International Journal of Applied Earth Observation and Geoinformation 30 (2014) 203–216

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag

Evaluation of forest cover estimates for Haiti using supervised classification of Landsat data

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ARTICLE INFO

Article history:
Received 14 August 2013
Accepted 31 January 2014
Available online 15 March 2014

Keywords:
Land cover
Deforestation
Image normalization
FAO
Supervised classification
Fuzzy classification

ABSTRACT

This study uses 2010–2011 Landsat Thematic Mapper (TM) imagery to estimate total forested area in Haiti. The thematic map was generated using radiometric normalization of digital numbers by a modified normalization method utilizing pseudo-invariant polygons (PIPs), followed by supervised classification of the mosaicked image using the Food and Agriculture Organization (FAO) of the United Nations Land Cover Classification System. Classification results were compared to other sources of land-cover data produced for similar years, with an emphasis on the statistics presented by the FAO. Three global land cover datasets (GLC2000, Globcover, 2009, and MODIS MCD12Q1), and a national-scale dataset (a land cover analysis by Haitian National Centre for Geospatial Information (CNIGS)) were reclassified and compared. According to our classification, approximately 32.3% of Haiti's total land area was tree covered in 2010–2011. This result was confirmed using an error-adjusted area estimator, which predicted a tree covered area of 32.4%. Standardization to the FAO's forest cover class definition reduces the amount of tree cover of our supervised classification to 29.4%. This result was greater than the reported FAO value of 4% and the value for the recoded GLC2000 dataset of 7.0%, but is comparable to values for three other recoded datasets: MCD12Q1 (21.1%), Globcover (2009) (26.9%), and CNIGS (19.5%). We propose that at coarse resolutions, the segmented and patchy nature of Haiti's forests resulted in a systematic underestimation of the extent of forest cover. It appears the best explanation for the significant difference between our results, FAO statistics, and compared datasets is the accuracy of the data sources and the resolution of the imagery used for land cover analyses. Analysis of recoded global datasets and results from this study suggest a strong linear relationship ($R^2 = 0.996$ for tree cover) between spatial resolution and land cover estimates.

1. Introduction

Since its founding in 1804, growth in Haiti's population, and the proportion of people living in urban settings, has led to an increase in demand for fuel wood and charcoal. As of 1999, the Haitian Ministry of Environment estimated that 85% of the Haitian population depends on biomass energy for domestic purposes with 3.3 million m^3 of fuel wood used in Haiti per year (CFET, 1997). Conversion of native forests for resource utilization has led to deforestation, soil loss, water quality degradation, and economic/political instability (Stevenson, 1989; Wampler, 2011; Wampler and Sisson, 2011).

Deforestation and tropical forest degradation in Haiti is arguably the most publicized in the world, but in many ways is the least examined (Versluis and Rogan, 2010). Remote sensing analyses of land-use and land-cover change have been done for locations in Central and South America (Broich, 2009; Clark, 2012; Clark et al., 2010; De Souza Soler and Verburg, 2010; Díaz-Gallegos et al., 2010; Guild et al., 2004; Ichii et al., 2003; Marsik et al., 2011; Mendoza, 2011; Morton et al., 2005; Renó et al., 2011; Sanchez-Azofeifa, 2001; Schulz, 2010), but relatively few focus on the Caribbean Island nations (Aide et al., 2012; Alvarez-Berríos et al., 2013; Clark, 2012; Evelyn and Camirand, 2003; Hernandez-Leal et al., 2006; Martinuzzi, 2007; Sanchez-Azofeifa, 2001); and even fewer are specific to Haiti (Grace et al., 2012; Versluis and Rogan, 2010; Wilson et al., 2001).

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http://dx.doi.org/10.1016/j.jag.2014.01.020
0303-2434

Table 1
Peer-reviewed articles that cite forest cover statistics in Haiti and their citation sources. Note that these are not independent land-cover analyses, but studies that cite a forest cover statistic for Haiti. All but two of the studies examined cite a United Nations body for the source of their statistic.

Peer-reviewed publications	Amount of forest cover reported	Source of data or citation
Bannister (2003)	Under 2% in 1994	UNDP (1996)
Dolisca et al. (2007)	3%	FAO (1988)
Erikson (2004)	<1%	The Miami Herald
Foxx (2012)	<2%	None given
Hedges (2006)	4%	FAO (2005)
Higuera-Gundy et al. (1999)	5%	None given
Hosonuma et al. (2012)	1–25%[a]	FAO (2010)
Huber et al. (2010)	<1%	Paryski et al. (1989)
Koyuncu and Yilmaz (2009)	10%	None given
Mainka and McNeely (2011)	1%	None given
Pellek (1990)	3%	None given
Rudel et al. (2005)	3.2%	FAO (2000)
Williams (2011)	<1%	None given
Wright (2005)	Supports less than 10% of potential closed-canopy forest	None given

[a] Hosonuma et al. (2012) classified forest cover between 1 and 25% into a single category called "phase 3". The actual number reported by the FAO for Haiti was not provided.

Recent disasters such as flooding in 2004, hurricanes in 2008, and the earthquake in 2010 have focused world attention on this region, the topic of deforestation in Haiti, and its related environmental consequences. The percentage of remaining forest cover is often central to reports by media and government organizations. However, the statistics of forest cover in Haiti cited by recent scientific publications vary widely, and most are not attributed to peer-reviewed sources (Table 1).

The lack of easily accessed, peer-reviewed data sources may contribute to the conflicting statistics regarding forest cover and deforestation in Haiti. After a thorough literature review and search for web-based data, only two recent analyses that provide national level forest statistics for Haiti were found: (1) the Food and Agriculture Organization of the United Nations (FAO) Global Forest Resource Assessment (FRA) 2010 (based on data provided by Haitian officials, not remote sensing-based data) (FAO, 2010b); and (2) a March 2013 land-cover/land-change study of the Greater Antilles region (Alvarez-Berríos et al., 2013). A national level land-use dataset produced by the Haitian National Centre for Geospatial Information (CNIGS) was also noted, however forest statistics were not extracted from Geographic Information System (GIS) data or tabulated (CNIGS, 2008).

Three freely available datasets that provide global level land-use data were also found. However, calculation of national level statistics requires a number of GIS operations such as re-projection, mosaicking, sub-setting, and recoding. These are as follows: (1) NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) derived global land-cover dataset at 500 m resolution (MCD12Q1, 2010); (2) the GLC2000 land-cover dataset at 1 km resolution (GLC2000, 2003); and (3) the Globcover (2009) dataset at 300 m resolution (Bontemps et al., 2011; Globcover, 2009) (Table 2).

Increased interest in Haitian forest cover and deforestation, coupled with the lack of easily accessible, and reliable, statistics has demonstrated the need for high resolution remote sensing analysis of the region. The FAO has been called by some "the main actor in assessing the world's forest" (Mather, 2005). This paper uses published remote sensing techniques and recent Landsat imagery to determine the extent of tropical forest cover in Haiti. The methods used to generate land-cover statistics presented by this study were tailored to be compatible with FAO land-cover definitions. Using a generalized FAO land cover classification system (LCCS), a supervised classification of recent (2010–2011) 30-m resolution Landsat 5 TM imagery was accomplished using ERDAS IMAGINE 2011 (Intergraph Corporation; Madison, Alabama) and ArcGIS 10 (ESRI; Redlands, California). Similar supervised classification methods have been widely used to extract land-cover features (Oyana et al., 2009; Sirikulchayanon et al., 2008; Sun, 2004; Sun et al., 2003). Classification results were compared to three global land cover datasets (GLC2000, Globcover, 2009, and MODIS MCD12Q1), and a national-scale dataset (CNIGS) produced for similar years, with an emphasis on the statistics presented by the FAO.

