

# Accuracy Assessment and Uncertainty in Baseline Projections for Land-Use Change Forestry Projects

**Louis Paladino**  
Research Scientist  
ISciences LLC  
685 Centre Street #207  
Jamaica Plain, MA 02130  
(617) 524-1115  
[loupaladino@yahoo.com](mailto:loupaladino@yahoo.com)

**R Gil Pontius, Jr.**  
Assistant Professor  
Clark University, Graduate School of Geography  
Department of International Development, Community and Environment  
950 Main Street, Worcester MA 01610-1477, USA  
508-793-7761  
[rpontius@clarku.edu](mailto:rpontius@clarku.edu)

**Keywords:** carbon, Kappa, land use/land cover change, model prediction, validation.

## Abstract

This paper uses state-of-the-art validation techniques to estimate uncertainty in the prediction of future disturbance on a landscape. Interpreted satellite imagery from 1975 to 1992 was used to calibrate the land change model. Data from 1992 to 2000 was used to assess the goodness-of-fit of validation as measured by the statistic Kappa for Location (Klocation), which is a variant of the traditional Kappa index of agreement. Based on the goodness-of-fit in the year 2000, Klocation is extrapolated to predict the goodness-of-fit for the year 2026. The extrapolation of Klocation allows the scientist to predict the model's accuracy with regard to the location of future disturbance. Based on the extrapolated Klocation, the scientist can estimate the conditional probability that a location will be disturbed in the future, given that the model says it will be disturbed.

For the validation year of 2000, Klocation is 0.22, which means that the model is 22% of the way between random and perfect in predicting the location of disturbed land versus undisturbed land. The predicted Klocation in the year 2026 is 0.008. Therefore, the estimated probability that a pixel will be disturbed in 2026, given that the model says it will be disturbed is 1.8%. The probability that a pixel will be disturbed given that the model says it will be undisturbed is 1.0%.

The results allow us to understand the uncertainty when using models for land-use change forestry project baseline estimates. In this example, the uncertainty is very high, which means that either models need to dramatically improve or carbon trading and Kyoto Protocol policy needs to be reevaluated.

## 1. Introduction

### 1.1 Accuracy Assessment in Spatial Models

Growing threats to climate stability have motivated the development of various antidotes, such as the Kyoto Protocol (KP) and the Chicago Climate Exchange, which call for a reduction in the concentration of greenhouse gasses like carbon dioxide. Both state that a viable means to reduce greenhouse gasses is through carbon management forestry projects that prevent or reduce anthropogenic land-use changes. In order to estimate the amount of carbon mitigated by the forestry project, a baseline projection needs to be established. The baseline projection is a description of what would have happened in the absence of a forestry project. One common method to construct the baseline projection is to use Land-Use/land-Cover Change (LUCC) models to extrapolate land-cover to the future.

Future anthropogenic land-use changes are not perfectly predictable, nor are land-use changes purely random. Anthropogenic changes can be predicted based upon a combination of cultural forces, biophysical factors, transportation networks, market accessibility, and agro-climatic suitability (Kaimowitz & Angelsen 1998). Any prediction of land-use has a level of uncertainty associated with it, and a prediction further into the future should have a greater level of uncertainty than a prediction to the near future. Recent discussions among land-change modelers have expressed the need for statistical methods to validate models and to state the uncertainty in land-change predictions (Lambin et al. 1999).

Currently, most land-change modelers fail to validate models and ignore uncertainty in future predictions. For example, cutting-edge research by Chen et al. (2002) and Lo and Yang (2002) use land-use change models to predict urban sprawl. However, their research vaguely addresses the issue of validation; furthermore, no attempt is made to address the uncertainty in model predictions.

## **1.2 The Kyoto Protocol and Emission Trading Markets**

Emissions trading markets have evolved out of the KP as a market-based solution to the global carbon budget problem. For example, the Chicago Climate Exchange (CCX) is a greenhouse gas (GHG) emission reduction and trading pilot program for emission sources and offset projects. The CCX is regulated and governed by members that have made a voluntary, legally binding commitment to reduce their emissions of greenhouse gases by four percent below the average of their 1998-2001 baselines by 2006, which is the last year of the pilot program. Eligible offset projects in the United States include landfill and agricultural methane reduction and carbon sequestration in U. S. forests and agricultural soils. Eligible offset projects include fuel switching, landfill methane destruction, renewable energy, and forestry management in Brazil, and in the near future Canada and Mexico (<http://www.chicagoclimatex.com/about/program.html>).

