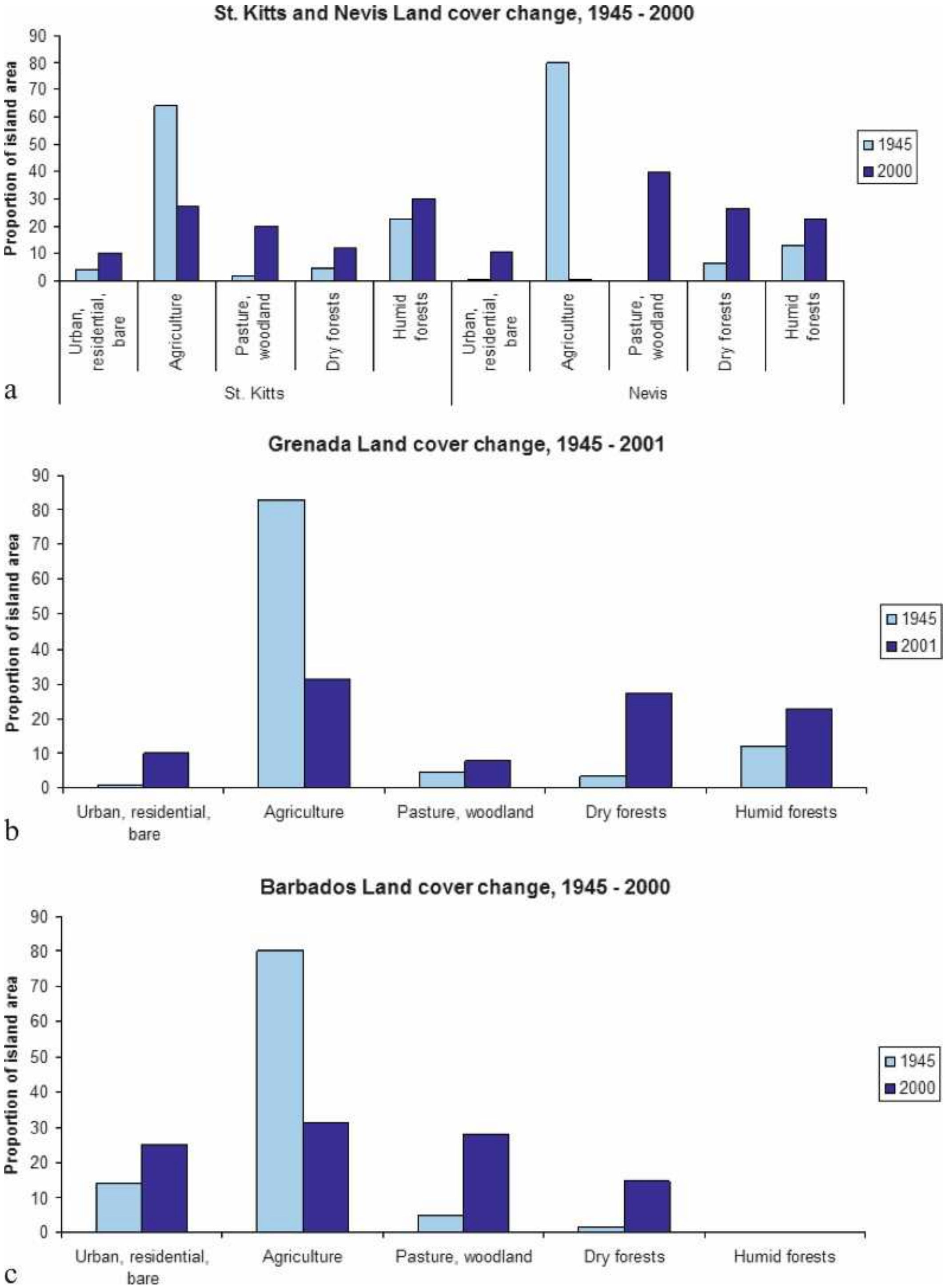

FIG. 5. Land-cover distributions estimated from this study and from Beard (1949) for a) St. Kitts and Nevis, b) Barbados, and c) Grenada.