Table 2
Data products used for land cover statistics comparison.

Study	Year	Satellite	Sensor/product	Bands used	Resolution	Overall accuracy	Agencies	Classification scheme
GLC2000	2000	SPOT-4	Vegetation	B (437–480 nm), R (615–700 nm), NIR (722–892 nm), SWIR (1600–1692 nm)	1 km	68.60%	United States Geological Survey (USGS)[b]	NCVS-FGDC
MCD12Q1	2010	Terra/Aqua	MODIS/MCD12Q1	Bi-directional Reflectance Distribution Function (NBAR), Land Surface Temperature (LST)	500 m	74.80%[a]	University of Boston[c]	UMD Land Cover Type 2
Globcover (2009)	2009	Envisat	MERIS-FR	All	300 m	58.00%	European Space Agency (ESA)[d]	UN-LCCS
CNIGS	1998	SPOT-5	Unknown	Unknown	Unknown	Unknown	Haitian National Centre For Geospatial Information (CNIGS)[e]	Unknown
This Study	2010	Landsat 5	TM	B (520–600 nm), R (630–690 nm) NIR (760–900 nm)	30 m	78.00%[f]	N/A	UN-LCCS FAO et al. (2009)

[a] Calculated using 2005 image composites.
[b] http://bioval.jrc.ec.europa.eu/products/glc2000/products.php.
[c] https://lpdaac.usgs.gov/get_data/data_pool.
[d] http://due.esrin.esa.int/globcover/.
[e] http://haitidata.org/data/geonode:hti_biota_landcover_spot_cnigs_041998_polygon.
[f] Overall accuracy improves to 83% using an error-adjusted estimate (see Section 4.2)

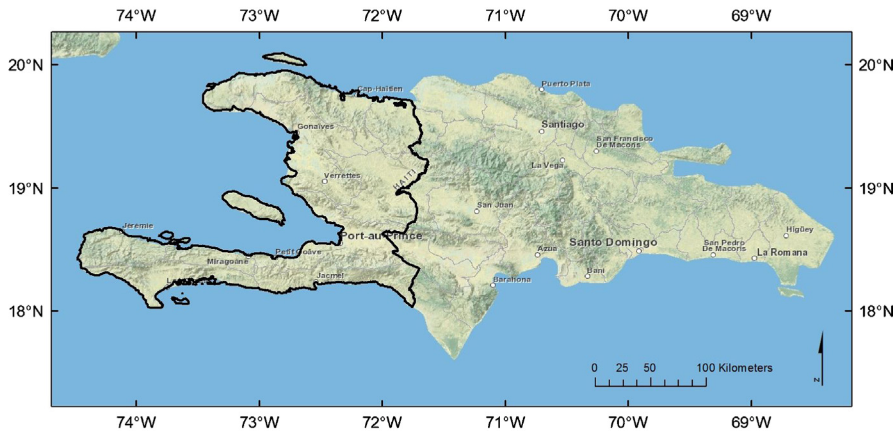

Fig. 1. Relief map of Haiti showing study area.

2. Study area and data preparation

2.1. Study area

The Island of Hispaniola has a land surface area of approximately 75,439 km^2 (Fig. 1). Roughly 35.8% of the island is occupied by the nation of Haiti while the other 64.2% is occupied by the Dominican Republic. Approximately two-thirds of the island has an elevation greater than 1600 m and the highest point on the island is 2680 m above mean sea level (CIA, 2013). The study area for our remote sensing analysis includes only the portion of Hispaniola which is within the Haitian political boundary (Fig. 1).

2.2. Landsat scene acquisition

Four Landsat 5 TM scenes, spanning the entire extent of the study area were obtained from the United States Geological Survey (USGS) *Earthexplorer* database (Fig. 2) (USGS, 2013a). All scenes were geo-referenced (UTM, WGS84) with an average root mean square error (RMSE) of 3.53 m, and were corrected to USGS "Standard Terrain Correction (Level 1T)" (USGS, 2013b). Only TM bands 2 (green; 520–600 nm), 3 (red; 630–690 nm), and 4 (near infrared; 760–900 nm) were used to ensure backward compatibility with Multispectral Scanner (MSS) imagery from Landsat 1–3 for future studies of forest cover change in Haiti. Scenes from January and February were used to coincide with the winter dry season (ORE, 2010). These dates minimize the error of the classification results which would otherwise be caused by increased ground vegetation and cloud cover during the wet season (Schwartz, 2003).

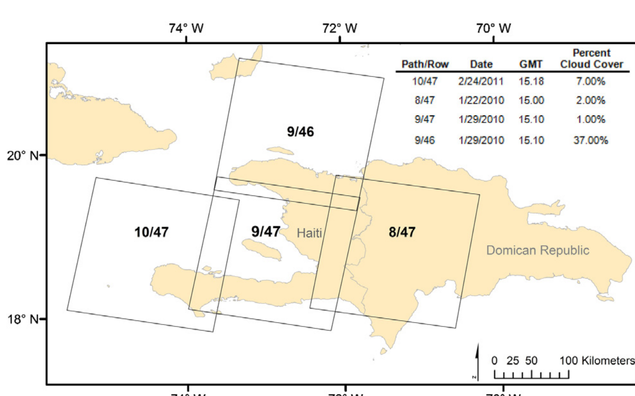

Fig. 2. Outline of Landsat 5 TM scenes used in this study. Table in the upper right provides scene specific details.

2.3. Acquisition and preparation of other land-cover data

The FAO forest cover statistics were obtained from the FRA 2010 global data tables (FAO, 2010a). The methods used to obtain these statistics are discussed in detail in Section 3.3.2. All other sources of GIS-based Haitian land-cover were downloaded from their associated contributor's website (Table 2). Each of the three global data products, as well as the CNIGS dataset, were projected into the UTM Zone 19 N, with a WGS 84 datum and clipped to a shapefile of Haiti (www.haitidata.org).

3. Methods

Methods included Landsat imagery preprocessing and supervised classification for our study; acquisition and modification of land cover data products from other studies; recoding of all land cover classification schemes to a common system (LCCS); translation of LCCS land-cover classes to land-use classes (FAO et al., 2009); and finally, area comparison between datasets (Fig. 3).

3.1. Landsat scene normalization

Image normalization typically involves normalizing band intensity of remote sensing data acquired on multiple dates (Schott et al., 1988), though it can also be applied to partially overlapping scenes acquired on the same date. We modified the normalization technique described by Schroeder et al. (2006) to include polygons of pixels, called pseudo-invariant polygons (PIPs), within the overlapping portion of images rather than individual points within pseudo-invariant features (PIFs) (Fig. 4) (Schott et al., 1988). Using polygons instead of individual points simplifies the process of selecting normalization targets and also permits use of a greater number of pixels, presumably improving the normalization. Because the acquisition dates between scenes used in this study were so close (largest difference was 392 days), it was assumed that no significant changes between dates occurred and the entire PIP could be considered invariant or unchanging.

