Integration of Hyperion Satellite Data and A Household Social Survey to Characterize the Causes and Consequences of Reforestation Patterns in the Northern Ecuadorian Amazon

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Abstract

The integration of Hyperion and Ikonos imagery are used to differentiate the subtle spectral differences of land-use/land-cover types on household farms in the Northern Ecuadorian Amazon (NEA) with an emphasis on secondary and successional forests. Approaches are examined that include the use of Principal Components Analysis to compress the Hyperion hyperspectral data to its most vital spectral channels; linear mixture modeling to derive sub-pixel fractions of land-use/land-cover types through the generation of spectral endmembers; and supervised and unsupervised classifications to map forest regrowth, agricultural crops and pasture, and other land-uses on 18 survey farms that are spatially coincident with the imagery. A longitudinal socio-economic and demographic survey (1990 and 1999) is used to characterize household farms; a community survey (2000) is used to assess nearby market towns and service centers; GIS is used to represent the resource endowments of farms and their geographic accessibility. Statistical relationships are examined using Spearman rank correlation coefficients to assess the linkages among a number of selected social, geographical, and biophysical variables and secondary and successional forest on household farms. Relationships suggest the importance of household characteristics, farm resources, and geographic access of secondary forests on surveyed household farms that were previously deforested and converted to agriculture through extensification processes. Results support the integrated use of hyperspectral and hyperspatial data for characterizing forest regrowth on household farms, and the use of multi-dimensional social survey data and GIS to assess plausible causes and consequences of land-use/land-cover dynamics in the NEA.

Introduction

The transformation of the Earth's surface is linked to a variety of scientific and policy issues that revolve around the social and ecological dynamics of land-use/land-cover (LULC) change. As forests are converted to alternate land-uses (or degraded), forests and the ecological services that they provide are profoundly transformed, as are the feedback mechanisms that link people and environment. While a significant amount of attention has been paid to deforestation as a transformative, socio-economic, and biophysical process in tropical forest environments, comparatively little attention has been paid to the evolution of forests through reforestation and secondary forest succession, as well as their direct and indirect impacts on population-environment interactions.

On a global basis, forests are essential as a major carbon sink. Additionally, they regulate climate and mediate greenhouse gases, influence the natural flora and fauna, and protect the land and their regenerative properties, as well as impact human behavior and agency in fundamental ways (Fearnside, 1996). Land conversion through deforestation and/or reforestation influences the human dimension. For instance, population migration patterns are affected by the push and/or pull factors of LULC change in migration source and destination areas, the adoption of alternative household livelihood strategies that may involve on-site land-use change, as well as remittances generated through off-farm employment of household members, usually young adults. Part of the calculus of household wealth and assets also involves household decision-making regarding agricultural extensification and intensification on farms and the exploitation of forest resources.

Despite the unprecedented advances in understanding the causes and consequences of tropical deforestation (e.g., Lambin *et al.*, 2001; Pan *et al.*, 2004; Messina *et al.*, 2006; Mena *et al.*, 2006; Lambin *et al.*, 2006), less is understood about tropical reforestation through secondary or successional forest processes. This is particularly true in the Amazon Basin as (a) secondary forests emerge after deforestation when land is abandoned, and (b) purposely left to successional reforestation on land parcels of functioning farms that are shifted to alternate uses in response to emerging market conditions, labor availability, and the demographic character and socio-economic needs of households. Reforestation also occurs following selective logging, forest patch removal through various forms of

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clear-cutting, and/or land degradation caused by road building, petroleum exploitation, and natural calamity.

The accurate characterization of the rates and patterns of secondary forest regrowth, as well as the social and biophysical relationships linked to forest dynamics are needed to effectively examine the motivations and trajectories of forest change, as well as carbon sequestration rates and patterns and carbon budgets calculated over space and through time (Ramankutty *et al.*, 2007). Also of critical importance is the realization that livelihoods of local populations depend on forest resources for some proportion of their household livelihoods (Toledo and Salick, 2006; Gavin, 2007), and that the impact of secondary forests on human-environment interactions have considerable implications for resource conservation and economic development as a consequence of direct and indirect uses of the forest.

The basic ecology of secondary forests and their pattern-process relations indicate that complex interactions emerge at different spatial and temporal scales (Brown and Lugo, 1990; Fearnside, 1996; Chokkalingam and De Jong, 2001; De Jong *et al.*, 2001). Compared to primary forests, nutrient cycling of secondary forest is generally marked by a rapid accumulation of nutrients, fast cycling through litter-fall, and rapid turnover of nutrients and their uptake by roots (Brown and Lugo, 1990). Secondary forests rapidly attain a forest structure similar, in many respects, to mature forests, i.e., canopy height and basal area (Pena-Claros, 2003). However, the species composition of secondary forests is generally simpler than mature forests, with indicator species of secondary forest succession that are common across secondary forest patches in a particular region. Additionally, secondary forests are often composed of a lower number of endemic species and a higher level of invasive species than mature forests (Lugo and Helmer, 2004).

In recent years, there have been considerable advances in the study of factors that promote the emergence and management of secondary forests in tropical settings (Coomes *et al.*, 2000; De Jong *et al.*, 2001; Perz and Skole, 2003b), their sustainability (Chokkalingam *et al.*, 2001; Kammesheidt, 2002), and their feedback to local or regional demographic or socioeconomic characteristics of the human dimension. Previous studies have often viewed reforestation through the lens of forest transition theory (Perz, 2001; Rudel *et al.*, 2002; Perz and Skole, 2003a; Rudel, 2005), household life cycle theory (McCracken *et al.*, 1999; Perz, 2001), and bid-rent approaches (Walker, 2004). These studies indicate that secondary forests occur as a result of a set of complex and interactive socioeconomic, demographic, and biotic factors that are dynamic across spatial and temporal scales. Further, secondary forests and human-environment interactions are context dependent: they respond to larger spatial processes that occur at the local, regional, and trans-national scales; vary in response to short- and long-term fluctuations in population-environment interactions; and influence decision-making of households, as well as higher order social units and institutions.

