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# A comparison between cluster busting technique and a classification tree algorithm of a moderate resolution imaging spectrometer (MODIS) land cover map of Honduras

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A national land cover map derived from moderate resolution imaging spectrometer (MODIS) imagery products was developed for Honduras, Central America. We compared two methods of image classification: a cluster busting (CB) classification technique and a classification and regression tree (CART) algorithm. Field data samples were used to validate the resulting classifications. In the classification process, we used: a Google Earth™ sampling scheme, a time series of MODIS's Enhanced Vegetation Index (EVI) and digital elevation data (shuttle radar topography mission, SRTM). The CART classification method provided a more accurate classification (Kappa coefficient, $K$ 74%, overall model accuracy 79.6%) while compared to the CB classification (Kappa coefficient, $K$ 9%, overall model accuracy 25.1%). The findings are useful to design more accurate MODIS classification protocols in tropical countries.

**Keywords:** mapping; MODIS; tropics; Google Earth; EVI

## 1. Introduction

Developing countries in the tropics are experiencing a rapid land use conversion. Forests lands are being cleared for pasture and agriculture at an alarming rate. Approximately 10 million hectares of tropical forests were converted to agriculture and pasture in the last five years (FAO 2005). Central America and Mexico have the second highest global deforestation rate after the huge Amazon reserve (Eggen-McIntosh *et al*. 1994, Global Forest Watch 2010). Deforestation is causing enormous environmental disruption, jeopardizing the already weak economy (DeFries *et al*. 2004) and the well-being of the countries.

In the1990s, the country of Honduras produced a land cover map using Landsat 5 TM imagery with the help of the German government (COHDEFOR 1996). This forest resources map contained eight land cover classes (dense conifer forest, sparse conifer forest, mangrove forest, broadleaf forest, mixed forest, water bodies,

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neighbouring country, non-forestlands) and was produced by a team of experts using an ocular inspection of Landsat imagery. The methodology to produce the map was time-consuming and not easily replicable, thus making it a useful product at a single moment in time, but not useful for monitoring purposes.

Over the last decade, there have been other attempts to create a national land cover map in Honduras. In 2001, a land cover map was developed by a World Bank sponsored initiative and another one by the Tropical Agricultural Centre for Higher Education and Research, CATIE (Ordóñez and House 2002). Neither of them had a transparent and replicable methodology and the government was still uncertain about how much area was covered by forest or other lands. In 2005, a forest inventory was conducted throughout the country. Around 300 sampling plots were established systematically all over the country. Due to the lack of funding, the inventory was not complemented with the remote sensing assessment and soon became obsolete (AFE-COHDEFOR 2006).

The lack of proven scientific methods of forest cover estimation has produced ambiguous results, with large discrepancies. Stonich (1993) suggests that the deforestation rate in Honduras is currently 80,000 ha per year, which is one of the highest deforestation rates in the Western hemisphere. According to the Food and Agriculture Organization's global assessment of forest resources, Honduras lost some 186,000 ha of forest between 2000 and 2005, the highest annual deforestation rate in Central America (FAO 2005). In summary, both studies suggest that forests in Honduras are being cleared rapidly.

The objective of this project was to create a contemporary land cover map for the country of Honduras using free and readily available imagery from the moderate resolution imaging spectrometer (MODIS) sensor. Our contemporary map would follow the design of the 1990s map produced from Landsat imagery with the aid of the German government. Given the availability of MODIS imagery, and the frequency with which it is available, MODIS offers an excellent imagery source for monitoring purposes.

Specifically, the objectives for this project were to:

(1) Develop a national-level land cover map for the country of Honduras that would form a baseline dataset from which forest monitoring could be carried out.
(2) Evaluate the accuracy of the land cover map using two avenues of image classification: cluster busting (CB) and a classification and regression tree (CART) algorithm.

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## Data and methods

### *Study area*

Honduras is placed in the middle of the Central American isthmus, between 13° and 16° latitude North and 83° and 89.5° longitude West (Figure 1). It has an area of 112,088 square kilometres. It is a rich country in terms of natural resources and has the largest forest cover among the other Central American nations (AFE-COHDEFOR 2006). Approximately 50% of the country is still covered by undisturbed forests (Gutierrez 1992, Laboranti 1992, Richards 1996) which include humid tropical forests, arid or deciduous tropical forests, cloud forests, mangrove wetlands and pine forests.