Our normalization method consists of four main steps (Fig. 5): (1) Selection of a reference image. One of the four images was selected as the reference image (Path 9 Row 47), to which the other three images were then radiometrically normalized in step 4. (2) Selection of PIPs and pixel extraction. PIPs were selected from the overlapping portion of the images, and the digital numbers (DNs) of all pixels in each PIP (8.3E+04 to 1.3E+06 pixels) were extracted and exported in ASCII (American Standard Code for Information Interchange) format. (3) Regression analysis. DNs of all pixels in each

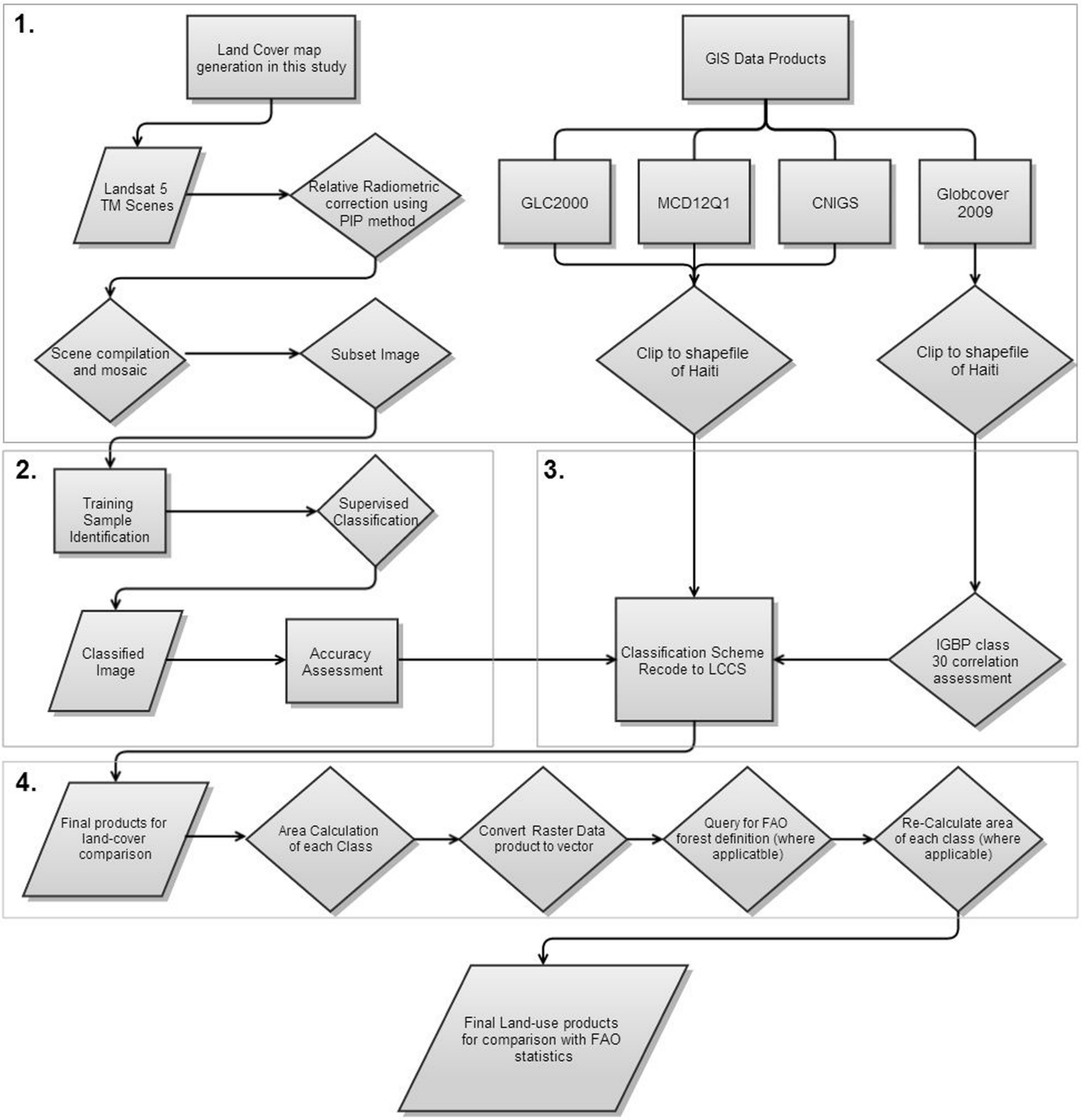

Fig. 3. Flow chart for remote sensing data analysis: (1) acquisition and preprocessing; (2) supervised classification; (3) recoding and translation; and (4) area calculation and comparison.

PIP were combined and used to estimate a linear regression model to rescale observed DNs in the image to be normalized so they would be as close as possible to observed DNs of the corresponding pixels in the reference image. Statistically, this is a conditional prediction problem, in which observed DNs of pixels in an image acquired at a place or time different from the reference image are used to predict the DNs that would have been observed if atmospheric and other conditions had been exactly the same as in the place and time at which the reference image was acquired (Schott et al., 1988). Since the goal of the analysis is to predict based on (or conditioned on) the observed DNs, the fact that DNs of the image to be normalized contain errors is irrelevant and ordinary linear regression is an appropriate tool for estimating the rescaling model. More specifically, we used ordinary least-squares linear regression separately for each Landsat band. (4) Image normalization. The coefficients of the linear regression models obtained from step 3 were used to compute a normalized dataset for each band of the three non-reference images.

3.2. Image classification

3.2.1. Classification system

The classification system used in this study was adapted from the FAO's Land-cover Classification System (LCCS). The FAO's LCCS was used in the Forest Resources Assessment's (FRA) Remote Sensing Survey (RSS) (FAO et al., 2009) and includes six land cover classes: tree cover, shrub cover, herbaceous, bare/non-vegetated, wetland, and water. In our classification system, the shrub cover class and herbaceous class were combined into one class due to difficulties differentiating between the two classes. Areas of cloud cover and shadows were classified separately, but were combined on the final thematic map into a single class named "no data".

Table 3
Class definitions and the criteria used to identify classes using high resolution imagery (Bing Maps).

Class[a]	Definition	Criteria used for reference and training samples
Tree cover[b]	Vegetation greater than 5 m in height with a canopy cover of ≥10%. Includes mangroves. Does not include fruit-tree plantations.	Clear physiognomic aspect of a body of trees. Crown cover is a minimum of 10% the pixel area; vegetative bodies are noticeably taller than others if broken or patchy cover.
Shrub cover/herbaceous	Vegetation less than 5 m in height or lacking definite structure such as stems or shoots. Woody vegetation included if crown cover is <10% and height <5 m. Includes all agriculture.	Vegetation with a height less than defined for "trees" above; patchy vegetation with <10% tree crown cover in the pixel area; identifiable patterned vegetation (agriculture)
Bare/non-vegetated	Complete lack of vegetation or <10% vegetated. Includes all urban areas.	Bright soil bodies and rock outcrops identifiable by sharp color contrast; any pixel with <10% vegetation; human or manmade structures that cover ≥20% of a pixel area
Wetland	Any vegetative body that appears permanently flooded with vegetation less than 5 m in height	Vegetation that appears to be underlain with water; vegetative bodies are shorter than those defined as trees
Water	Both turbid and non-turbid water of varying depths.	Both turbid and non-turbid water inland water bodies, rivers (salt water not included)
No data	Clouds and shadows from clouds	Original Landsat image used

[a] Modified from LCCS classes Di Gregorio (2005).
[b] Patterned bodies of trees were included in the shrub cover/herbaceous class, as these were interpreted to represent some form of agriculture.

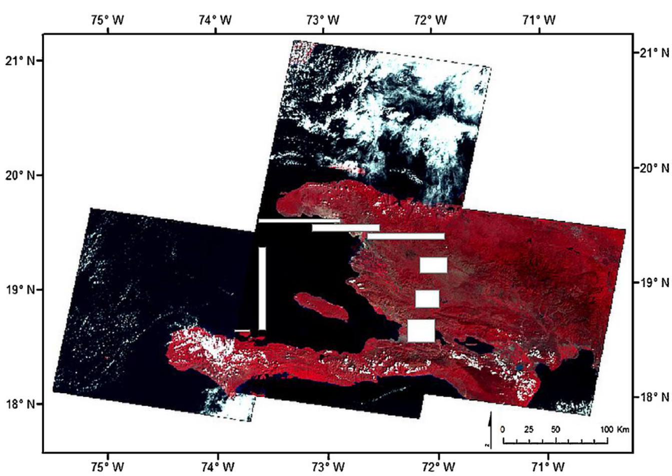

Fig. 4. PIPs (white polygons) chosen from overlapping areas shown on combined false color composite Landsat 5 TM image (band combination 4, 3, 2).