The perceptions and uses of secondary forest among local populations (i.e., indigenous groups versus colonists) are different, and therefore, have varying implications for resource conservation and sustainable economic development. Indigenous groups, for instance, use secondary forest plots (i.e., agricultural gardens that are partially abandoned or made inactive) mostly for fruit collection and as hunting magnets. An ethnographic study, carried out in eight indigenous communities in the Ecuadorian Amazon by the University of North Carolina, Ecuador Project Team, indicates that inactive gardens are used in different ways after cultivation by various ethnic groups (Bilsborrow *et al.*, 2003). Gardens are used for about three years and then left fallow for one to eighteen years. Post-cultivation use in the fallow period is diverse depending upon whether the plot was used for cash or subsistence crops, collection of fruit, and less frequently, for hunting. Colonists, on the other hand, occasionally allow secondary forests to regenerate to recharge soil nutrients and prevent soil erosion, and often renew cultivation after a relatively short period of fallow. While land abandonment on colonist farms has been relatively rare in the Ecuadorian Amazon, parcel abandonment on functioning farms is part of the agricultural matrix practiced as a consequence of declining soil fertility, changes in labor availability and household demographics, improvement in geographic accessibility to other farms and market towns, and constraints imposed by market conditions.

Some of the possibilities, limitations, and uncertainties of using remote sensing to characterize secondary forests in tropical regions have been described by Foody and Curran (1994), Rignot *et al.* (1997), Kimes *et al.* (1998 and 1999), Tokola *et al.* (1999), Castro *et al.* (2003), and Lu *et al.* (2003a). While the repetitive and broad area coverage of landscape-level satellite systems, coupled with their spatial, spectral, and temporal resolutions, have been regularly used to map forest dynamics, considerable challenges remain in assessing secondary forests that include, for instance: (a) the temporal synchronization of satellite and field data, including the collection of socio-economic and demographic data through social surveys to examine the practices and motivations of land conversion, (b) ambiguity in the trajectory of secondary forest succession between image dates of an assembled time-series, (c) atmospheric contamination of spectral response patterns and cloud concealment (and their shadows) of landscape features, (d) topographic effects related to moisture patterns and spectral biases, and (e) the applicability of relatively new remote sensing systems, including hyperspectral Hyperion data for mapping different levels of reforestation occurring on household farms, with the intent to link mapped reforestation patterns to socio-economic and demographic survey data, and derived biophysical and geographical forces and factors, to assess the causes and consequences of LULC change.

Image classifications used to identify and characterize the composition and spatial structure of secondary forests in tropical environments are further constrained by traditional methods and commonly-used sensor systems (Carreiras *et al.*, 2006). For instance, in the Northern Ecuadorian Amazon, households are the chief proximate cause of land dynamics, and as such, deforestation, reforestation, and agricultural intensification and extensification activities are often represented as relatively small patches of land-use change occurring across the agricultural landscape. On a year to year basis, change can be benign or relatively robust, but generally constrained to small geographic areas on household farms that are approximately 50-hectares in size. Assessment of parcel-level changes on household farms is limited by medium to coarse resolution landscape-level remote sensing systems such as MODIS and, to a lesser degree, Landsat or ASTER, thereby necessitating the integration of higher spatial resolution imagery (e.g., Ikonos) into the analytical process. Also, the spectral resolutions of multispectral sensor systems may constrain detailed discrimination of subtle differences in reforestation types and conditions, thereby, requiring the application of hyperspectral data, such as Hyperion satellite data, to characterize secondary forests (Arroyo-Mora *et al.*, 2005).

The objectives of this study are to characterize reforestation patterns on household farms in the Northern Ecuadorian Amazon through a process that integrates Ikonos and Hyperion satellite data with a socio-economic and demographic household survey to assess the causes and consequences of

land transformations in a forested frontier. The analytical approach integrates (a) Principal Components Analysis of Hyperion data to compress the hyperspectral data, generate independent and orthogonal axes associated with the 242 spectral channels of Hyperion, and characterize the spectral variance of the principal components through eigenvectors that represent reforestation patterns; (b) apply linear mixture modeling of the Hyperion data to generate fractional measures of vegetation density using spectral endmembers; (c) classify Hyperion data using a derived feature set (i.e., vegetation density from the mixture modeling) to characterize reforestation on survey farms; (d) use the panchromatic Ikonos data, GPS-referenced ground control data, and field sketch maps of land-use/land-cover on household farms, collected during the social surveys, to calibrate and validate the Hyperion classification of reforestation patterns and intensities on household farms; and (e) examine the mapped reforestation patterns through a statistical analysis of a suite of social, demographic, biophysical, and geographical variables that represent hypothesized forces and factors of reforestation patterns in the Northern Ecuadorian Amazon.

Study Area

The Northern Ecuadorian Amazon (NEA) is a region that covers approximately 20,000 km^2 and encompasses exceptional biological and cultural diversity (Figure 1). It has been characterized as a hotspot of biodiversity (Myers, 1990) with very high levels of alpha biodiversity (Pitman *et al.*, 2003). Cultural diversity is also high. The NEA is home to many indigenous communities from different ethnic groups that have adapted to the demands and opportunities of the Amazonian environment.

LULC changes are taking place in this region over a relatively small temporal scale. About four decades ago, this landscape was used primarily for subsistence agriculture by indigenous people and very few colonists. The discovery of oil in 1964 triggered infrastructure development and spontaneous agricultural colonization. Rapid land-cover changes in the region contributed to Ecuador's rank as the country with the highest deforestation rate in Latin America over the last decade (FAO, 2005). More oil infrastructure development is expected soon, because of the large petroleum reserves confirmed in the region. Ecuador is ranked third for oil reserves in South America (Energy Information Administration, 2003).