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Figure 1. Location of Honduras, Central America.

***Land use classification***

We used a modified land use classification system used by the International Geosphere – Biosphere Programme (IGBP) (UNESCO 1973, Jensen 2005). This classification system was selected because it has been used by the Honduran government authorities and because it approximated the land cover legend from the map produced in the 1990s. This classification system has also been largely used by other projects either globally (Loveland *et al*. 2000, Friedl *et al*. 2002) or in the Central and South American regions (Latifovic *et al*. 2000, Muchoney *et al*. 2000, Brown *et al*. 2007), due to its capacity to fit the MODIS resolution.

In the final map, 11 classes were delineated (Table 1). Initially, our intention was to map eight classes (dense and sparse pine forest, broadleaf forest, mixed forest, urban, mangrove forest, water bodies and agriculture farms/pasture), however, through the process of field sampling, three more classes were added to the classification (commercial agriculture, shrublands and savannas).

***Image selection and preparation***

The MODIS sensor provides an ideal remotely sensed platform for developing a national-level land cover/resource monitoring programme (Loveland *et al*. 2000, Muchoney *et al*. 2000, Brown *et al*. 2007). With 500 m pixel resolution it was considered a moderate resolution imaging sensor and could not be used for highly detailed land cover mapping (by comparison, the Landsat sensor offers 30 m pixel resolution). However, MODIS has several key advantages that make it highly

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Table 1. Legend used in the land cover mapping of Honduras.

| Label | Symbol | Classification system (Adapted from IGBP, Jensen, 2005) |
|---|---|---|
| Dense evergreen needleleaf forest | BPD | Lands dominated by trees with a per cent canopy cover >60% and height exceeding 2 metres. Almost all trees remain green all year. Canopy is never without green foliage |
| Sparse evergreen needleleaf forest | BPR | Lands dominated by trees with a per cent canopy cover between 30–60% and height exceeding 2 metres. Almost all trees remain green all year. Canopy is never without green foliage |
| Broadleaf forest | BLF | Lands dominated by trees with a per cent canopy cover >60% and height exceeding 2 metres. Almost all trees remain green all year. Canopy is never without green foliage |
| Mixed forest | BMX | Lands dominated by trees with a per cent canopy cover >60% and height exceeding 2 metres. Consists of tree communities with interspersed mixtures or mosaics of the other four forest cover types. None of the forest types exceeds 60% of landscape |
| Shrublands | MAT | Lands with woody vegetation less than 2 metres tall and with shrub canopy cover is >60%. The shrub foliage can be either evergreen or deciduous |
| Mangrove | BMG | Lands with a permanent mixture of water and herbaceous or woody vegetation that cover extensive areas. The vegetation can be present in either salt, brackish, or fresh water |
| Water bodies | LYL | Oceans, seas, lakes, reservoirs and rivers. Can be either fresh or salt water bodies |
| Agriculture and pasture | AGP | Lands covered with temporary crops followed by harvest and a bare soil period (e.g. single and multiple cropping systems). It also includes natural or planted pasture for livestock |
| Commercial agriculture | AGC | Land covered by perennial crops such as bananas, pineapple and oil palm |
| Urban | URB | Land covered by buildings and other man-made structures. Note that this class will not be mapped from the AVHRR imagery but will be developed from the populated places layer that is part of the Digital Chart of the World |
| Woody savannas | SAB | S Lands with herbaceous and other understory systems, and with forest canopy cover between 30–60%. The forest cover height exceeds 2 metres |

suitable for mapping large areas such as an entire nation. For example, a single MODIS scene covers the entire country. Additionally, with seven spectral bands, MODIS provided adequate spectral resolution to map vegetation. These seven bands approximate the six spectral bands offered by the Landsat sensor. The comparative advantages of using MODIS are described in Vermote (2008). Imagery and products derived from MODIS are offered without cost from the United States Geological Survey (USGS) and can be downloaded from the World Wide Web (www.glovis.gov).