Fig. 5 live 4/C

TABLE 5. Area and proportion (in parentheses) of existing forest formations within informal or formal reserves in St. Kitts, Nevis, St. Eustatius and Grenada (excludes Grenada islands in the Grenadines)[1]. The "protected" forests in St. Kitts, Nevis and Barbados are protected informally (with the exception of Brimstone Hill National Park in St. Kitts). The Grenada protected areas include Mt. St. Catherine reserve, which is not yet formally designated as a reserve.

	St. Kitts	Nevis	St. Eustatius	Barbados	Grenada
	Protected area in ha (% of existing forest protected)				
Drought Deciduous or Semi-Deciduous Forest, Forest/Shrub, and Shrubland (Dry, Dry-Moist), Lowland or Submontane					
Deciduous, Evergreen Coastal and Mixed Forest or Shrubland, with or without Succulents	5.7 (0.8)	0 (0)	219 (67)	83 (2.8)	140 (6.5)
Drought Deciduous Forest/Shrub	6.7 (9.3)	0 (0)	14 (16)	0 (0)	—
Semi-Deciduous and Drought Deciduous Forest on Limestone (includes Semi-Evergreen Forest)	—	—	—	138 (4.8)	—
Semi-Deciduous Forest (includes Semi-Evergreen Forest)	45 (3.9)	26 (1.4)	108 (68)	0 (0)	0 (0)
Evergreen Forest and Forest/Shrub (Moist, Moist-Wet, Wet, Rain), Lowland or Submontane	—	—	—	—	1,771 (28)
Evergreen Forest with Coconut Palm	0 (0)	0 (0)	—	—	—
Seasonal Evergreen Forest	251 (17)	326 (32)	10 (100)	0 (47)	C
Evergreen Forest (includes some Sierra Palm forest)	2,674 (98)	737 (98)	—	—	C
Evergreen Forest—Cloud Forest (Moist-Wet, Wet, Rain), Lower Montane	—	—	—	—	—
Sierra Palm, Transitional and Tall Cloud Forest	575 (100)	110 (100)	—	—	—
Elfin and Sierra Palm Cloud Forest	194 (100)	45 (100)	—	—	578 (87)
Forested Wetlands					187 (94)
Mangrove	0 (0)	0 (0)	—	1.3 (18)	0 (0)
Seasonally Flooded Savannas and Woodland	—	0 (0)	—	—	—
Proportion of land area under formal or informal protection (%)	25	14	28	2.8	9.1

[1]A dash indicates that the forest formation is not present; a "C" indicates the forest formation was mapped to a more generalized class, at a higher level in the hierarchy.

[2]On Barbados, this class includes a mosaic of deciduous and seasonal evergreen forest/shrub northeast of Mt. Hillaby.

clears some secondary forest. The huge proportional increases in pasture, grassland or woodland in Barbados and Nevis (sugar cane once dominated Nevis agriculture) suggest that, like Puerto Rico (Kennaway and Helmer 2007), sugar cane shifts first to pasture, grassland or woodland.