Since 1990, the NEA has become more densely populated, due to population growth, continued population in-migration, and the fact that many large areas have been set-aside as national parks and conservation areas, or have been legally titled to indigenous populations. In addition, colonist families have been sub-dividing plots for their children, as well as selling portions to new migrants coming into the region. With the Ecuadorian economy still depressed, migrants continue to arrive in significant numbers, in search of work in the burgeoning towns, as well as for land for agriculture. Population also continues to grow rapidly from natural population growth. More recently, official reports have shown evidence of international in-migration: refugees from the southern province of Putumayo in neighboring Colombia have come to escape the violence of the armed conflicts related to the drug war (UNHCR, 2007). Today, the NEA has one of the highest population densities in the Amazon Basin (ECORAE, 1996). Population growth is strongly related to urbanization, subdivision of property, and creation of new agricultural markets. Among other things, population growth produces intensification and extensification of land-use, consolidation of services in developing communities, and increased rents to local populations in the short-term, followed by a decrease in the natural resource base, increased poverty, and negative consequences for the biotic communities. Macro-economic shocks, including the fall of international commodity prices also create feedbacks to land-use change patterns.

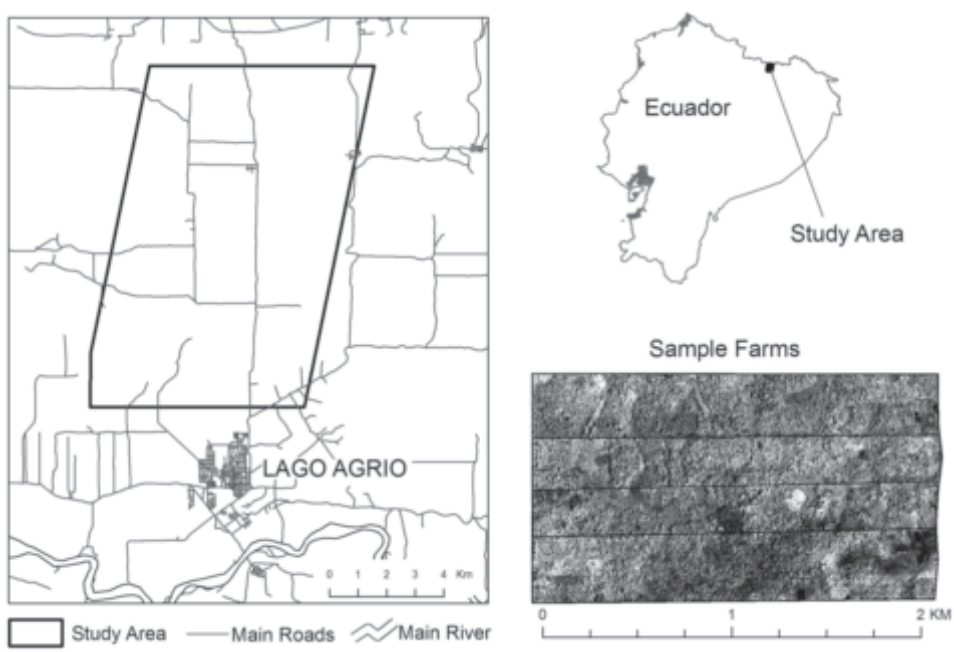

Figure 1. Study area location in the Northern Ecuadorian Amazon (NEA). Image source: Ikonos 2001, UNC Ecuador Project.

Data Types

Remotely Sensed Data

A 2002 Hyperion image was acquired for this analysis. Hyperion is a hyperspectral system that collects 242 unique spectral channels that range from 0.357 to 2.576 μm with a 10-nanometer bandwidth. The instrument operates in a push-broom fashion, with a spatial resolution of 30-meters for all channels. The standard scene width is 7.7-kilometers and the standard scene length is 42-kilometers. In addition to the Hyperion data, a 2001 Ikonos image was also acquired in panchromatic and multi-spectral modes. In the panchromatic mode, the spatial resolution is 1-meter and the spectral resolution ranges from 0.45 to 0.90 μm. In the multispectral mode, Ikonos provides data at a 4-meter spatial resolution in four spectral channels: channel 1 is 0.45 to 0.52 μm; channel 2 is 0.52 to 0.60 μm; channel 3 is 0.63 to 0.69 μm; and channel 4 is 0.76 to 0.90 μm. The image swath is 11-kilometers, acquired from a sun-synchronous orbit and a 1030 local time, equatorial crossing.

Figure 1 shows a sub-sample of the farms that were surveyed in 1990 and 1999 as part of a longitudinal household survey, used in this analysis. The farms in Figure 1 have a panchromatic Ikonos image background. The nearby community of Lago Agrio is also indicated, because, as the region's central market town, its location and characteristics influence household decision-making regarding land-use change on farms (Pan and Bilsborrow, 2005).

Ground Control Data

We established a series of "control" farms in the NEA in which land-use types and conditions have been spatially-referenced and tracked through time using GPS technology and informant surveys of heads of farm households. As part of a longitudinal household survey, in 1999 a survey team geographically-referenced the corner points of land parcels on the "control" farms, interviewed the farmer about land-use changes, prepared a field sketch map, and created a database of land change attributes for each farm and for each land parcel for the respective time periods. Such information helped guide the image analyst in subsequent land-use/land-cover classifications for different time periods. The sketch maps from the control farms were used to help the visual interpretation used in this study. In addition to the use of spatial and compositional LULC data collected for the farms, GPS-referenced data were collected in the field during April and May 2007 to support other land-use project initiatives. Finally, 18 survey farms were contained within the foot-print of the Hyperion and Ikonos imagery. Using polygon shapefiles generated for these farms and a comprehensive set of social and biophysical characteristics recorded in 1990 and 1999 as part of our longitudinal socio-economic and demographic survey, the analysis focused on reforestation patterns on these farms.