### *Cluster busting modelling approach*

Identification of land use classes using a CB method is popular due to its versatility and ability to produce fast and accurate results (Muchoney *et al.* 2000). In essence, CB classification involves using a clustering algorithm such as ISODATA (iterative self-organizing data analysis technique algorithm) in an unsupervised fashion to produce a set of spectral clusters. The analyst assigns labels to the clusters, so he/she can confidently label, and return all remaining unclassified pixels to be clustered once again with the clustering algorithm. The process continues until the analyst no longer feels confident in labelling additional clusters. Any remaining pixels remain unknown, or unclassified.

### *Classification and regression tree (CART) modelling approach*

CART was developed by Breiman *et al*. (1984) and was quickly recognized as a valuable tool for discriminating complex relationships among environmental variables (Friedl *et al*. 2002, Falzarano *et al*. 2005). Classification decision trees readily accept a variety of measurement scales in addition to categorical variables, and have demonstrated improved accuracies over the use of traditional classifiers (Hansen *et al*. 1996, Pal and Mather 2003).

Several predicting layers were used in the primary classification. Spatial data layers used to map land cover included image-derived and ancillary datasets such as MODIS images from 2007 and 2008 (seven bands), the Enhanced Vegetation Index (EVI) and the 30-m digital elevation models (DEM) obtained from the NASA's shuttle radar topography mission (SRTM) (http://www2.jpl.nasa.gov/srtm/).

Using the National Land Cover Dataset (NLCD) mapping tool (Homer *et al*. 2004), decision tree models were generated in See5© (RuleQuest Research 2004) with the boosting option, and then spatially applied in ERDAS Imagine©. Modelling was iterative and subsequent iterations were tested using different combinations of predictor datasets, or additional samples in an attempt to improve the model. An iterative process of adding/subtracting predictive layers from the model produced a more refined map.

### *Sampling training data using Google Earth™*

Our sampling approach can be described as a systematic-selective hybrid sampling design. There were 311 site areas on a grid covering the entire country, used by past studies (AFE-COHDEFOR 2006). Between 10–15 points were chosen for each site area. Image interpretation was conducted using Landsat ETM with ArcGIS© ver 9.3.1 and high resolution orthophotography using Google Earth. The image interpretation of Landsat ETM involved the assigning label attribute to each point location on a systematic grid of site areas. Table 1 identifies the classes that we anticipated would be identifiable with the sampling method (Jensen 2005). A total of 5616 samples were collected to build the training dataset.

### *Ground truth data and model validation*

We collected 240 ground-based field samples by traversing navigable roads in three different mapping areas (North coast, South and Western part of the country) and opportunistically selecting plots that met criteria of appropriate size (500 by 500 m or 25-ha minimum) and composition (stand homogeneity). Each plot was identified with a UTM coordinate using a GPS. Field data were recorded onto paper field forms and subsequently entered into a database. Due to accessibility and economic

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constraints, only nine classes out of eleven were field sampled. After the classification process, the 240 samples were dropped over the classified layers (CB and CART).

Model validation has the purpose of objectively measuring the accuracy of the map. Usually this is given by providing a measure of map accuracy (Gopal and Woodcock 1994, Congalton and Green 1999). The map validation was conducted using the Kappa Index (*K*) described by Jensen (2005). It is calculated from an error matrix table where the classes of reference data are horizontally arranged while the classified classes are vertically arranged. The Kappa Index is calculated as follows (Equation (1)):

$$K = \frac{N \sum_{i=1}^{k} x_{ii} - \sum_{i=1}^{k} \left( x_{i+} \times x_{+i} \right)}{N^2 - \sum_{i=1}^{k} \left( x_{i+} \times x_{+i} \right)} \qquad (1)$$

where $x_{ii}$ represents the number of combinations along the diagonal, $x_{i+}$ is the total observations in row *i*, $x_{+i}$ total observations in column *i* and *N* is the total number of cells.

## Results

### *Land cover map*

The most relevant mapped classes were broadleaf forest (BLF) and pine forest (sparse and dense) (BPD, BPR) that cover close to 60% of the country (Table 2, Figures 2 and 3). These forest types are located following the steep terrain that runs from west to east and north to south in the central part of the country. The broadleaf forest is located along the north coast and in a corridor that goes from the middle to the north-western part of the country, following areas of higher precipitation. Pine forests are located in drier areas in smaller patches scattered all over the central and western part of the country.