Therefore, our classification system includes six land cover classes: tree cover, shrub cover/herbaceous, bare/non-vegetated, wetland, water, and no data (Table 3). Land-cover class definitions were adapted from Appendix A in the LCCS Concepts and User Manual (Di Gregorio, 2005).

The FAO's LCCS was chosen for three reasons:

1. To ensure consistency of our classification system and land-use definitions with published FAO statistics.
2. The system is traceable, expandable, and contractible to make it compatible with different classification systems. It allows more complex regional products to be generalized into a simplified data product with fewer classes (Di Gregorio, 2005; McConnell and Moran, 2002).
3. There are published equivalencies between the FAO's classification system (LCCS) and classification systems used by the three global land cover data products compared in this study, i.e., MCD12Q1, GLC2000, Globcover (2009) (Bartholomé and Belward, 2005; Bontemps et al., 2011; Herold et al., 2009).

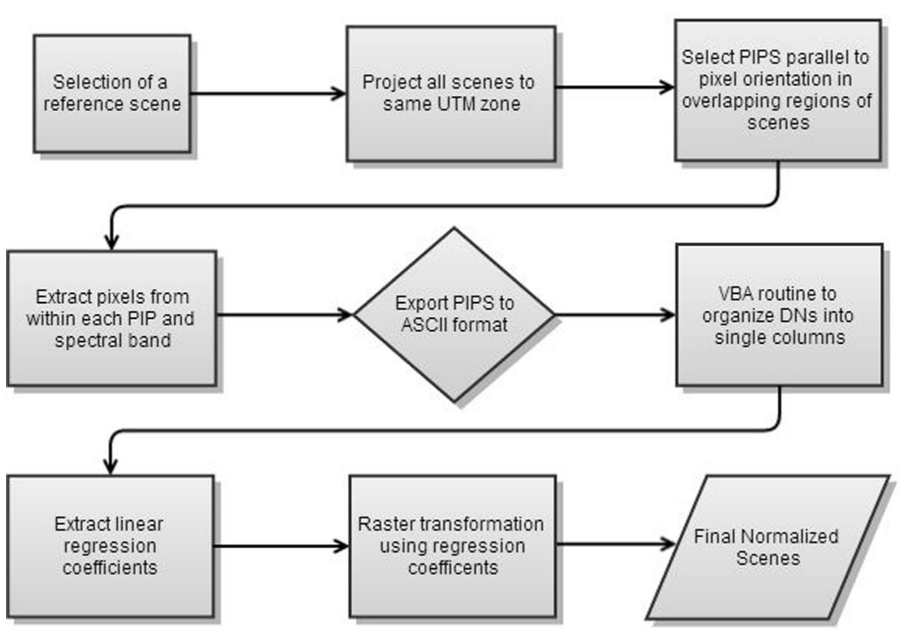

Fig. 5. Flowchart of methods used to normalize Landsat scenes.

Table 4
Land cover equivalencies.[a]

LCCS	GLC2000	CNIGS	Globcover (2009)	MCD12Q1
Tree Cover (1)	Temperate or Sub-polar Broadleaved Deciduous Forest – Closed Canopy Temperate or Sub-polar Needleleaved Evergreen Forest – Open Canopy Temperate or Sub-polar Mixed Broadleaved or Needleleaved Forest – Closed Canopy Tropical or Sub-tropical Broadleaved Evergreen Forest – Open Canopy	Dense agroforestry systems Forest Mangroves	Closed to open (>15%) broadleaved evergreen or semi-deciduous forest (>5 m) Mosaic grassland (50–70%)/forest or shrubland (20–50%) Mosaic forest or shrubland (50–70%)/grassland (20–50%) Mosaic vegetation (forest/grassland/shrubland) (50–70%)/cropland (20–50%)[b]	Evergreen Needleleaf forest Evergreen Broadleaf forest Deciduous Needleleaf forest Deciduous Broadleaf forest Woody savannas
Shrub cover/herbaceous (2)	Temperate or Subpolar Broadleaved Evergreen Shrubland – Closed Canopy Temperate or Subpolar Needleleaved Evergreen Shrubland – Open Canopy Temperate or Subpolar Grassland Cropland	Dominant pastures Pastures with presence of other Savannah Savannah with presence of other Dense crops Moderately dense crops	Closed to open (>15%) (broadleaved or needleleaved, evergreen or deciduous) shrubland (<5 m) Mosaic cropland (50–70%)/vegetation (grassland/shrubland/forest) (20–50%) Closed to open (>15%) herbaceous vegetation (grassland, savannas or lichens/mosses) Rainfed croplands Sparse (<15%) vegetation	Savannas Grasslands Croplands Open shrublands
Wetland (3)	Herbaceous Wetlands	Wetlands	Closed (>40%) broadleaved forest or shrubland permanently flooded – Saline or brackish water	–
Bare/non-vegetated (4)	Urban and Built-up Consolidated Rock Sparse Vegetation	Outcrop of rocks and bare soil Salt production Beaches and dunes Mining Ports and airports Continuous urban Discontinuous urban Industrial zone Recent alluvial river beds	Artificial surfaces and associated areas (Urban areas >50%) Bare areas Permanent snow and ice	Urban and built up Barren or Sparsely Vegetated
Water (5)	Water bodies	Water	Water bodies	Water
No data (6)	–	–	No data (burnt areas, clouds, etc.)	Unclassified/fill value

[a] Class translations were compiled from Bartholomé and Belward (2005), Bontemps et al. (2011), Herold et al. (2009).
[b] See text and Table 5 for further details regarding class equivalency determination.

3.2.2. Supervised classification

A total of 555 training samples were selected for the Maximum Likelihood Classification (Otukei and Blaschke, 2010; Paola and Schowengerdt, 1995; Sun, 2004); 162 for the shrub cover/herbaceous class, 15 for wetlands, 79 for the water class, 150 for bare/non-vegetated, 52 for the no data class (clouds/shadow), and 97 for the tree-cover class. Training sample locations for each class were delineated using high resolution aerial imagery from Bing Maps (Microsoft Corporation, Redmond, WA) and a priori knowledge of the region (Wampler, 2011; Wampler et al., 2013; Wampler and Sisson, 2011). Bing Maps image tiles used in the training sample selection were dated from February 2010 to January 2012. It should be noted that our definition of "tree cover" for use in training sample selection was any group of trees, notably taller than surrounding vegetation, with greater than ten percent (>10%) canopy cover as identifiable through the use of Bing Maps imagery (Table 3). Any group of trees whose pattern appeared anthropogenically influenced (e.g. linear rows of trees) was not included in our tree cover class type. These groups of trees were assumed to represent fruit tree plantations and were trained to be included in the shrub cover/herbaceous class during training sample selection.

3.3. Land-cover data product re-coding

3.3.1. Global dataset classification scheme translation and re-code

The classification schemes associated with the three global land-cover datasets (GLC2000, Globcover, 2009, and MCD12Q1; Table 2) were re-coded to conform to the FAO's LCCS using published translations independent of this study (Bartholomé and Belward, 2005; Bontemps et al., 2011; FAO et al., 2009; Herold et al., 2009) (Table 4). For the Globcover (2009) dataset, the published translation of one class, the Mosaic Vegetation (grassland/shrubland/forest) (50–70%)/cropland (20–50%), class 30, did not adhere to the LCCS used in this study (it was too general). In order to ensure proper translation to the LCCS used in this study, an interpretative assessment was run on class 30 following the suggested procedure in the Globcover (2009) validation report (Bontemps et al., 2011). Fifty random points were created for class

Table 5
Proportions used to translate Globcover (2009) class 30 to the classes used for this study for comparison purpose.