Socioeconomic and Demographic Surveys

In 1990, the first University of North Carolina at Chapel Hill survey of socioeconomic and demographic characteristics of households in the region was carried out. A two-stage sampling design was used to select a sample of farm plots, settled by spontaneous migrant families, i.e., 408 settler plots on which 418 families were living, representing 5.9 percent of the colonist plots in the main colonization area. In 1999, the same 408 plots were revisited, and all farms and new subdivisions in the same geographic space were re-interviewed, resulting in a sample of 768 farms. Detailed questionnaires were administered separately to the head of household (usually male) and spouse. The location of each household farm was geo-located using GPS technology. In 2000, questionnaires were administered to community leaders, farmers, teachers, women, and health professionals. Retrospective data were collected to allow the assessment of changes over time and space in the 59 relevant communities that were also geo-located using GPS technology and assessed relative to their degree of market integration, administrative and service centers, and general support infrastructure for commerce, trade, and social services.

Linkages between rural and urban areas, especially between product and labor markets, are particularly important in the overall development of farms and hence land-use of the region. This research uses a sub-sample of 18 survey farms located in an area coincident with the Hyperion and Ikonos imagery. From the household surveys, the following variables were extracted to generate basic descriptive statistics for the sample farms: *Subdivision*, the number of subdivisions on the original (1990) farm; *Forest*, the proportion of forest change in the period 1996 to 2002 (dates of Landsat TM imagery in our assembled image time-series); *Year*, year of settlement of the farm; *Male*, the number of adult males in the farm household; *Female*, the number of adult females in the farm household; *Children*, the number of children in the farm household; *OFE*, worker-days of off-farm employment on the farm during the preceding year; *HLabor*, worker-days of hired labor on the farm in the preceding year; *Educ*, highest level of education achieved by the head of household; *Title*, percentage of the farm with legal title; *Walk*, walking distance to the nearest main road; *PriRoad*, distance to main town on the nearest primary road; *SecRoad*, distance to primary road using nearest secondary road; *Fertility*, reported soil fertility decrease on the farm (dummy variable); *Flat*, flat topography on the farm (dummy variable); *Access*, vehicle access to the farm (dummy variable); *BlackSoil*, black soil (high fertility) on the farm (dummy variable); and *Wetland*, wetland within the farm (dummy variable).

Methods

This study focuses on the development of secondary and successional forest on 18 survey farms in the NEA. Reforestation on farms plots that have undergone deforestation are assessed through the image analysis of Hyperion data. Statistical relationships are examined between remotely-sensed measures of reforestation and household characteristics from the socio-economic and demographic surveys. Information about access reported by households in the surveys are used to measure the distance of the 18 study farms to primary and secondary roads and surveyed communities. Below, we describe the approaches used to assess reforestation and the statistical tests used to examine plausible causes and consequences of LULC change at the household farm-level.

Mixture Modeling

Linear mixture modeling (LMM) was used to derive the proportion of vegetation in each of the 30-meter pixels of the Hyperion imagery to better represent the land-use/land-cover conditions on relatively small farm parcels. Commonly used procedures in the "unmixing" of hyperspectral data include: data preprocessing, feature selection and transformation, endmember selection, and the estimation of sub-pixel proportions (Kruse *et al.*, 2003). Preliminary processing of the Hyperion data began with a visual interpretation of the image channels and their histograms. For this study, 149 of the 242 spectral channels were used for subsequent data analysis (i.e., channels 10 to 57, 77 to 78, 82 to 97, 100 to 119, 135 to 164, and 188 to 220). A simple global "destriping" method was used to remove the vertical "stripe" effect from the Hyperion data (Kruse *et al.*, 2003). No atmospheric

corrections were applied, because of a lack of the availability of atmospheric parameters at the time of image acquisition over the study area.

The spectral signals of endmembers are often derived using a semi-automatic approach that combines feature reduction approaches (e.g., Principal Component Analysis) and the use of the Pixel Purity Index. For this study, a Minimum Noise Fraction (MNF) was used to reduce the spectral dimensionality of the Hyperion data using a cascading Principal Components Analysis (PCA) that eliminated spectral noise in the data cube (Green *et al.*, 1988; Boardman and Kruse, 1994). The potential image endmembers were then identified using the Pixel Purity Index (PPI) that is designed to identify pixels located at the extremes of the randomly oriented, *n*-dimensional spectral space (Boardman *et al.*, 1993; Boardman *et al.*, 1995). The "pure pixels" were further analyzed through the generation of two-dimensional scatterplots in the MNF feature space. The "pure pixels" also were compared to the actual LULC types based on visual interpretation of the Hyperion image and the high spatial resolution Ikonos image. The "pure pixels" of three land-cover types were retained as endmembers for building the linear mixture models: vegetation, shadow/water, and bare soil. These three land-cover types are major components of the spectral mixing in the study area, and they also satisfied the requirement of a successful unmixing. The first three MNF components were used as inputs to estimate sub-pixel LULC proportions. The three class model was found to well represent the spectral mixing in the study area, and the model sufficiently estimated forest abundance, based on the hyper-spatial satellite data and the ground-control data.

Supervised Classification

Sub-pixel land-cover proportions derived from spectral unmixing provide useful information for separating primary forest, secondary forest, and other LULC types. Using spectral unmixing of Landsat TM data, Adams *et al.* (1995) found that primary forest has relatively higher shadow proportions than secondary forest. This is largely due to the canopy roughness and forest structure. Adams *et al.* (1995) used "thresholding" of shadow proportions to separate primary and secondary forest (i.e., 50 percent of shadow in a pixel). In this study, we used a supervised classification approach to derive LULC types from the results of the linear mixture modeling of the Hyperion satellite data. In a GIS, polygons of primary forest, secondary forest, and other LULC types were delineated by visual interpretation of the high, spatial resolution Ikonos imagery and *in situ* data collected as part of the social surveys. The training polygons were then overlaid onto the Hyperion satellite data, and the sub-pixel proportions of shadow and vegetation were plotted in feature space. Figure 2 shows a scatterplot of selected training pixels in the sub-pixel proportional feature space, where the *X*-axis indicates the percentage of vegetation cover, and the *Y*-axis indicates the percentage of shadow cover at the 30 m sub-pixel level. Figure 2 indicates that the three LULC classes show cohesive clustering in the feature space. For instance, pixels of secondary forest typically have greater than 70 percent of vegetation proportions and less than 20 percent of shadow proportions. Pixels of primary forest have vegetation proportions between 50 percent and 80 percent, and also have greater levels of shadow proportions (i.e., greater than 20 percent). Training pixels for the "other" class are mainly from agricultural fields (i.e., coffee and cacao), as well as pasture and bare soil.