In between these patches, subsistence agriculture and pasture lands areas are found, forming a mosaic of agricultural and forest patches. In bigger patches, agro-

Table 2. Areas of land use and cover as a result of the land cover mapping of Honduras.

| Legend (name – code) | Area from CART classification | | Area from cluster busting classification | |
|---|---|---|---|---|
| | km$^2$ | % | km$^2$ | % |
| Commercial agriculture – AGC | 4135 | 3.71 | 8895.3 | 7.98 |
| Agriculture pasture –AGP | 28,961 | 25.98 | 36,377.5 | 32.63 |
| Dense pine forest – BPD | 13,859 | 12.43 | 8169.3 | 7.33 |
| Sparse pine forest – BPR | 11,919 | 10.69 | 9071.0 | 8.14 |
| Broadleaf forest – BLF | 39,249 | 35.21 | 35,038.7 | 31.43 |
| Mangrove forest – BMG | 1067 | 0.96 | 1454.8 | 1.31 |
| Mixed forest – BMX | 673 | 0.60 | 0.0 | 0.00 |
| Waters bodies – LYL | 689 | 0.62 | 10,759.8 | 9.65 |
| Shrublands – MAT | 8592 | 7.71 | 1103.5 | 0.99 |
| Urban – URB | 204 | 0.18 | 0.0 | 0.00 |
| Woody savanna – SAB | 2121 | 1.91 | 598.1 | 0.54 |
| Total | 111,468 | 100.00 | 111,468 | 100.00 |

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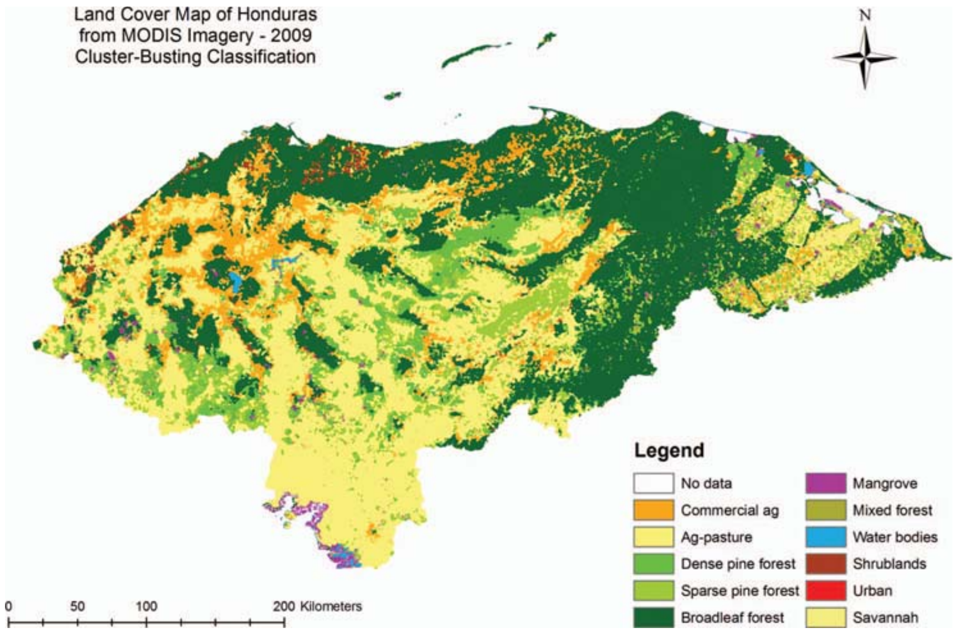


Figure 2. Land use and cover obtained from a cluster-busting classification of MODIS data from Honduras, Central America.