The objective of the KP is to assist developing countries in achieving sustainable development and to assist developed countries in reducing greenhouse gas emissions to 1990 levels. Article 3.3 of the KP states that verifiable changes in carbon stocks attributable to direct anthropogenic land-use change and forestry activities can be used to meet the commitments agreed upon in the Protocol. The Land Use Change Forestry (LUCF) activities are limited to afforestation, reforestation, and deforestation since 1990.

Article 6.1 of the KP states that developed countries may trade or acquire from developing countries emission reduction units, referred to in this paper as carbon credits. The carbon credits are generated by reducing emission sources by altering anthropogenic forces or enhancing emission sinks of greenhouse gases. Article 6.1b stipulates that carbon credits can be generated provided that a reduction in emissions by sources, or enhancement of removals by sinks, is additional to that which would otherwise occur.

Article 12 defines the Clean Development Mechanism (CDM), whose purpose is to assist developing countries in achieving sustainable development, while at the same time assist developed countries in achieving compliance with their quantified emission limitation and reduction commitments under Article 3. In 2001, the CDM was modified to limit LUCF activities to afforestation and reforestation (UNFCCC 2001).

The focus of this paper is a pilot LUCF project that could meet the conditions of Articles 3, 6, and 12. Specifically, this paper analyzes the phrase in Article 6.1b 'that would otherwise occur.' The pilot LUCF analyzed in this study is the Noel Kempff Mercado project in Bolivia, which aims to conserve 1.5 million acres of Bolivian forest. Using state of the art goodness-of-fit validation techniques and newly acquired data for the study site, this paper determines the accuracy of LUCC model predictions when used for the baseline projection of the Noel Kempff Mercado LUCF Project. Central to this study is the concept of baseline or business-as-usual projections, referred to in this paper as baseline projections.

## **1.3 Baseline or Business as Usual Projections**

A commonly accepted practice by land change modelers is to analyze and attempt to understand past human impact patterns on the landscape as a means to provide scientists with a window to the future. Land-use/land-cover change models are the instruments used to analyze anthropogenic landscape changes in order to extrapolate those past changes to the future. Land-change models will never be able to predict the future exactly, nor are they suppose to. Models provide a scientific hypothesis as to how landscape change might unfold over time. Land-change models are useful to various researchers in various contexts: to urban planners for infrastructure planning, to conservation organizations for biodiversity assessment, and to those involved with emission trading for

quantification of future carbon gains or losses to the global carbon budget (Brown et al. 2002). Determining the predictive power of a land-use/land-cover change model is critical to our ability to accurately award carbon credits. Sound statistical methods are absolutely necessary in order to state within a level of confidence how well land-use/land-cover change models perform, especially considering the money involved in carbon credit trading.

This paper analyzes the accuracy of LUCC model baseline predictions when used to quantify the amount of carbon credits awarded to organizations for conserving or creating carbon sequestering forests. Investors receive carbon credits for conserving forests. These credits may be traded on greenhouse gas emission trading markets. If the land-use/land-cover change model simulates a greater amount of future land-use disturbance, more carbon credits will be awarded. It is important to ensure that investors receive the correct amount of carbon credits, which are dependent on the land-use/land-cover change model prediction.

This paper also applies new statistical methods to estimate the level of confidence in a LUCC model's extrapolation to an unknown future, and assesses the reliability of those statistical methods. Constituents with a stake in carbon monitoring need both statistical results that state confidence in the estimates, and confidence in the statistical methods themselves. Specifying the uncertainty in land-use change predictions is important to both greenhouse gas trading markets and LUCC modelers.

### 1.4 Study Area

The Noel Kempff Mercado Climate Action Project was funded primarily by three U.S. energy companies (i.e. American Electric Power, PacifiCorp, and BP America) who invested \$9.6 million to buy logging rights on 2 million acres of Bolivian government owned land, which was added to the existing Noel Kempff Mercado National Park (NKMNP). The strategy was to prevent logging by the previous owner. The NKMNP is located in the north-eastern portion of the Santa Cruz Department in Bolivia near its border with Brazil. The NKMNP lies between 13°31'-15°05'S and 60°14'-61°49'W.

Less than 30 people live within the borders of the NKMNP, making the NKMNP one of the largest undisturbed wilderness areas in Latin America. The park encompasses five distinct ecosystems: upland evergreen forests, deciduous forest, upland cerrado savanna, savanna wetlands, and forest wetlands (Killeen and Schulenberg 1998).

## 2. Methodology

### 2.1 Strategy

There are three major steps to the analysis: 1-calibration, 2-validation, and 3-extrapolation, Figure 1 illustrates the flow of the analysis.