Higher elevation forest formations on the islands studied are generally protected in formal or informal reserves (Table 5). Land development is prohibited above 1000 ft elevation on Nevis. In St. Kitts, most lands above the 1000-ft elevation contour fall into the new central forest reserve designated in 2007. Before that, land development was also prohibited above 1000 ft. Although protected informally on both islands at the time of this study, 98% to 100% of evergreen and cloud forests are above the 1000-ft elevation contour on St. Kitts and Nevis. Land cover above 1000 ft elevation included only 75 ha of sugar cane and 152 ha of pasture/grass on St. Kitts, and about 41 ha of pasture/grass on Nevis. The remaining land cover above 1000 ft was forest or other montane vegetation, suggesting that the limitation on development above 1000 ft elevation has provided some protection for those forests. Also above 1000-ft elevation were 17% and 32% of the seasonal evergreen forests on St. Kitts and Nevis, respectively. On Grenada, cloud forests are 87% to 94% protected, and 28% of the forest classified as evergreen and seasonal evergreen forests is protected. The protected forest estimates for Grenada include the proposed Mt. St. Catherine reserve. It encompasses 76% of the protected palm and elfin cloud forest. It also includes 21% of the protected evergreen and seasonal evergreen forest, and 33% of the protected transitional and tall cloud forest. Informal watershed protection in Grenada also helps to protect much of the forest in montane areas. On Barbados, the 20-ha area of seasonal evergreen forest at Turner's Hall Woods has always been protected even though it is not legally a reserve. On St. Eustatius, seasonal evergreen forest occurs only in the mouth of the volcanic mountain known as The Quill, which is protected. The Quill National Park also protects 68% of the semi-deciduous forest present on the island.

Much smaller proportions of drier forest types are protected on St. Kitts, Nevis, Grenada and Barbados. Although the proportions of existing drier forest formations that are protected range from 0.1 to 4.8%, the areas of protected drier forests are small. For example, the area of protected deciduous, evergreen coastal and mixed forest or shrubland on St. Kitts is only 8.3 ha, though it is 1.2% of the total area of that formation. A substantial portion of the drier forest formations that persist in Barbados are in an extensive limestone, gully network. In St. Eustatius, Boven and The Quill National Parks protect 67% of the driest forest. No forested wetlands are protected on St. Kitts, Nevis or Grenada. An estimate of the proportions of protected areas in lowland ecological zones might better reflect the fact that protected land areas at low elevations on these islands are small. These islands, then, are also similar to Puerto Rico in protected area distribution. Protected lands are mainly at higher elevations, which is important for water resources. At the same time, lowland ecological zones and ecosystems are not well protected, but pressure for land development is greatest at lower elevations (Helmer, 2004).

Conclusions

Decision tree classification of Landsat image mosaics combined with ancillary geospatial data is an effective approach to mapping detailed forest formations and land cover in complex tropical landscapes. First, decision tree modeling "learns" the relative importance of various image bands and ancillary data for classifying forest or land cover. Consequently, distinguishing between spectrally similar forest formations does not require ecological zone maps, which are often unavailable or too coarse for these landscapes. Secondly, training data collection is simplified when the data can be collected from image mosaics that minimize cloud cover yet are relatively seamless. Finally, imagery from two seasons reveals the relative extents of drought deciduous forests, shrublands and woodlands. Accurate land-cover and forest formation maps are derivable, then, with only one set of training data instead of separate datasets for the clear parts from each image date and for each ecological zone.

Formal or informal reserves in St. Kitts, Nevis, and Grenada protect almost all cloud forests. These reserves also protect substantial amounts of existing evergreen forest formations. Higher elevation forests are also well-protected on St. Eustatius, as are drier forest types. Drier forest formations have little protection St. Kitts, Nevis, Grenada, and Barbados, and the reserve systems do not protect mangroves or other wetlands.

At the same time, land under cultivation has declined and forest areas have increased over the second half of the 20th century on these islands, which may make more land available for conservation at lower elevations. Development and construction have also increased on all of the islands, mostly at lower elevations. Drier forest types, which are at lower elevations, underwent proportional increases that were greater than evergreen forest formations. Given that 1) relatively small proportions of drier forest formations or mangroves are protected, and 2) most land development occurs at lower elevations, protection and restoration of drier forests on formerly cultivated lands, as well as mangroves, are probably among the most important conservation priorities for these countries.

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APPENDIX A. Error matrix for the classification of St. Kitts, Nevis and St. Eustatius from a stratified random sample of points over St. Kitts and Nevis. The Kappa coefficient of agreement after manual editing was 0.69 ± 0.04.

