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Accuracy of Neural Network and Regression Leaf Area Estimators for the Amazon Basin

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Abstract: The ability to map and monitor leaf area index throughout the Amazon Basin is important to assess and predict environmental degradation. This study measured leaf area index (LAI) values at 64 locations characteristic of many different cover types including mature forest, secondary succession, pasture, cropped land, barren land, and urban area throughout the Santarem, Brazil area. The field data were used in conjunction with ASTER visible and infrared data to compare the accuracy of multiple regression and artificial neural network models for LAI prediction. Assessments of model accuracy were determined by calculating RMSE. Results indicate that artificial neural networks are more accurate than traditional statistical techniques to estimate LAI in this part of the Amazon Basin. In addition, it was found that lower LAI values modeled the poorest because of a mix of spectral signatures.

INTRODUCTION

Many environmental changes in the Amazon have been attributed to human colonization and settlement. For example, the Brazilian Amazon state of Rondônia has experienced much deforestation over the past four decades, when many people migrated into the region and set up agricultural fields and cattle ranches. The main result of this migration was massive deforestation, with very little economic reward

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for the farmers and ranchers (Dale et al., 1993). Because similar patterns of deforestation occur throughout the Amazon basin, model-based ecological studies are critical for assessing vegetation structure in the region. Ideally, these models should estimate biophysical variables, and provide data that would be useful for policy makers.

Leaf Area Index

One such biophysical measure is leaf area index (LAI). LAI is one of the most important variables in ecological canopy research (Running et al., 1986), and is defined as the amount of leaf area per unit ground area (Wulder, 1998). LAI is an important biophysical variable for vegetation modeling, and its variation is related to canopy structure and spectral reflectance (Asner, 1998). Traditionally, measuring LAI was highly destructive because trees had to be felled for accurate measurements. Fortunately LAI can now be accurately measured with non-destructive instruments such as an LAI2000, LAI-léger (LAIL; Cournac et al., 2002), or Accupar ceptometer (Jensen, 2000).

Leaf area index is related to atmospheric gas exchange that controls local carbon cycling. Leaf retention of gases such as CO_2 in the canopy is directly related to the amount of carbon released into the atmosphere (White et al., 1997). LAI is also a key variable in analyzing energy absorption for photosynthesis (Cournac et al., 2002), rates of photosynthesis, and for estimating primary and net primary production (Jensen, 2000).

Given the importance of LAI and its relationship to other biophysical variables in the rainforest environment, new and accurate means must be developed to remotely estimate LAI. Satellite remote sensing data may provide a means of overcoming this problem. Using *in situ* LAI values in conjunction with satellite data has been cited in the literature as an accurate means of estimating LAI. In these types of studies, regression models function based on the assumption that reflectance characteristics are related to the leaf area of the canopy. Several studies have used linear regression as an effective model-developing technique for LAI and biomass (Ogawa et al., 1965; Crow, 1978; Jensen, 2000; Jensen, 2002).

Artificial Neural Networks

A second technique used to model LAI is artificial neural networks (ANNs). ANNs provide an adaptive learning environment that is capable of predicting output variables based on input variables. Several studies have found that the use of ANNs for modeling biophysical characteristics is more accurate than that of regression (Hilbert and Muyzenberg, 1999; Nelson et al., 2000; Jensen and Binford, 2004). Although these studies yielded promising results, only one was performed in the Amazon basin, where forest age was found to be important for biomass modeling (Nelson et al., 2000).

The purpose of this study was to analyze satellite remote sensing data in conjunction with *in situ* LAI values collected in and around the city of Santarem in the central Amazon basin. The objective was to compare ANNs and multiple regression to determine the most effective technique for remote LAI modeling.