Class	Count	Percent of total (%)
Tree cover	30	60%
Shrub cover/herbaceous	13	26%
Wetland	1	2%
Bare/non-vegetated	4	8%
Water	0	0%
No data	2	4%
Total	50	100%

30. Using Bing Maps high resolution imagery, the LCCS class used in this study was identified at each point (Table 3). Globcover (2009)'s class 30 was proportionally re-coded to the classes used in this study. For example, 30 of the 50 random points (60%) were identified as tree cover on Bing Maps, therefore 60% of the class 30 area was recoded as tree cover (Table 5).

3.3.2. FAO data

The main resource utilized for inference of FAO Haitian forest cover statistics was the organization's publication *Global Forest Resource Assessment 2010 (FRA 2010)* and data associated with that publication. The Global Forest Resource Assessment provides national- and regional-level statistics relating to forest extent, utilization and health (FAO, 2010b). This publication reports forest statistics in two categories: (1) Forest; and (2) Other Wooded Land. These statistics are provided in "global data tables" on the website for the FRA 2010 publication (FAO, 2010a). The national level statistics for Haiti, as reported in the FRA 2010 publication, do not document the use of remote sensing data for determination of land cover statistics. The amount of land area classified as Forest reported by the FAO's *Global Forest Resource Assessment 2010* for Haiti was 4% (FAO, 2010a). No area (0%) was classified as Other Wooded Land by the FAO (FAO, 2010a).

4. Results and discussion

4.1. Landsat scene normalization evaluation

Regression coefficients for linear relationships between the reference image (Path 9 Row 47) and the three other scenes before and after PIP normalization were generated using randomly sized and positioned polygons (1.6E+03 to 5.1E+05 pixels) within areas of pair-wise overlap, independent of the original PIPS. Effectiveness of the modified normalization procedure was judged by examining the before and after regression coefficients, coefficients of determination, and root mean squared error (Table 6) and by visually examining the before and after regression plots (Fig. 6) and Landsat scenes.

Regarding the regression coefficients, a slope of one and a *y*-intercept of zero would indicate that DN values in the normalized scene are the same as those of the corresponding pixels in the reference scene within the area of overlap. Of the nine bands normalized, eight had slopes that were closer to one (0.986–1.08), and all nine bands showed intercepts closer to zero (−2.28 to 0.564) (Table 6). Since the resulting slope and y-intercepts within the overlap area improved after correction, it is assumed that DNs for the entire normalized image were improved, as well. It is anticipated that the PIP method would work best when merging temporally similar scenes covering a large geographic extent. In areas where land features are largely invariant, the PIP method may be applicable between images with large time differences. However, where land surface changes are rapid, it would be difficult to delineate PIPs, resulting in smaller or fewer polygons. As the size and number of PIPs decreases, fewer pixels are compared and the main benefit of using this method for normalization consequently decreases. Ultimately, this could approach the number of pixels used by PIF methods (Schott et al., 1988; Schroeder et al., 2006).

4.2. Classification accuracy assessment

A "confusion matrix" was utilized to infer classification accuracy (Congalton and Green, 2008; Foody, 2002; Jensen, 2005; Olofsson et al., 2013). An unaligned stratified random sampling technique was used to generate 1525 reference points for use in the confusion matrix (Haining, 1993). Random reference points were stratified to the distribution of thematic layer classes (Cochran, 1977).

The raster pixel value (our class value) of each random point was extracted from our classified map. The points were added to a high resolution imagery base layer provided by Bing Maps, where the actual class of each point was determined. The Bing Map-derived class (reference class) was compared with our classification to calculate producer's accuracy, user's accuracy, and Kappa statistics using reference points (Table 7). Olofsson et al. (2013) suggested that some classes may be inaccurately represented by a traditional sample count error matrix. They suggest using a statistical approach which accounts for rare classes and provides 'misclassification corrected' estimates of class area (Table 8). Other statistical parameters calculated include: (1) The area of each class using pixel counts; (2) An "error-adjusted" area estimate of each class (see Eq. (2) and discussion in Olofsson et al., 2013); and (3) the standard error of the error-adjusted area estimate (calculated using a 95% confidence interval; see Eqs. (3)–(5) in Olofsson et al., 2013) (Table 9).

Table 6
Regression data between the reference image (path 9 row 47) and adjacent images using the pseudo-invariant polygon (PIP) normalization method.

Scene	Band	Before correction					After correction[a]				
		# of pixels	Slope	Y-intercept	R^2	RMSE	# of pixels	Slope	Y-intercept	R^2	RMSE
Path 9 Row 46	2	1.35E+06	0.997	0.084	0.994	0.697	3.12E+05	1.00	−0.040	1.00	0.001
	3	1.35E+06	0.996	0.093	0.993	1.00	5.14E+05	1.00	−0.058	0.997	0.984
	4	1.35E+06	0.996	0.241	0.992	1.97	5.14E+05	1.00	−0.229	0.999	0.987
Path 8 Row 47	2	8.32E+04	0.934	0.579	0.806	2.74	8.32E+04	0.997	0.564	0.773	2.30
	3	8.32E+04	0.936	0.969	0.810	4.43	8.32E+04	1.01	−0.037	0.816	4.28
	4	8.32E+04	0.887	3.35	0.771	6.02	2.05E+05	1.01	0.540	0.738	4.64
Path 10 Row 47[b]	2	6.20E+05	0.974	−2.96	0.844	3.97	1.61E+03	1.08	−2.28	0.876	1.88
	3	6.20E+05	1.08	−6.16	0.811	4.97	1.61E+03	0.986	−0.484	0.860	2.81
	4	6.20E+05	1.06	−4.07	0.981	5.12	1.61E+03	1.02	−1.36	0.977	4.66

[a] After correction statistics were calculated from a set of pixels independent of the original PIPS used to derive the regression coefficients ("before correction").
[b] Note this scene was taken 392 days from the reference image.

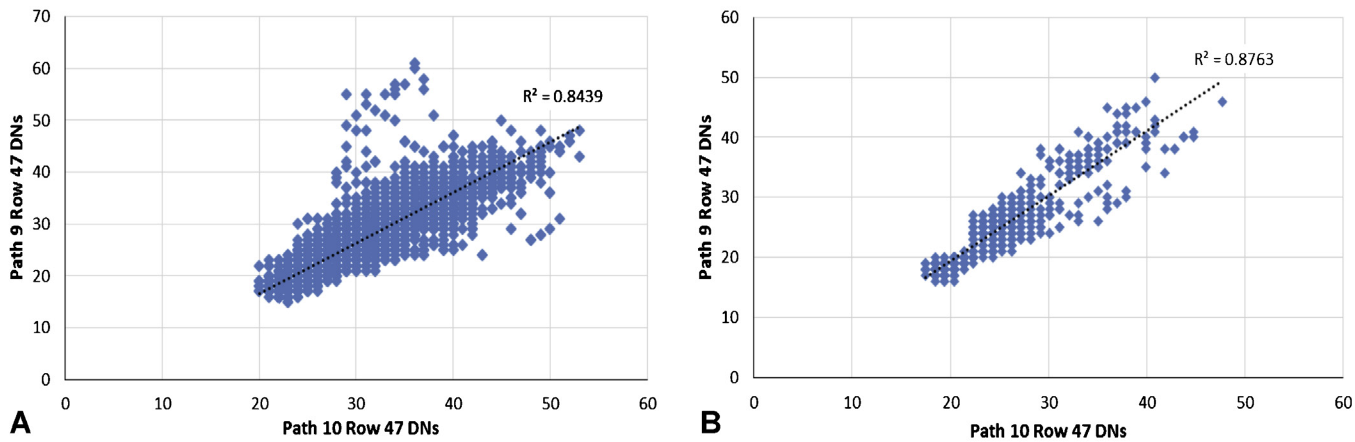

Fig. 6. Example comparison of DNs before and after normalization. (A) Pixels from original PIP; and (B) pixels from independent polygon after normalization.