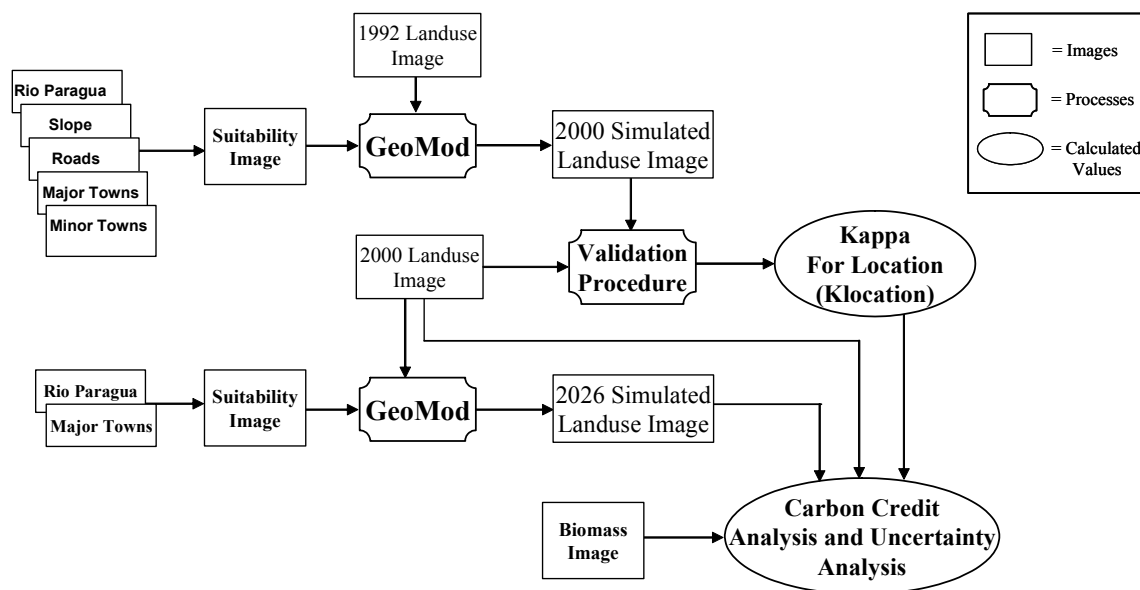


Figure 1 shows the methodological flow of the analysis.

In order to calibrate the land-use change model, we gathered biophysical and cultural data prior to 1992. The validation step requires the extrapolation of land-use changes to the year 2000, which is a point in time for when a reference image exists. Validation in a known point in time allows us to state the level of confidence that we have in the model. In addition, we are able to find the driver images that best describe future change through an iterative process of running the model from 1992 to 2000 with various combinations of driver maps. Next we extrapolate from 2000 to 2026: (1) the quantity of deforestation, (2) the kappa for location, and (3) land use changes. Finally we use the result of step (3) to compute anticipated carbon credits.

## **2.2 Data**

The data used to perform the land-use change extrapolation consist of several types of images. Driver images represent factors believed to determine the location of anthropogenic land-use change. The driver images in this analysis are: roads, towns, major rivers, and elevation. The dependent variable is shown by land-use images from two points in time. This research uses images from 1992 and 2000 consisting of two categories: undisturbed land and disturbed land.

Winrock International supplied road and town vector data of the study area. Raster data supplied by Winrock consists of a 30-meter resolution raster image, interpreted from Landsat TM imagery depicting: anthropogenic disturbed and undisturbed pixels, water, barren rock, no data, and background for 1992. In addition, a 60 meter resolution image depicting deforestation in 1975 from Pathfinder imagery was supplied by Winrock. A 90-meter resolution Digital Elevation Model (DEM) was downloaded from USGS's seamless mosaic (<http://seamless.usgs.gov>).