METHODOLOGY

Study Area

This research was conducted in and around Santarem, Para, Brazil (2º26' S and 54º41' W). The city and surrounding area are characterized by lush forests, nutrient poor Fe_2O_3 soils, developed land, and abandoned land that was previously cropped. Santarem is the third largest city in the Amazon region, and has average minimum and maximum temperatures ranging from 30º C to 35º C (Ashton, 1958). The dry season in Santarem stretches from July to December, with most rainfall in January and May (Ashton, 1958).

The study area was approximately 180 × 60 km in size (Fig. 1). The area contains many different land cover types such as initial, intermediate, and advanced secondary succession. Moran et al. (1996) stated that the initial stage of succession is dominated by herbaceous and woody species with small saplings contributing to most of the biomass. The intermediate stage demonstrates a further increase in saplings, with a reduction in grassy and herbaceous species, and the advanced stage is characteristic of layering between canopy and large understory vegetation (Moran et al., 1996). Other types of land cover include mature forests, cropped fields, cattle pastures, barren land, and urban development. As evident by these different land cover types, the region is extremely diverse. Mature forest is scant throughout the study area, and exists in large patches only the Tapajos National Forsest (FLONA) located along the Tapajos River in the western part of the study area. All of these cover types were sampled in this study to make the models as representative of the Amazon landscape as possible.

Field Data Collection

In situ LAI values were collected throughout the study area. LAI measurements were made using an Accupar ceptometer that measures photosynthetically active radiation (PAR) both above and below the canopy to calculate LAI. The ceptometer calculates LAI based on the gap-fraction principle:

$$IL/IO = e^{-kLAI(L)},$$

where IL/IO represents the percentage of light at the tree tops (canopy) reaching a certain depth L, e is the base of natural logarithms, LAI(L) is the cumulative LAI from the top of the canopy at location L, and k is a stand-specific constant (Aber and Melillo, 1991).

The sampling scheme established 64 points (Table 1) characteristic of the following cover types: mature forest, initial secondary succession, intermediate secondary succession, advanced secondary succession, barren land, and urban area. Data collection was performed during June 2003 from 10 a.m. to 2 p.m. The LAI points were divided into four classes based on their LAI values. Class 1 consisted of values from 0 to 3 and contained cover types such as barren area, urban land, pastures, cropped fields, and mixes of water and vegetation. Class 2 had a range of values from 3.01 to 6, and contained initial and intermediate secondary succession. Class 3, with values

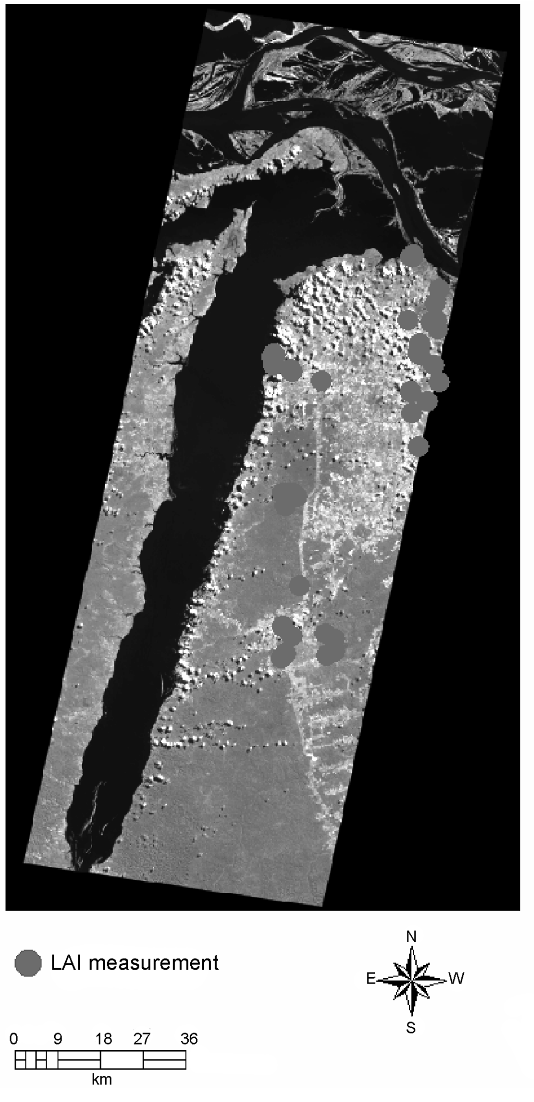

Fig. 1. Near-infrared image of Santarem, Brazil. *Source*: NASA; acquired June 8, 2002.