A maximum likelihood classifier was applied to the Hyperion sub-pixel LULC proportions (from the linear mixture model), using the training polygons described above. Sub-pixel, land-cover proportions were used instead of other image transformations to construct a supervised classification, because secondary forest pixels provided a "characteristic" composition of LULC proportions that enhanced our understanding of forest structure as a consequence of physical composition. In addition, the spectral unmixing model reduced the large number of features (i.e., 242 channels of Hyperion data) to three land-cover composition clusters

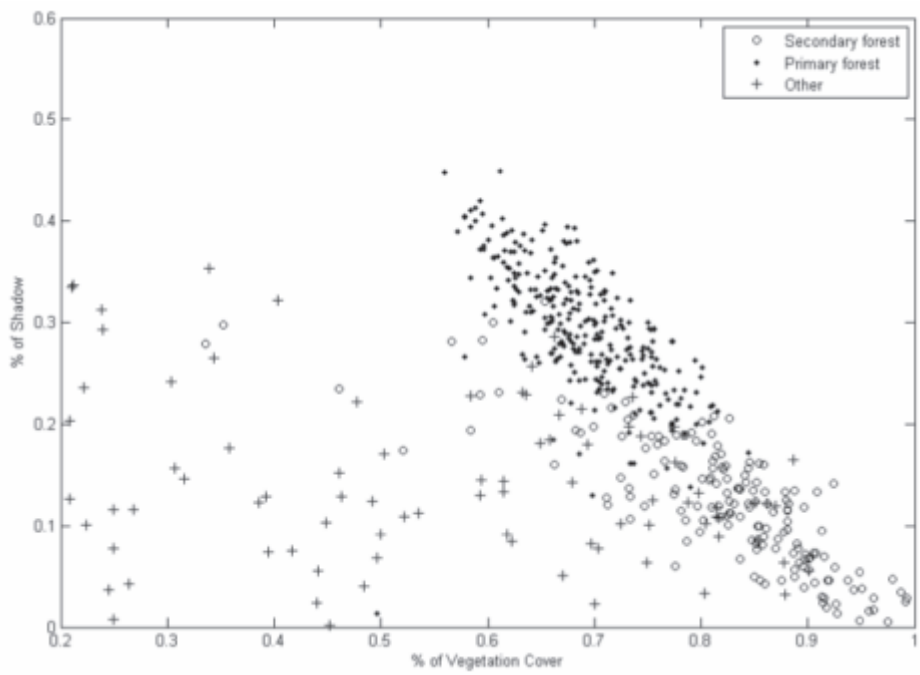

Figure 2. Scatterplot of selected training pixels in the sub-pixel feature space.

(i.e., vegetation, soil, and water/shadow), which reduces the dimensionality of the data to its most vital elements (Bishop, 1995). The performance of the supervised classification was evaluated using a standard error matrix. A total of 20 pixels were randomly selected for each of the LULC classes that corresponded to the 18 survey farms and previously collected field data.

Unsupervised Image Classification

A standard approach in Linear Mixture Modeling (LMM) is to compare the results of the supervised classification of sub-pixel proportions to an unsupervised classification approach. To compare the classification results, a typical ISODATA algorithm was used to create clusters (i.e., 30) with relatively homogeneous spectral responses. The first three Principal Components were the input data for the unsupervised classification. The resulting spectral clusters were attributed through a visual interpretation of high spatial resolution Ikonos imagery. The classification used the same three-class LULC scheme as the supervised classification including primary forest, secondary forest, and "other" land-cover types. While it was relatively straightforward to label the derived spectral clusters, there were several clusters that showed confusion between secondary forest, bare soil, and agricultural land.

One possible approach to decrease the spectral confusion within clusters is to increase the number of initial clusters in the unsupervised classification. This type of automated clustering, however, may not always generate the desired LULC classes (Richard and Jia, 1999). Therefore, to decrease spectral confusion between the defined clusters we carefully examined the histogram plots for 149 Hyperion channels (the number of channels used in this analysis) for each of the spectral clusters. We found that the visible channel ranges of 10 to 12, 18 to 21, and 33 to 35 were particularly useful for separating secondary forest and bare soil based on plant pigmentation, whereas the near-infrared channel range of 88 to 92 was best for delineating primary forest, secondary forest, and agricultural fields based on chlorophyll content. Natural breaks in the histogram plots were used to split the groups of confused pixels into more spectrally homogenous clusters. A final classification map was derived using this iterative cluster-splitting and merging approach; the remaining clusters were then attributed. The classification results were assessed using a standard error matrix and the same approach used for the supervised classification.

Statistical Analysis

The total amount of secondary forest was calculated for each of the 18 survey farms. A number of socio-economic and demographic and geographic access variables were also derived for the survey farms. For continuous variables (e.g., population), Spearman rank correlation coefficients were used to evaluate relationships between the amount of secondary forest and the socio-economic and demographic variables. Spearman rank correlations were generated, because the variables involved in the study were not normally distributed. There were several categorical variables used in the analysis that had only two categories (i.e., 0 and 1), and for those variables a simple T-test was also used to compare the differences in the amount of secondary forest on the study farms for those categories.