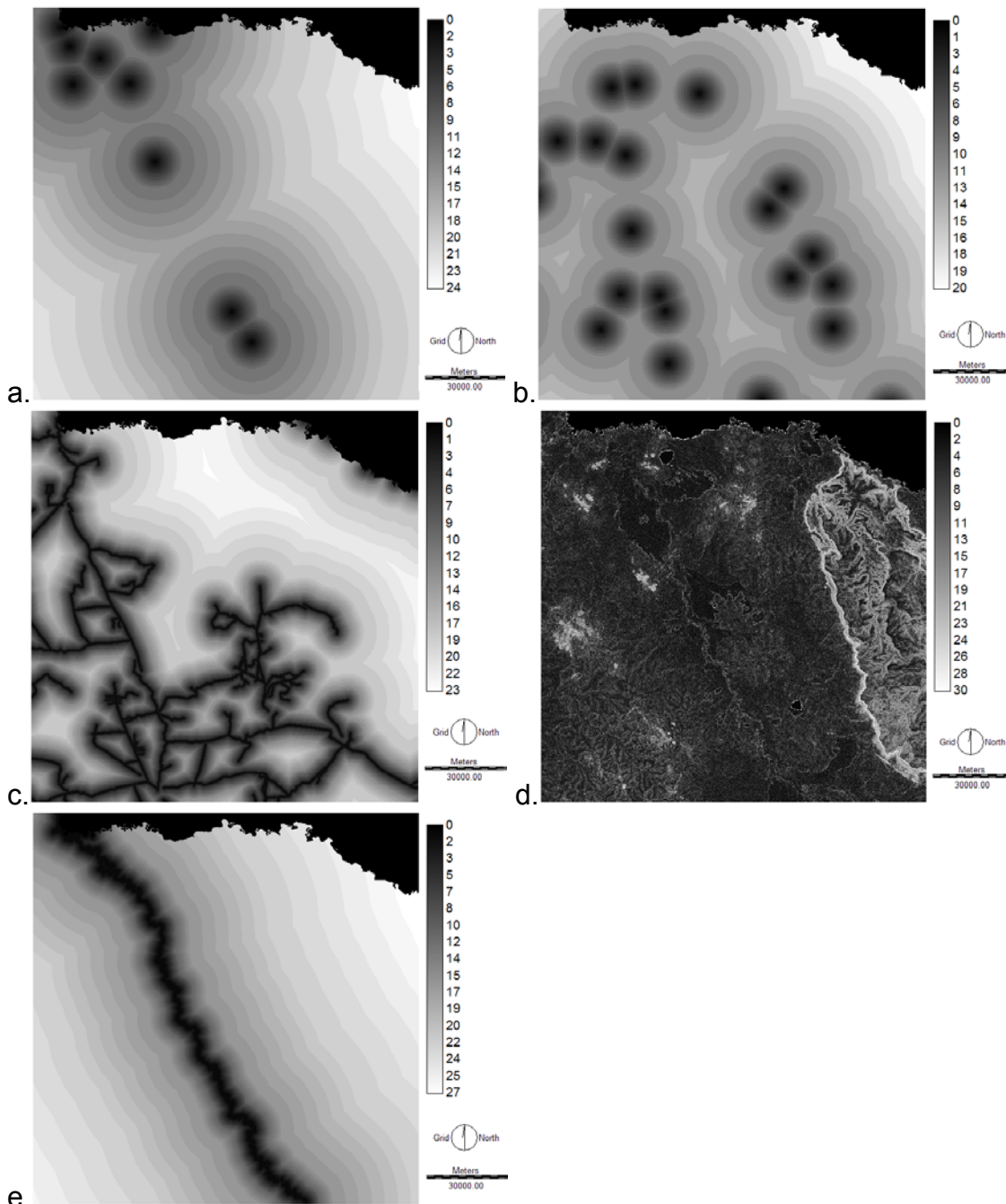
The satellite imagery necessary to create a categorized image for the year 2000 of the study area was downloaded from the University of Maryland (<http://glcf.umiacs.umd.edu>), supplied and georeferenced by Earth Satellite Corporation. Landsat TM images p230r069 and p230r070, and p229r070 were necessary to cover the Noel Kempff Mercado Climate Action project.

## **2.3 Calibration**

In order for the LUCC model to assess the location of land-use change, a suitability map that represents the likelihood of change is required. The suitability map is created from driver images believed to be independent variables that drive the location of anthropogenic land-use change. Driver maps were created in order to analyze which parameters performed best at simulating the location of change between 1992 and 2000 (Figures 2a-e).

The driver images are: proximity to major towns, proximity to minor towns, proximity to roads, proximity to the Paragua River, and slope. It is necessary that all driver images were created from data prior to 1992, because the validation process in this study extrapolates land-use patterns from 1992 to 2000. If driver images were created from data subsequent to 1992, then overconfidence in the model would result due to the fact that the validation procedure assumes the year 2000 is a point in the unknown future.