of 6.01 to 9, contained advanced secondary succession and some mature forest, and class 4 (with values greater than 9) contained only mature forest. There were 28 points measured for class 1, 12 for class 2, 18 for class 3, and 6 for class 4 (Table 1). The Universal Transverse Mercator (UTM) location of each point was determined using a Magellan 2000 global positioning system (GPS) unit. Sixteen understory PAR readings were taken randomly within 20 × 20 m quadrats surrounding each GPS point. These understory PAR readings were averaged and placed into the equation above with the above-canopy PAR reading in order to calculate the overall LAI value for each location.

Table 1. Number of Points in Each Class

Class	Range	Number of points
1	0–3	28
2	3.01–6	12
3	6.01–9	18
4	> 9	6

Table 2. ASTER Bands Used in the Study

Band number	Name	Spectral range, μm	Spatial resolution, m
1	Green	0.52–0.60	15
2	Red	0.63–0.69	15
3	Near-infrared	0.76–0.86	15
4	Mid-infrared	1.60–1.70	30
5	Mid-infrared	2.145–2.185	30
6	Mid-infrared	2.185–2.225	30
7	Mid-infrared	2.235–2.285	30
8	Mid-infrared	2.295–2.365	30
9	Mid-infrared	2.360–2.430	30

Satellite Data

Multiple Regression. After the *in situ* LAI values were collected, multiple regression was performed using bands from the ASTER sensor to establish their relationship with LAI. The bands chosen were from the visible, near-infrared, and mid-infrared portions of the spectrum (Table 2). The sensor brightness values were used as the independent variables while LAI represented the dependent variable. For each regression, a separate predictive linear equation in the form of $y = mx_1 + mx_2 \ldots + b$ was calculated, where y = LAI, m is the slope obtained for each band, x was the brightness value, and b was the y-intercept. To test the accuracy of each linear equation, the root mean square error (RMSE) was determined. RMSE has been discussed by various authors including Curran et al. (1995) and Manly (1992), and is expressed as follows:

$$\mathrm{RMSE} = [1/N * \Sigma (x_p - x_e)^2]^{1/2}$$

where N = number of observations, x_p is the predicted LAI value and x_e is the expected LAI value determined from the field measurements. This residual error was used to determine the technique that provides the best modeling accuracy.

Table 3. RMSEs Derived from Multiple Regression with All Possible Points

LAI class	Range	RMSE
1	0–3	4.01
2	3.01–6	0.88
3	6.01–9	3.26
4	≥9.01	4.21
Aggregate	>0	3.36

Table 4. RMSEs Derived from Artificial Neural Network Regression with All Possible Points

LAI Class	Range	RMSE
1	0–3	2.72
2	3.01–6	1.85
3	6.01–9	3.2
4	≥9.01	2.55
Aggregate	>0	2.62

Artificial Neural Networks. Following the completion of multiple regression analysis, ANNs were trained to model LAI. While creating a back propagation network, experimentation was performed with various parameters such as learning rates, momentums, and neurons per network. The network's rate of learning was an important consideration because of the trade-offs between fast and slow rates. For example, if a high learning rate was selected, the network would "learn" quickly. However, this same network may quickly lose stability, and if different training data were applied to the network, a different solution may result (Cunningham et al., 2000). This was compensated for by adding a momentum term that allowed for faster learning with less chance of stability loss (Haykin, 1994). As is common with neural network studies (Hardin, 2000), optimum network configurations were determined through brute force by calculating RMSEs for each individual network,. This allowed for the most accurate network configuration for LAI estimation to be determined. The results provided by these networks were used for accuracy comparisons with the multiple regression results.