Results

Figure 3 shows the proportions of vegetation cover from the linear mixture modeling of the Hyperion data. Only an image subset is presented here to highlight the differences among primary forest, secondary forest, and other land-cover types. The darker shades indicate a higher percentage of vegetation cover in the 30 m pixels, while the lighter shades

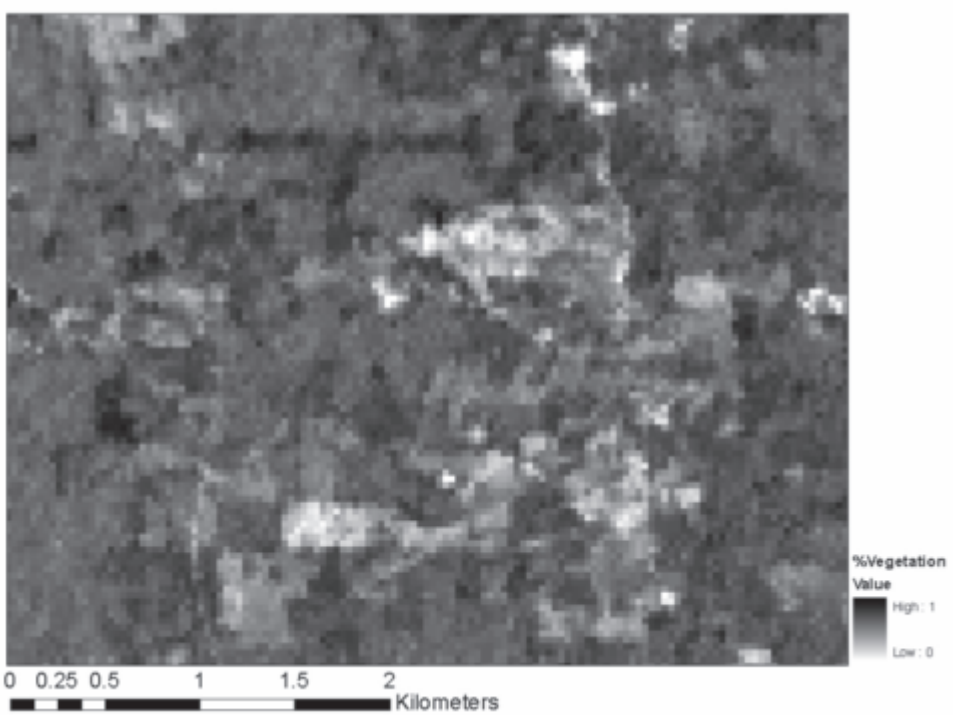

Figure 3. Percent of vegetation cover derived from spectral unmixing.

indicate lower vegetation cover (i.e., bare soil). Across the entire image, the secondary forest pixels had the highest vegetation proportions (i.e., >70 percent), whereas the primary forest pixels had moderate levels of vegetation proportions (i.e., between 50 to 80 percent) and higher levels of shadow proportions (i.e., between 20 to 50 percent).

Using the proportional land-cover maps derived from the spectral unmixing of the Hyperion data as inputs, a maximum likelihood supervised classification was used to classify primary forest, secondary forest, and "other" land-cover types. A classification error matrix is presented in Table 1. The overall classification accuracy is 67 percent. The users' and producers' accuracies for the primary forest class are 85 percent and 77 percent, respectively. The users' and producers' accuracies for the secondary forest class are 55 percent and 58 percent, respectively. Considerable confusion exists between the secondary forest class and the "other" land-cover class. It should be noted that the "test pixels" used for the "other" class were selected primarily from agricultural fields and pastures. Figure 4 shows the spectral signals of Hyperion data for selected test pixels, which indicates that primary forest, secondary forest, and "other" (i.e., pasture and agricultural land) have similar curves across the spectrum. The spectral responses from secondary forest and agricultural fields (i.e., coffee and cacao) are almost identical that causes difficulties in the classification and subsequent separation of secondary forest.

TABLE 1. ERROR MATRIX OF THE SUPERVISED CLASSIFICATION

	Reference Data			
	Primary Forest	Secondary Forest	Other	Total
Primary Forest	17	2	1	20
Secondary Forest	3	11	6	20
Other	2	6	12	20
Total	22	19	19	60

The error matrix for the unsupervised classification of the Hyperion data is presented in Table 2. The overall classification accuracy is 72 percent. The users' and producers' accuracies for the primary forest class are 90 percent and 78 percent, respectively. The users' and producers' accuracies for the secondary forest class are 70 percent and 67 percent, respectively. Although we do not deal directly with coffee, cacao, and pasture, these crops are important in that they cover a large proportion of the landscape and, in the case of coffee and cacao, they have similar spectral characteristics as compared to secondary forest. In this study, these LULC classes were grouped in the "other" class and, therefore, do not generate specific proportions of error. However, our experience in the field and in the lab suggests that a large portion of the error in their characterization can be explained by the spectral similarities of coffee and cacao, especially in agricultural plots that have been abandoned, with secondary forest. Further studies will be designed to discriminate these important commercial crops using a similar methodology that was followed here, but involving multi-temporal hyper-spectral imagery, or a design that follows Cordero-Sancho *et al.* (2007).

The overall accuracies reported in the use of the unsupervised classification approach in the characterization of secondary forest on the 18 survey farms in the NEA, using a single image of Hyperion data and Ikonos imagery, showed higher accuracies than those reported for the supervised classification, although the differences were not considerable. Therefore, the statistical analysis that follows reports on results achieved using the unsupervised classification as inputs.