Table 7
Confusion matrix used to determine the accuracy of the classified map of Haiti for the current study. Kappa statistics were calculated following the method outlined in Jensen (2000).

Class	TC[a]	SC/H[b]	B/NV[c]	Wetland	Water	No data	Total
TC[a]	356	55	1	2	0	0	414
SC/H[b]	51	462	23	3	1	0	540
B/NV[c]	0	74	171	0	0	19	264
Wetland	0	2	0	24	0	75	101
Water	0	1	2	0	51	8	62
No data	6	18	1	0	1	118	144
Total	413	612	198	29	53	220	1525
Producers	86%	76%	86%	83%	96%	54%	
Users	86%	86%	65%	24%	82%	82%	
Kappa	0.81	0.76	0.60	0.22	0.82	0.70	
Overall accuracy	78%						
Overall kappa	0.70						

[a] Tree cover.
[b] Shrub cover/herbaceous.
[c] Bare/non-vegetated.

4.3. Area calculation comparison

The final thematic map from our classification and the maps derived from global data products are shown in Fig. 7. These maps were used to calculate the area for each of the six classes (Table 10). The percentage of tree cover relative to total land area for each of the data sources (this study, Globcover, 2009, GLC2000, MCD12Q1, and CNIGS) after re-coding ranged from 7.0 to 32.4%. The percentage for tree cover in Haiti calculated using pixel counts from our thematic map was the greatest, 32.3% (32.4% using an error-adjusted area estimate (see Section 4.2)). This number is reduced to 29.4% after conversion to forest cover using the FAO criteria (see Section 4.4). According to the FAO, only 4% of Haiti's total land area is classified as Forest (FAO, 2010b).

All datasets compared for this study have some error associated with class translation between different classification systems, however translation uncertainties were greatest with Globcover (2009) and CNIGS. The recoding of Globcover

Table 8
Confusion matrix of class proportions presented following methods outlined in Olofsson et al. (2013). Parameters for each class in the confusion matrix are shown using proportions determined from sample counts. User and producer accuracies were estimated using these probabilities (see Olofsson et al., 2013 for further explanation).

Class	TC[a]	SC/H[b]	B/NV[c]	Wetland	Water	No data	Total (Wi[d])
TC	0.277422	0.042860	0.000779	0.001559	0	0	0.322620
SC/H	0.043156	0.390940	0.019462	0.002539	0.000846	0	0.456943
B/NV	0	0.037906	0.087593	0	0	0.009733	0.135231
Wetland	0	0.000016	0	0.000196	0	0.000611	0.000823
Water	0	0.000223	0.000446	0	0.011382	0.001785	0.013837
No data	0.002939	0.008818	0.000490	0	0.000490	0.057809	0.070547
Total	0.323517	0.480763	0.108771	0.004293	0.012718	0.069938	1.0
Producers	86%	81%	81%	5%	89%	83%	
Users	86%	86%	65%	24%	82%	82%	
Overall accuracy	83%						

[a] Tree cover.
[b] Shrub cover/herbaceous.
[c] Bare/non-vegetated.
[d] Wi represents class proportion with respect to total land area (2,703,933 ha).

Table 9
Area estimates for each class using techniques outlined in Olofsson et al. (2013).

Area parameters (ha)	TC	SC/H	B/NV	Wetland	Water	No data
Classified map area[a]	872,343	1,235,543	365,655	2225	37,414	190,754
Error adjusted area estimate[b]	874,769	1,299,952	294,108	11,607	34,389	189,108
Difference	−2426	−64,410	71,547	−9382	3025	1645
Standard error (95% CI)[c]	42,688	51,598	30,263	9704	6302	16,882
High estimate	917,457	1,351,550	324,372	21,311	40,691	205,990
Low estimate	832,080	1,248,355	263,845	1903	28,087	172,226
Standard error as % class area	4.9%	4.0%	10.3%	83.6%	18.3%	8.9%

[a] Calculated using the pixel count of each class.
[b] See Eq. (2) in Olofsson et al. (2013).
[c] See Eqs. (3)–(5) in Olofsson et al. (2013).

(2009) class 30 (Mosaic Vegetation (grassland/shrubland/forest) (50–70%)/cropland (20–50%)) may have incorporated error in area calculations for this dataset. For example, if class 30 were not proportionally recoded the resulting tree cover calculated from the Globcover (2009) would be lower; and if recoded as shrub cover/herbaceous the resulting area would be greater for this class.

The CNIGS dataset used to estimate 19.5% tree cover was translated from French to English and recoded to conform to the LCCS classification scheme. Uncertainty may have been introduced when translating certain classes. For example, the “Savannah with presence of other” class in the CNIGS dataset was recoded to shrub cover/herbaceous, had this class been recoded to tree cover, the resulting percent tree cover would have been greater.

One of the largest sources of error associated with our classification is shadow and cloud cover (7.1% mapped as no data). Large portions of clouds were present on the tip of the southwest peninsula (Fig. 4). Subsequently, large amounts of land area in this region were classified as “No data”. Based on this fact, other classes, including tree-cover, are likely slightly under-estimated.

4.4. Forest definition standardization

The FAO defines forest as “land spanning more than 0.5 ha with trees higher than 5 m and cover of more than 10 percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use.” (FAO, 2010b). This differs from our “tree cover” class in that a minimum area criterion was not established. The exclusion of agricultural areas was implicit in our supervised classification method. In order to apply the FAO minimum area criterion for forest cover to our thematic map: the raster thematic map was converted into vector format. Polygons classified as “tree cover”, which were less than 0.5 ha in area, were removed from our total tree cover area calculation and added to the shrub cover/herbaceous class. Removal of polygons not meeting FAO criterion converted our tree cover class to a forest cover class compatible with FAO criteria. Subsequent percent forest reported using our thematic map was calculated using the queried features (Table 8). Standardization to the FAO’s forest cover class definition reduces the tree cover class of our supervised classification from 32.3% (using pixel counts) to a forest cover class, consistent with FAO’s forest cover class definition, of 29.4%.

The FAO forest standardization procedure was not applied to the other global land-cover datasets compared (Globcover, 2009, MCD12Q1, and GLC2000). The minimum FAO area criteria applied to our classification need not to be applied to these datasets, as the individual pixel size used to derive each dataset is larger than 0.5 ha (Table 2). Also, a land use criterion for fruit tree plantations was not inherent in the classification scheme for these datasets. Fruit-tree plantations are not considered forest according to the FAO’s forest definition. No reliable statistics exist which detail the total land area occupied by fruit tree-plantations in Haiti. Therefore, our classification reports both on tree-cover and forest-cover. The global land-cover datasets report only tree-cover.

4.5. Evaluation of results

Our tree cover class (forest cover) had high producer’s accuracy (86%), user’s accuracy (86%), and Kappa statistic (0.81). The overall classification accuracy was 78.0% using reference point counts (Table 7) and 83% using class proportions (Table 8) (Olofsson et al., 2013). Error associated with overall classification accuracy is believed to be in large part due to the inability to spectrally differentiate wetland from shadows created by clouds, and shrub cover/herbaceous from forest, using only bands 2, 3, and 4. The effectiveness of the Olofsson et al. (2013) methods is highlighted by comparing the calculated accuracy (user and producer) of the wetland class. Wetland would be considered a rare class and error-adjusted area estimates for this class, using the methods outlined in Olofsson et al. (2013), would be more accurate. This is reflected in the change in producer’s accuracy (user accuracy did not change) from 83% using reference points to 5% using class proportions. The original area estimates using pixel counts (0.1%) was likely

Table 10
Area[1] comparison between our study, recoded data products, and FAO statistics.