RESULTS AND DISCUSSION

In all cases, ANNs proved to be more accurate remote modellers of LAI than multiple regression. For the models with all points included, the error derived by multiple regression was 3.36 and from ANNs was 2.62 (Tables 3 and 4). It was discovered early on that pasture LAI points needed to be removed from the models to

Table 5. RMSEs Derived from Multiple Regression with Pasture Points Removed

LAI class	Range	RMSE
1	0–3	3.6
2	3.01–6	0.94
3	6.01–9	2.53
4	≥9.01	3.25
Aggregate	>0	2.77

Table 6. RMSEs Derived from Artificial Neural Network Regression with Pasture Points Removed

LAI class	Range	RMSE
1	0–3	2.14
2	3.01–6	0.59
3	6.01–9	2.3
4	≥9.01	2.2
Aggregate	>0	1.94

eliminate the problem of vegetation registering reflectance underneath the ceptometer, resulting in inaccurate predictions. After removing the pasture points, the errors were 2.77 from multiple regression and 1.94 for the ANN, respectively (Tables 5 and 6).

ASTER's spectral resolution in the middle infrared (bands 4 through 9) probably helped the ASTER models' LAI estimating abilities. Mid-infrared may also have proven valuable for vegetation modeling because the field data were collected during the dry season. When leaves are less turgid, mid-infrared reflectance increases, making it a good indicator of vegetation cover. Noting the performance of the mid-infrared band is important in this analysis because other studies have proven its usefulness for biomass modeling (Lu, 2001). This finding can now be further extended to LAI estimation.

Network Configurations

Previous studies, such as Jensen (2002) and Jensen and Binford (2004), were used to assess the best network configuration for modeling LAI. These studies found that a three-neuron multiplayer perceptron was the most accurate network for LAI estimation in north central Florida, USA. This environment is much less complex than the Amazon basin. Therefore it may be expected that different network configurations are required to produce accurate LAI models in the Amazon.

In this study, the best network configurations were found to contain either 6 or 7 neurons. When the data are highly complex, more neurons are required to process the information. It is likely that more neurons were required to produce accurate LAI models because of the heterogeneity of the Amazon landscape. A simpler three-neuron network was found to be insufficient for this purpose. In addition, models should not include too many neurons because this may cause over-fitting. Using too great a number of neurons can result in rigidity in the LAI predictions, resulting in no compensation for the error derived during LAI collection.

Other key components of network configurations are the learning and momentum rates. This study found that a learning rate of 0.2 and a momentum of 0.2 were the most accurate LAI estimators. The momentum rate of 0.2 was consistent with Jensen (2002), who found a momentum of 0.25 to be the most accurate. However, a slower learning rate of 0.2 was required, where Jensen (2002) was able to use a faster rate of 0.5. Again this may relate to the complexity of the Amazon landscape. A neural network may need more time to learn the information in very heterogeneous environments. It appears that if allowed to learn the information slowly enough, ANNs can produce accurate models even when environmental complexity is high.

Individual Class Accuracies

Past studies have demonstrated that different LAI classes model with differing degrees of accuracy. For example Jensen (2002) and Weiss and Baret (1999) found an inverse relationship between class accuracy and increasing LAI. In other words, as the canopy increases in thickness, LAI becomes more difficult to model. This is probably due to NIR saturation in the canopy. If NIR energy does not reach the lower canopy layers, then NIR reflectance cannot be efficiently used for LAI estimation.