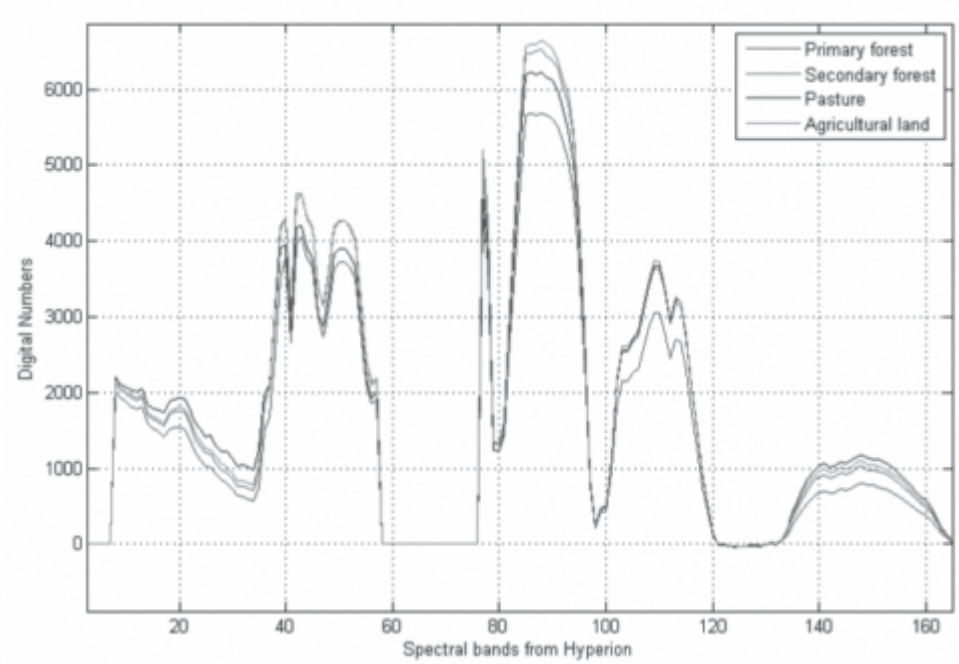

Figure 4. Spectral signals from four LULC types. A color version of this figure is available at the ASPRS website: **www.asprs.org**.

Table 2. Error Matrix for the Unsupervised Classification

	Reference Data			
	Primary Forest	Secondary Forest	Other	Total
Primary Forest	18	2	0	20
Secondary Forest	2	14	4	20
Other	3	6	11	20
Total	23	22	15	60

Figure 5 shows a subset of results from the unsupervised classification. The secondary forest is shown in lighter shades of gray, primary forest is shown in darker shades of gray, and "other" LULC classes are shown as intermediate shades of gray. The farm boundaries are overlaid on the classification results. Correlation analysis and T-tests were used to link secondary forest to a number of socio-economic and demographic variables. Recall that secondary forest at the farm-level is summarized using results from the unsupervised image classification.

The Spearman rank correlation coefficients of the amount of secondary forest and socio-economic and demographic variables at the 18 survey farms are presented in Table 3. Several socio-economic and demographic variables (i.e., *Subdivision, Males, Age*, and *Female*) are negatively correlated with the amount of secondary forest on each farm (i.e., the presence of more adult males than adult females result in less secondary forest and more farm subdivisions). The Spearman correlation coefficients for these socio-economic and demographic variables are less than −0.30, indicating moderate to strong relationships, especially for the linkages between socio-economic and demographic variables and forest patterns (Walsh *et al.*, 1999). *Title* and *PriRoad* are positively correlated with the amount of secondary forest. Land security facilitates the temporal abandonment of farm plots and contributes to forest regrowth. Conversely, roads are an important factor that leads to deforestation of household farms, a precursor to parcel conversion to secondary and successional forests. Only two socio-economic and demographic variables (*Male* and *Female*) show statistical significance ($p < 0.05$). It should be noted, however, that the small sample size (i.e., 18 survey farms) used in this study reduces the statistical power of the analysis, and, therefore, these results should be interpreted as "indications" of suggested relationships, but theory does support the general nature of their associations.

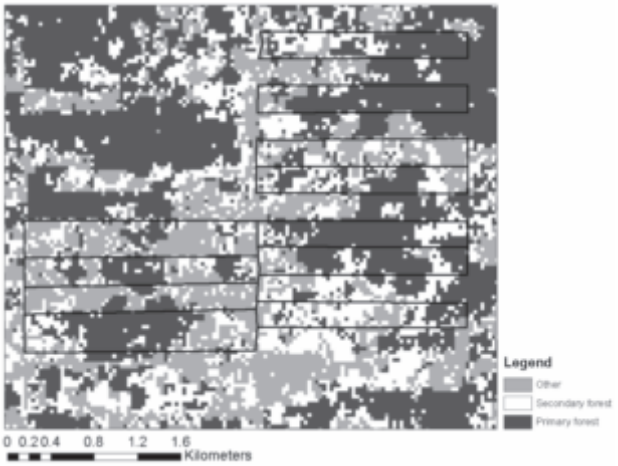

Figure 5. Secondary forest mapped at the farm-level. The outlines of the 18 survey farms are indicated, as well as the LULC classes defined through the unsupervised classification approach.

Table 3. The Spearman's Rank Correlation Coefficient

	Secondary Forest from Unsupervised Classification
Subdivision	−0.34 (p = 0.154)
Forest	−0.24 (p = 0.324)
Year	0.26 (p = 0.280)
Male	−0.46 (p = 0.054)
OFE	−0.22 (p = 0.357)
HLabor	−0.21 (p = 0.387)
Educ	0.17 (p = 0.512)
Title	0.39 (p = 0.107)
Age	−0.33 (p = 0.196)
Walk	−0.26 (p = 0.290)
Female	−0.49 (p = 0.045)
Child	−0.22 (p = 0.355)
PriRoad	0.42 (p = 0.084)
SecRoad	0.05 (p = 0.843)

Table 4. T-test for Selected Terrain and Resource Endowment Variables

	Secondary Forest from Unsupervised Classification
Fertility	$t = -1.75$ (p = 0.100)
Flat	$t = 0.14$ (p = 0.890)
Access	$t = -0.19$ (p = 0.851)
BlackSoil	$t = -0.06$ (p = 0.950)
Wetland	$t = -1.80$ (p = 0.091)

Table 4 shows the results of the T-test. The farms are grouped into two categories based on the socio-economic and demographic variables listed in Table 4. The T-test suggests that farms with *Fertility* values of 1 have more secondary forest than those farms with a *Fertility* value of 0 ($t = -1.75$, $p = 0.1$). In addition, those farms with a *wetland* value of 1 have more secondary forest than the farms with a wetland value of 0 ($t = -1.8$, $p = 0.09$). The p-values are higher for variables such as *Flat, Access*, and *BlackSoil*. This suggests very weak relationships between those variables and the amount of secondary forest at the farm-level.