Study/data product	TC % Area	SC/H % Area	Wetland % Area	B/NV % Area	Water % Area	No data % Area
GLC2000	7.0	77.6	11.9	0.1	0.8	2.6
MCQ12CD	21.1	77.2	0.0	0.9	0.8	0.0
Globcover2000	26.9	66.6	0.8	2.9	1.3	1.5
CNIGS	19.5	75.8	1.1	2.9	0.7	0.0
This study[a]	32.3	45.7	0.1	13.5	1.4	7.1
This study (error-adjusted)[b]	32.4	48.1	0.4	10.9	1.3	7.0
This study (FAO Forest Def.)[c]	29.4	48.6	0.1	13.5	1.4	7.1
FAO[d]	4.0	0.0	–	–	–	–

[a] Total area used for percentage calculations was 2,703,933 ha.
[b] See Eq. (2) in Olofsson et al. (2013).
[c] See text for details on the recoding using FAO land use definitions.
[d] These statistics are not remotely sensed, forest cover is the only statistic presented that conforms to our LCCS.

underestimated based on the error-adjusted area (0.4%). The area estimates and calculated accuracies of the two classes that are of most interest to this study, tree cover and shrub cover/herbaceous, remained largely unchanged using both methods (Table 9).

4.5.1. FAO methodology evaluation

An external review of the FRA 2010 publication included a survey used to evaluate data use. The most common use of FAO data and information were: research and analysis, academic papers,

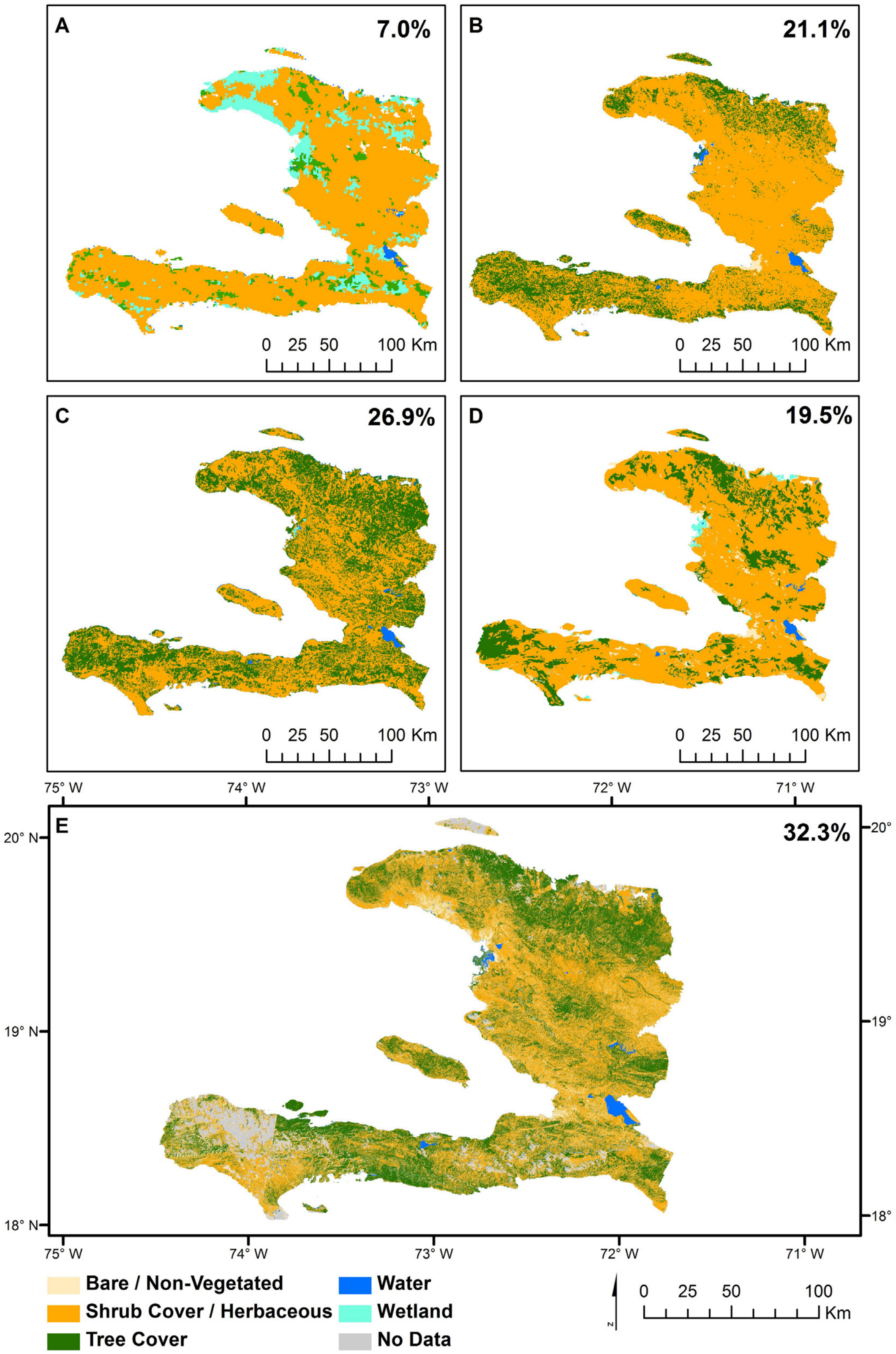

Fig. 7. The land-cover maps compared in this study. Each was classified using LCCS (FAO et al., 2009) land cover classes. (A) GLC2000, (B) MCD12Q1, (C) Globcover (2009), (D) CNIGS, and (E) Current study. Upper right: percent tree cover for each dataset. Note: 32.4% was the error-adjusted area estimate for (E) (see Section 4.2).

FAO-related work, policy documents, and education (Jankovic, 2010). Additionally, over half of the users of FAO data stated that this data was their primary source of information on global forest resources (Jankovic, 2010). This is consistent with the degree to which the FAO is cited by researchers (Table 1).

Our results (29.4% forest, 32.3–32.4% tree-cover) differ significantly from the reported FAO forest statistics (4.0% forest, 0% other wooded land). Differences between FAO reported statistics and independent remote sensing analyses are not unique to this study (Dong et al., 2012; Eva et al., 2012; Potapov et al., 2012). Remote sensing studies of forest cover in Africa found that forest cover loss was 12.1 million hectares lower than estimated by the FAO's Global Forest Resources Assessment 2010 (Bodart et al., 2013). Another remote sensing study in the Congo showed a net increase in forest cover between 2005 and 2010, contradicting the FAO's estimated net loss during the same period (Sánchez-Cuervo et al., 2012). Furthermore, FAO statistics indicate that Haiti experienced a net forest loss between 1990 and 2010, while other researchers have published results that indicate a forest increase between 1990 and 2010 (Aide et al., 2012; Alvarez-Berríos et al., 2013).

It appears that the best explanation for the significant difference between our results and the published FAO statistics involves the accuracy of the data sources. Several researchers have critiqued the FAO methodology, in particular its inconsistent data sources and class definitions across nations (Hoare, 2005; Mather, 2005; Matthews, 2001). The FAO recognizes this problem, as it admits that "differences among datasets from the various countries can be great owing to the methods applied" (FAO, 2000). National-level statistics provided by the FRA 2010 publication are acquired through individual country reports which are "compiled by an officially nominated national correspondent assisted by a team of national experts" (FAO, 2008). Examination of the Haitian Country Report (translated from French to English) on which the FRA 2010 publication was based reveals poorly documented methods and outdated data sources (Louijame et al., 2010). All forest area statistics for the years 1990–2010 were estimated using a linear extrapolation of a "planting rate" from an unspecified source and year (Louijame et al., 2010).