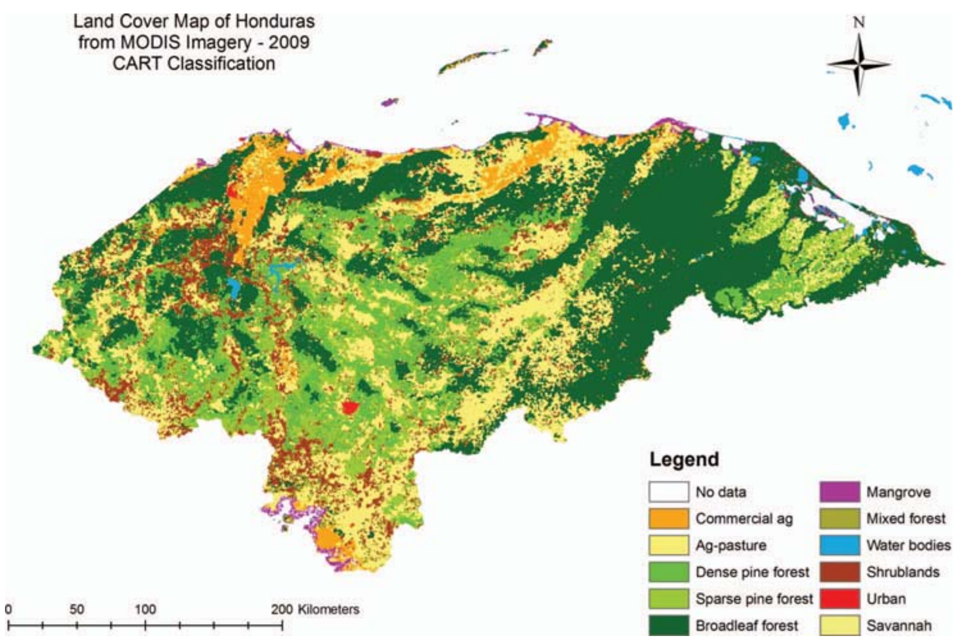


Figure 3. Land use and cover obtained from a CART classification of MODIS data from Honduras, Central America.

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commercial activities (AGC) are located in the intermountain larger valleys. These areas are dedicated to high yield crops. Mangrove forest was mapped in the pacific coast where most of this coastal ecosystem is located. We were able to identity these large areas. Shrublands (MAT) were also located mostly in the western and central regions and are often seen as areas of transitions where the forest has been cleared and/or burned and most of the cleared areas have remained untouched to produce a secondary forest. This is true for most of the cleared and/or burned areas for either pine or broadleaf forest.

The urban class (URB) identified only when urban settlements were large (more than 200,000 inhabitants). Smaller urban centres were not mapped given the spatial and spectral resolution of the MODIS signal. All urban settlements were not mapped with CB method. The mixed forest was detected in the transitional zones between the pine forest and BLF. Due to its foliar composition, its detection was not very accurate. An explanation for this is discussed later in this article.

Honduras has only two important lakes (LYL): they both are located in the central part of the country and were accurately mapped. The last class detected by the MODIS sensor was the woody savanna. A peculiar ecosystem located in the northern and eastern portion of the country, close to the Caribbean coast. This is typically composed by grass and shrub vegetation accompanied by sparse pine trees.

## *Model validation*

### *Cluster busting*

The results showed that the Kappa Index for the CB classification (CB) was: $K$ 0.09 and overall accuracy 25.1%, see Table 3 (Figure 2). By examining the numbers in the off-diagonal cells, the error matrix for the CB land cover map (Table 3) tells us that the overall accuracy of the map was very low: 25%. It also shows two types of error: (1) errors of commission, and (2) errors of omission (Jensen 2005). Errors of commission represent reference locations that were

Table 3. Accuracy assessment results of the cluster busting classification land cover map of Honduras.

| | Reference data | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| CB model | AGC | AGP | BPD | BPR | BLF | BMG | BMX | LYL | MAT | Row total |
| AGC | **14** | 9 | 9 | 2 | 0 | 0 | 1 | 0 | 1 | 36 |
| AGP | 28 | **23** | 3 | 33 | 5 | 0 | 1 | 0 | 3 | 96 |
| BPD | 0 | 1 | **3** | 2 | 0 | 0 | 0 | 0 | 0 | 6 |
| BPR | 2 | 3 | 2 | **3** | 1 | 0 | 0 | 0 | 0 | 11 |
| BLF | 39 | 11 | 0 | 0 | **9** | 13 | 0 | 0 | 0 | 72 |
| BMG | 1 | 0 | 0 | 1 | 0 | **6** | 0 | 0 | 0 | 8 |
| BMX | 0 | 0 | 0 | 0 | 0 | 0 | **0** | 0 | 0 | 0 |
| LYL | 2 | 0 | 0 | 0 | 0 | 0 | 0 | **1** | 0 | 3 |
| MAT | 0 | 2 | 0 | 0 | 0 | 1 | 0 | 0 | **0** | 3 |
| Column total | 86 | 49 | 17 | 41 | 15 | 20 | 2 | 1 | 4 | **235** |
| Accuracy | **16.3%** | **46.9%** | **17.6%** | **7.3%** | **60.0%** | **30.0%** | **0.0%** | **100.0%** | **0.0%** | |