Discussion and Conclusion

In this study, we examined two image classification approaches to identify secondary forest. In the first approach, spectral unmixing of Hyperion satellite data was used to derive sub-pixel LULC proportions of vegetation, shadow/water, and bare soil. A subsequent supervised classification of the sub-pixel proportions was used to delineate primary forest, secondary forest, and "other" land-cover classes. The primary advantage of spectral unmixing in this study is the generation of LULC proportions at the sub-pixel level that were used as a set of inputs to reduce the feature set and to enhance model interpretability. In the second approach, a typical unsupervised classification approach was applied to the Hyperion data, and where spectrally mixed clusters existed, a cluster splitting and

merging technique was used to improve the classification performance. Overall, the unsupervised classification generated better classification results compared to the linear mixture modeling/supervised classification approach, assessed using the limited test data that occurred on the 18 survey farms. However, more human interpretations (i.e., cluster splitting, merging, and pixel labeling) were involved in the classification process. The performance of the unmixing approach could be improved by including more training data for use by the maximum likelihood classifier or an alternative classification approach involving neural networks and classification trees (e.g., Paolo *et al.*, 1995; Walsh *et al.*, in press).

The derived patterns of secondary forest were described relative to a set of socio-economic and demographic variables that were collected on the 18 household survey farms. The farm and household characteristics examined are regulated by a complex set of exogenous forces and endogenous factors that influence household livelihood strategies and decision-making about the use of the land. For instance, the decision to allow pastures to become forested in response to lower prices for cattle and/or reductions in labor availability, the replacement of coffee in favor of cocoa, the inter-cropping of cocoa with coffee in response to market conditions, and the persistence of *rastrojo* or young secondary forest succession across the agricultural frontier in response to economic constraints or opportunities all influence the spatial pattern of reforestation with implications for people and environment. For people, the relatively simple conversion of *rastrojo* to coffee, cocoa, or palmito as market and labor conditions dictate may suggest that *rastrojo* is a transformative land-use type that is a semi-active element in household livelihood strategies. For the environment, successional forests can sequester carbon, possibly at a higher rate than the forests that they replace, depending upon species, age structure, and site conditions, but the ecological services that successional forests provide are substantially different than those provided before deforestation.

Specific to the NEA, remote sensing challenges are diverse. For example, older coffee and cacao plantations (the main cash crops) and secondary forests have similar spectral responses and spatial patterns. Coffee and cacao, cultivated during the period of study, are often inter-cropped, thereby, further confusing their spectral separation through the concept of the integrated pixel for landscape-level remote sensing systems. Finally, the small area of older *chacra*s or successional gardens in indigenous communities (often <1 ha in size) are difficult to categorize as they appear similar to surrounding primary forest, particularly, when characterized using mid-spatial resolution sensors such as Landsat and Hyperion.

The characterization of secondary and successional forests in the Northern Ecuadorian Amazon, and in tropical forest environments more broadly, requires a spatial-temporal analysis of the rates and patterns of forest dynamics that is further linked to social, geographical, and biophysical variables to assess the causes and consequences of LULC change. In the NEA, LULC changes on household farms occur as a consequence of household demographics and socio-economic conditions that are mediated by resource endowments on the farm, geographic accessibility of farms to other farms and to market towns, commodity prices, labor availability, and the characteristics of communities as market and service centers. The availability of alternative household livelihood strategies, such as off-farm employment, also influences land-use practices on the farm including decisions to allow land parcels to reforest following deforestation and agricultural extensification.

It should be noted that an internal forest frontier exists on individual farms, and, therefore, agricultural extensification can be considered within the context of the farm boundaries. While the farm plots that are managed through a variety of LULC types are generally small in size, they are fundamentally important to a diversified agricultural portfolio that reflects some mix of subsistence and commercial agriculture, including crop cultivation and pasture for cattle, as well as old and young secondary and successional forest. The matrix of forest and non-forest, crop and pasture, and secondary and successional forest varies according to strategies and circumstances that are local, regional, and global and represent social, geographical, and biophysical conditions.

In this study, we have emphasized the characterization of LULC on 18 survey farms through the application of hyper-spectral Hyperion data, using Ikonos imagery to aid in visual interpretation of the mixture modeling and attribution of the classifications. Our general intent was to assess hyperspectral data and alternate processing approaches to map secondary and successional forests, a challenge confirmed through our prior efforts to discern reforestation patterns on our survey farms using the multi-spectral capabilities of Landsat. We hypothesized that to separate the different ages and types of secondary and successional forests would require additional spectral definition that Hyperion offered, but the limitation of the 30-meter pixel persisted. Therefore, our design included the spectral unmixing of the Hyperion data to fractions of LULC types to further differentiate pixels based on the type and condition of LULC percentages. The spectral similarity of the LULC types that comprise the farms and the secondary and successional vegetation that occurs there was considerable, and, hence, its differentiation was a challenge. Another challenge was the relatively small number of survey farms that occurred on the Hyperion and Ikonos images. Because our studies have been historically designed to examine LULC change on survey farms through the interactions of population and environment variables, our studies have generally covered relatively large geographic areas that were afforded by the large scene size of Landsat. With the reduced areal coverage of Hyperion and Ikonos, the number of survey farms was reduced to 18, which affected the statistical tests we could reasonably apply and the power of the analyses. Also problematic was the common challenge of the lack of temporal coherence between the remotely-sensed images and the field control data used for calibration and/or validation efforts. We relied upon a diverse set of field data that covered a range of periods, but convergence of the field samples to the exact image dates was not possible.

In sum, the results of the Hyperion data analysis demonstrate considerable potential for differentiating the subtle distinctions between the types and conditions of secondary and successional forests in the NEA, a region whose LULC is primarily affected by farmers made about the use of the land by small-scale farms operating on household farms. Spectral unmixing remains a useful approach for deriving sub-pixel measures of fractions of LULC defined through spectral endmembers. The extension of the spectral resolution of Hyperion to a broader range of responses was important in assessing reforestation patterns on survey farms. Multi-temporal analysis of Hyperion data may offer additional potential to map subtle differences in forest regrowth on our survey farms, and data fusion of hyper-spectral and hyper-spatial data may offer important synergisms not specifically addressed here.

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