National correspondents responsible for reporting national statistics often lack the training and assistance needed to produce accurate results (Jankovic, 2010). In order to produce more accurate statistics, that are consistent across national boundaries, the FAO is transitioning to a more automated approach in the form of a global Remote Sensing Survey (RSS) (FAO and JRC, 2012; Ridder, 2007). The RSS used systematically sampled Landsat Imagery and MODIS Vegetation Continuous Field Index (VCF) imagery to produce global forest land-use and change maps (Potapov et al., 2011). National level statistics for Haiti from the FAO's RSS have yet to be released. However, future FRA publications, published by the FAO, will include remote sensing derived statistics at the national level for selected countries (FAO, 2013; Potapov et al., 2011). This dataset will provide a means of verifying the results of this study.

4.5.2. Spatial resolution and land-cover statistics

Differences between the extent, resolution, and type of land-cover statistics produced by global datasets have been well documented (Fritz and See, 2008; Fritz et al., 2010, 2011; Giri et al., 2005; Hansen and Reed, 2000; Herold et al., 2008; Jung et al., 2006; Kaptué Tchuenté et al., 2011; McCallum et al., 2006). While low resolution imagery may prove useful for rough continental estimates, moderate resolution images such as those obtained from the Landsat satellite are more reliable in producing accurate forest cover estimates on the national and regional scale, especially in areas where unique vegetation dynamics are present, such as Haiti's highly fragmented forest (Cihlar, 2000; Franklin and Wulder, 2002; Marceau et al., 1994; Mayaux and Lambin, 1995; Song and Woodcock, 2002; Treitz and Howarth, 2000; Wulder et al., 2004, 2008).

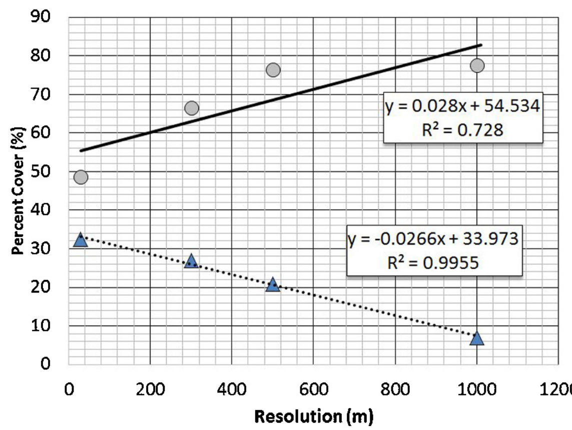

Fig. 8. Correlation between spatial resolution and percent land cover. The tree cover class is shown using triangles. Circles represent the shrub cover/herbaceous class.

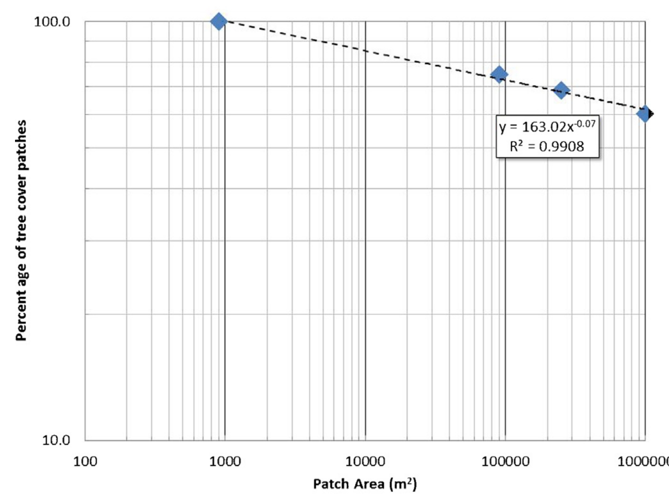

Fig. 9. Size distribution of tree cover patches in Haiti.

Plotting the recoded land cover statistics calculated for this study (Table 10) and data product resolution (Table 2) suggests a correlation between spatial resolution and land cover percentages (Fig. 8). The best fit trend-line for tree cover suggests a linear relationship with an $R^2 = 0.996$. For the shrub cover/herbaceous class the correlation with a linear trend is not as good, $R^2 = 0.728$. The trend suggests that coarse resolution imagery will tend to underestimate the amount of tree cover and potentially overestimate the amount of shrub cover/herbaceous cover.

As an independent means of verifying this result, polygons with a tree cover attribute were selected from the vector thematic map (see Section 4.4). These polygons were binned using four different size criteria (9.0E2, 9.0E4, 2.5E5, and 1.0E6 m^2), each area criterion corresponding to a resolution (pixel resolution^2) of the compared global datasets (Fig. 9 and Table 11).

As the area of each patch of tree cover increases, the percent of total tree cover identified decreases. For example, 68.5% of the patches classified as tree cover were greater than $\geq$2.5E5 m^2 (500 m pixel resolution). Based on our calculated tree cover for Haiti of 32.3%, a total tree cover area of 22.1% would be predicted using a 500 m pixel dataset. This compares favorably with the 21.1% tree cover area calculated from the recoded MCD12Q1 dataset (a 500 m resolution dataset). Accurate predictions using this model were possible for all datasets except the GLC2000 (Table 11). We

Table 11
Comparison of predicted and calculated tree cover for different patch sizes.

Patch length (m)	Patch area (m^2)	Identified (%)	Predicted tree cover area (%)	Calculated tree cover (%)
30	9.0E2	100.0	32.3	32.3[a]
300	9.0E4	74.9	24.2	26.9[b]
500	2.5E5	68.5	22.1	21.1[c]
1000	1.0E6	60.3	19.5	7.0[d]

[a] This study.
[b] Globcover2009.
[c] MCD12Q1.
[d] GLC2000; If wetlands were reclassified to tree cover, the result would have been 18.9%.

suspect this is due to misclassification of wetlands (11.9%). This class is an order of magnitude higher than any other estimate (Table 10). Visual inspection of the regions classified as wetland on the GLC2000 dataset using Bing Maps suggests many of these areas could be classified as tree cover.

We believe these two observations can be attributed to the fragmented and patchy nature of Haiti's forests. At a coarse spatial resolution, there are more mixed pixels containing small patches of forest and shrub cover/herbaceous compared to a higher spatial resolution. If forest patches occupied a small fraction of one of these mixed pixels it would most likely be classified as shrub cover/herbaceous. When a higher spatial resolution is employed, small forest patches can be recognized as individual forest pixels, separated from shrub cover/herbaceous pixels. In order to test the hypothesis that forest patch size and image resolution affect the accuracy of land cover calculations, additional patch size analysis in other geographic areas using a range of spatial resolutions are needed.

5. Conclusions

There is no doubt that deforestation is a serious and well documented occurrence in Haiti. However, accurate forest cover and deforestation data is needed to make sound political and economic decisions. Revision to the methodology used by FAO will likely yield more accurate land cover assessments, however there remains a significant cost in terms of accuracy when low resolution datasets are used to cover larger areas as part of global land cover assessments. As a result, reliable and accurate national-level land cover will likely only come from detailed national-scale studies which use land use cover classification systems which are both reproducible and scalable. If the results of this study are consistent with future results, revision of the FAO statistics reporting procedure is needed. Using forest patch size and distribution to select optimal image resolution, prior to image classifications, may result in more efficient and accurate national-scale land use evaluation.

Acknowledgements

We would like to thank Dr. James McNair, Dr. Richard Rediske, and Dr. Gang Xu for technical reviews of early manuscripts, and the anonymous reviewers for their helpful comments.

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