	Reference																	User's Accuracy (%)
Class	UrbHi	UrbLo	Cane	Past	Golf	DWoodl	Mntshr	NonfStp	DMxdfor	Dforshr	SDfor	EVforC	EVSEfor	CLDforT	CLDforE	Bare	Watr	
NUrbHi	38	10	0	0	2	0	0	0	0	0	0	0	0	0	0	2	1	72
UrbLo	1	18	5	3	0	2	0	0	0	0	0	0	0	0	0	0	0	62
Cane	1	5	44	6	0	1	0	0	0	1	2	0	2	0	0	0	0	71
Past	3	6	14	51	1	11	0	1	3	0	5	0	3	0	0	4	2	49
Golf	0	1	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0	96
Dwoodl	2	4	1	5	0	31	0	0	4	2	4	0	0	0	0	1	0	57
MntShr	0	0	0	0	0	0	6	0	0	0	0	0	1	0	0	0	0	86
NonfStp	0	0	1	1	0	0	0	9	0	0	0	0	2	2	1	0	0	56
DMxdFor	0	0	1	0	0	3	0	0	48	2	4	0	0	0	0	2	1	79
DForShr	0	0	2	0	0	2	0	0	0	41	5	1	1	0	0	0	0	79
SDfor	0	3	2	3	0	1	0	0	0	6	39	3	6	0	0	0	0	62
EVforC	1	0	0	0	0	0	0	0	1	2	1	12	0	0	0	1	0	67
EVSEfor	0	1	2	2	0	0	0	1	0	0	6	1	83	5	2	0	0	81
CLDforT	0	0	0	0	0	0	0	1	0	0	0	0	2	26	7	0	0	72
CLDforE	0	0	0	0	0	0	1	0	0	0	0	0	1	4	17	0	0	74
Bare	4	4	1	0	0	1	0	0	1	0	0	0	0	0	0	42	1	78
Watr	0	1	0	1	0	0	0	0	1	0	1	0	0	0	0	1	47	90
Producer's Accuracy (%)	76	34	60	71	88	60	86	75	83	76	58	71	82	70	63	79	90	Overall Correct 71%

APPENDIX B. Error matrix for classification of Grenada from a stratified random sample of points. The Kappa coefficient of agreement after manual editing was 0.76 ± 0.03.

	Reference															User's Accuracy (%)
Class	UrbHi	UrbLo	WdAgN	WdAgC	Past	Woodl	DMxdfor	SDfor	EVSEfor	CLDforT	CLDforE	EMWetl	Mangrv	Bare	Watr	
UrbHi	41	7	0	0	1	0	1	0	0	0	0	0	0	1	2	77
UrbLo	1	38	1	0	5	0	3	3	1	0	0	0	0	0	0	73
WdAgN	0	2	31	0	1	0	0	5	7	0	0	0	0	1	0	65
WdAgC	0	0	0	32	0	0	0	9	0	0	0	0	1	1	0	73
Past	0	5	2	0	35	0	3	2	0	0	0	0	0	0	0	71
Woodl	0	0	0	0	1	39	6	0	0	0	0	0	1	2	0	80
DMxdfor	0	1	0	0	0	2	38	5	1	0	0	0	0	0	0	81
SDfor	0	0	6	0	1	0	3	46	0	0	0	0	0	0	0	82
EVSEfor	0	0	5	0	0	0	0	2	38	4	0	0	0	0	0	78
CLDforT	0	0	0	0	0	0	0	0	10	36	3	0	0	0	0	73
CLDforE	0	0	0	0	0	0	0	0	1	17	29	0	0	0	0	62
EMWetl	0	0	0	0	0	0	1	0	4	0	0	41	1	0	2	84
Mangrv	0	0	0	1	0	0	1	2	0	0	0	1	39	0	1	87
Bare	0	4	0	1	3	2	2	2	0	0	0	0	0	79	2	83
Watr	0	1	0	0	0	0	0	1	0	0	0	3	0	0	41	89
Producer's Accuracy (%)	98	66	69	94	74	91	66	60	61	63	91	91	93	94	85	Overall Correct 78%