This study showed that, in most cases, class 4 (highest LAI class) modeled with poor accuracy. However, in almost every case class 1 was the most inaccurate. This result is in direct contradiction with Jensen (2002) and Weiss and Baret (1999), although not beyond reasonable explanation. It would be attributable to the complexity of the Amazon landscape. Class 1 had the greatest variety of cover types such as barren land, cattle pasture, cropped fields, urban area, and mixes of water and vegetation. This heterogeneity of spectral signatures within this class played a key role in reducing the models' ability to predict LAI.

The results also showed that class 2 modeled with the highest accuracy in most situations. This is also directly related to the nature of the Amazon landscape. As classes become more homogeneous, their ability to be modeled accurately increases. This class primarily consisted of secondary succession. Since all three levels of succession are very similar in spectral response, the models were able to accurately predict LAI values.

Another reason why the middle LAI classes modeled with the highest accuracy may be based on the LAI values and spectral signatures gathered. For class 1, many of the points were over-predicted because a recorded LAI of 0 was not characteristic of the vegetation cover. If the ceptometer had been placed on the ground, LAI readings higher than 0 may have been gathered, resulting in better LAI predictions. With respect to class 4, canopy saturation may have played a role in making the spectral signatures gathered inaccurate. For example, near-infrared reflectance was registering lower than it probably would have without saturation. Therefore, LAI values in this class were typically under-predicted. In contrast, since class 2 points consisted of thinner canopies, LAI measurements were probably collected with little near-infrared saturation. The result was highly accurate LAI estimations for this class.

CONCLUSIONS

ANNs proved more accurate modelers of LAI than multiple regression. This result has been observed in many other research projects such as Jensen (2000, 2002) in other ecosystems. The conclusion is that the superior predictive ability of neural networks can now be extended to LAI estimations in the Amazon.

Conclusions can also be made with respect to individual class accuracies. Many past studies such as Wulder (1998) and Jensen (2000) have found that the lower LAI classes model with the highest degree of accuracy. This was not the case in the Amazon basin. This research discovered that when the lowest LAI class contains many different spectral signatures such as barren land, pasture, cropped fields, urban development, and mix of vegetation and water, the predictive accuracy diminishes. In addition, most of the class 1 points were measured with an LAI of 0, which is not characteristic of vegetation that registered below the ceptometer. Thus, class 1 was commonly over-predicted in the Amazon and the most difficult to model. The next most difficult class to estimate contained the highest LAI values, class 4. The poor modeling of this class was attributable to canopy saturation. Since near-infrared reflectance cannot penetrate to the lower layers of the canopy, LAI is under-predicted for most mature forest points. The classes that were estimated with the highest level of accuracy were numbers 2 and 3 (middle LAI classes). This was because they did not suffer from as much canopy saturation as class 4, or contain a large mixture of spectral signatures such as class 1.

Future Studies. This study generated many questions that could be addressed in future research. The models derived in this analysis need to be extended to other Amazon regions to assess if the model could be transferred. In the future, more data could be collected in alternate locations within the basin to compare LAI estimations with those obtained in this study. It is likely that the models would not transfer to other locations due to differences in climate, topography, species compositions, and available cover types throughout the basin.

A future study could involve the incorporation of textural information into the models. If variables such as species composition could be added, the LAI estimations would be improved (Wulder, 1998). The difficulty with this procedure is the need to locate an individual with sufficient understanding of Amazon vegetation to identify trees at the species level. At this time, the identification of Amazon species has only begun.

Future studies could also focus on employing other satellite sensors in the Amazon basin for LAI modeling. Many more sensors with differing spectral and spatial resolutions (such as ETM+, MODIS, and IKONOS) may also prove useful for LAI estimations. For example, the following questions could be asked: Would similar results be obtained with these sensors as with ASTER? Could one individual sensor stand out above all the rest as the best LAI modeler in Amazon-related studies? It may also be useful to apply thermal and microwave bands to the models, and the following could be asked: Would increasing the spectral resolution in these portions of the electromagnetic spectrum result in better estimations? It is hoped that this study will be a starting point in the quest to answer these questions.

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