Note: Kappa Index, $K$ 0.09; overall accuracy 25.1.

incorrectly mapped as other mapped classes, and are presented as the percentages at the right of the row totals. Tables 2 and 3 tell us that the CB classification mapped better the following classes: BLF with 60% accuracy followed by agriculture-pasture (AGP) 47%. Table 2 also confirms that these two classes were better mapped when compared to the CART classification. Water bodies (LYL) resulted with 100% accuracy; however, we had only one sample that fell in this class. There was 30% accuracy when mapping mangrove forest (BMG). The other classes (AGC, BPD, BPR, BMX and MAT) showed less than 20% accuracy.

### *CART classification*

The results showed that the Kappa Index for the CART classification (CART) was: $K$ 0.74 and overall accuracy 79.6%, see Table 4 (Figure 3). The error matrix for the CART land cover map (Table 4, Figure 3) tells us that the overall accuracy of the map was 79.6%. Errors of commission represent reference locations that were incorrectly mapped as other mapped classes, and are presented as the percentages at the right of the row totals (Jensen 2005). For example, there were 86 reference samples that 'landed on' AGC, but only 81 of those were AGC. The four samples that were not AGC, but landed on AGC, these are considered errors of commission. Errors of omission represent locations on the map that were not mapped correctly, and are presented as the percentages at the bottom of the column totals. For example, there were a total of 86 AGC reference locations, but only 84 (94.2%) were in locations mapped as AGC. The remaining 5.8% were mapped as something else and are considered errors of omission.

By examining the error matrices for the map, we can see that some land cover classes were mapped very well, while others were mapped quite poorly. If we consider any class mapped with accuracy greater than 80% (mapped well), we note that AGC, AGP, BLF, BMG and LYL were all mapped very well. Classes mapped moderately well (50–80%) were BPD, BMX and MAT. Classes mapped poorly ($<50\%$) were only BPR. For example, in the map, we noted that almost 50%

Table 4. Accuracy assessment results of the CART classification land cover map of Honduras.

| CART model | Reference data | | | | | | | | | Row total |
|---|---|---|---|---|---|---|---|---|---|---|
| | AGC | AGP | BPD | BPR | BLF | BMG | BMX | LYL | MAT | |
| AGC | **81** | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 81 |
| AGP | 4 | **47** | 1 | 4 | 3 | 0 | 1 | 0 | 1 | 61 |
| BPD | 0 | 0 | **13** | 1 | 0 | 0 | 0 | 0 | 0 | 14 |
| BPR | 0 | 0 | 1 | **10** | 0 | 0 | 0 | 0 | 0 | 11 |
| BLF | 1 | 0 | 2 | 1 | **12** | 0 | 0 | 0 | 0 | 16 |
| BMG | 0 | 0 | 0 | 0 | 0 | **20** | 0 | 0 | 1 | 21 |
| BMX | 0 | 1 | 0 | 22 | 0 | 0 | **1** | 0 | 0 | 24 |
| LYL | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **1** | 0 | 1 |
| MAT | 0 | 1 | 0 | 3 | 0 | 0 | 0 | 0 | **2** | 6 |
| Column total | 86 | 49 | 17 | 41 | 15 | 20 | 2 | 1 | 4 | **235** |
| Accuracy | **94.2%** | **95.9%** | **76.5%** | **24.4%** | **80.0%** | **100.0%** | **50.0%** | **100.0%** | **50.0%** | |

Note: Kappa Index, $K$ 0.74; overall accuracy 79.6.

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(22 samples) of BPR reference locations were erroneously mapped as BMX. In general, we can conclude that BPR was 'confused' with BMX, and that more reference samples are needed to make a better assessment of CART classification performance on the MAT and BMX classes.

**Discussion**

The CART classifier made a more accurate MODIS image classification. Even though the CART method was considerably a more time-consuming one, we found that it performed much better than the CB method. The CART classifiers are a more powerful tool for discriminating land cover classes. Our results were very consistent with other investigations (Latifovic *et al*. 2000, Friedl *et al*. 2002). They are also a very interpretable and explicit method, because their hierarchical decision rules and splits can be revealed and explained (Lowry *et al*. 2007). The Google Earth sampling scheme proved to be a very cost-effective procedure. No references were found on the previous use of this approach for training data collection of a land map use.

Although the CB method resulted in a less accurate image classification, we were able to identify some advantages over the CART method. With sufficient expert knowledge of the area, the CB classification method was able to identify and discriminate classes represented by large and continuous patches, for instance, BLF and AGP classes. The resulting areas of these two classes are similar to the ones found for the CART classification (see Table 2). They were able to be discriminated in a short time, with relative easiness and moderated accuracy – between 45% and 60%. This proved that the CB method can be used for a preliminary classification, targeting the large and continuous classes. These findings coincide with other studies using unsupervised approaches (Muchoney *et al*. 2000, Lotsch *et al*. 2003).

By examining the error matrices for the map we can observe that some land cover classes were mapped very well, while others were difficult to mapped. If we consider any class mapped with accuracy greater than 80% mapped well, we note that AGC, BPD, BLF and BMG are all mapped very well. Classes mapped moderately well (50–80%) are AGP, LYL, URB and SAB. Classes mapped poorly ($<50\%$) are BPR, BMX and MAT.

MODIS capability and the classification procedure exceeded the project expected goals. At the beginning of the study, eight classes were set up in such way that can potentially be discriminated and mapped. As the project progressed, three (3) more classes were added to the classification algorithm. The accuracy assessment of the map was very high particularly for some classes such as BLF, mangrove forest (BMG) and commercial agriculture (AGC).

We also found that MODIS data had some disadvantages, especially at discrimination of some classes such as: sparse pine forest (BPR), mixed forest (BMX) and shrublands (MAT). This is basically a limitation of the sensor to clearly detect these classes at a moderate resolution of 500 m, which are transitional classes; however, these classes are considered a transition of secondary forest which is constantly growing to become primary forest or fully grown forest. In the case of shrublands, they will grow until they become adult trees. Similarly, in the mixed forest (BMX), trees will mature until either conifer or broadleaf species become dominant. Therefore, we believe that the MODIS signal does not work very well at discriminating different vegetation stages at this resolution, although it does very

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well differentiates fully grown or developed vegetation classes and types. Others have found these MODIS limitations in the past (Latifovic *et al*. 2000, Muchoney *et al*. 2000). Similarly Eggen-McIntosh *et al*. (1994) found the same obstacles using course resolution imagery such as AVHRR imagery.

## Summary

The use of MODIS imagery and the procedure employed for classification provided outstanding results in term of classification accuracy. MODIS imagery proved to be very affordable and successful by identifying and discriminating land use classes at the country level. The accuracy assessment of the map was very high particularly for some classes such as BLF, mangrove forest and commercial agriculture. The objective of the accuracy assessment was to quantitatively measure the accuracy of a MODIS derived land cover map product. Eleven land cover classes were mapped and their agreement assessed with an error matrix and Kappa statistics. Overall accuracy was 76% for the CART map product. This level of accuracy was found similar to other mapping efforts at a country level scale (Laba *et al*. 2002, Lotsch *et al*. 2003).

The Google Earth sampling protocol seems very promising as a cost-effective method to collect training samples without needing costly field visits. It showed a high accuracy as was used to collect the sampling training data. This has a scientific and environmental visualization tool and has been increasingly used since its launch in 2005 (Sheppard and Cizek 2009). With minor training sessions, analysts were able to operate and collect samples. Despite the tedious work involved in the sampling collection, very few mistakes were made when interpreting the images.

We can conclude that classes with large and continuous patches can be more easily mapped using a CB classification approach. These classes can be BLF and AGP. Then, a CART classification approach can be better used to map classes such as BPD, BPR, AGC and BMG, which represent smaller, but more solid and more heterogeneous patches. Fully grown vegetation classes such as AGC, BPD, BLF and BMG were all mapped very well using the CART approach. Transitional vegetation classes such as BMX, BPR and MAT were very poorly mapped and were highly confused among them. We detected that the cause may be attributed to a MODIS sensor limitation. We suggest that using a higher resolution image such as Landsat or ASTER images may be a more viable option to map these confusing classes.

The present study also demonstrates that it is possible to perform a national land cover mapping procedure with an acceptable level of accuracy and publicly available moderate resolution satellite data.

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