There are five driver images, four of which describe proximity to features by measuring the Euclidian distance between each cell and the nearest pixel representing a feature in the driver image. The driver images were then reclassified from real numbers to categorical bins (Figures 2a-e). After analyzing 1986 and 1992 imagery, we discovered that some urban settlement activities had noticeably disturbed the landscape prior to the year 1992. Therefore, we extracted these settlements for the 'major towns' driver image. The towns where no landscape disturbance occurred by the year 1992 were used for the 'minor towns' driver image. Satellite images from the mid 1970's to 1992 reveal that the Paragua River had a high correlation to settlement patterns. Therefore, this river was extracted from the 1992 land-use image and used as the 'rivers' driver image. We also used a 'roads' image. The hypothesis is that humans need roads to access areas where resources will be used resulting in land change. Finally, a 90 meter resolution DEM from the Shuttle Radar Topographic Mission (SRTM) was used to derive a slope image. The hypothesis is that humans will tend to use land with flatter slopes due to the ease of clearing land and the higher long-term utility, compared to land with steeper slopes.



(Figures 2a-e). Five driver maps were created in order to analyze which parameters performed best at simulating the location of change between 1992 and 2000. The driver images are: a- proximity to major towns, b-proximity to minor towns, c- proximity to roads, d-slope, and e- proximity to Paragua River.

Images from two points in time are necessary to state the level of confidence in the model. The image from 1992 is a categorized image that was provided by Winrock International. The image for 2000 was created using ERDAS Imagine from a combination of unsupervised and supervised classification methods of Landsat TM imagery.

Once the data are established we are able to perform numerous LUCC model runs, which attempt to predict a future landscape. Geomod is the grid-based LUCC model used in this analysis. Geomod simulates a one-way transition from one land-cover class to one other land-cover class. Pontius et al. (2001) provide a complete description Geomod.

All possible combinations of driver images and the 1992 land cover image are input into the LUCC model. The outputs are 32 suitability images and 32 predictions of the 2000 landscape. We then perform a geospatial

statistical analysis in order to measure our trust in the LUCC model. First, we make a validation statement about quality of suitability images that the LUCC model produces. Second, we make a statement about our trust in the LUCC model's 2000 landscape prediction.

## 2.4 Validation

We rely on the Relative Operating Characteristic (ROC) in order to understand the quality of driver images and identify the best combination of driver images that produce the suitability image. This method quantifies how well a suitability map describes future change. Pontius and Schneider (2001) explain how to use the ROC technique to examine how well a suitability map portrays the true locations in a Boolean image--for our case the Boolean image represents actual deforestation between 1992 and 2000. The ROC method was used to measure the goodness-of-fit between each of the 32 suitability images and an image representing disturbed land from 1992 to 2000. This comparison allows us to quantify whether high suitability values are located on truly disturbed land. The advantage of the ROC technique is that it validates the suitability image in a way that it does not require us to specify the quantity of disturbed and undisturbed grid cells. A ROC value of 1 represents a perfect spatial agreement between the suitability map and an image representing disturbance between 1992 and 2000. A ROC value of 0.5 is the agreement that would be expected if the suitability image values were assigned to random locations.

Next we must make a statement about our trust in the LUCC model's 2000 landscape prediction. In order to quantify this assessment of the model, this paper applies statistical methods developed by Pontius (2000, 2002). The statistical methods separate error and agreement by components due to specification of quantity and location. The simulated map of 2000 is compared to the reference map of 2000, and a Kappa for Location statistic is derived. The Kappa for Location (Klocation) statistic measures the goodness-of-fit between two images based on the grid cell-level location of categories, given that the category quantities are specified (Pontius 2000). A Klocation value of 0 means that a spatial model's ability to specify the grid cell-level location of future change is equal to random. A Klocation of 1 means that a model's ability to specify the grid cell-level location of future change is perfect. Equation 1 is the formula for Klocation (Pontius 2000).

$$\text{Klocation} = (M-Q) / (Z-Q) \quad \text{equation (1)}$$

Where

M = proportion agreement between reference image and predicted image

Q = proportion agreement due to quantity

Z = maximum possible agreement between the reference image and a perfect predicted image, given the specification of quantity of each category

This analysis focuses on the locational predictive power of the LUCC model; therefore, the true quantity of disturbance for the year 2000 is used for the extrapolation from 1992 to 2000. Before calculating the Klocation statistic, grid cells that represent disturbed land in 1992 were removed from the images in order to control for persistence of already disturbed areas.

## 2.5 Extrapolation

Up to this point we have calibrated and validated the model for numerous runs, each with a different combination of drivers. Next, we must extrapolate two values. First, we must predict the quantity of anthropogenic disturbance that will occur between 2000 and 2026, assuming no conservation project exits. Quantities of anthropogenic disturbance were extracted from categorized images of 1975, 1992, and 2000 land-use. A linear trend-line was fit to the three points and then extrapolated to the year 2026. The predicted percent of cumulative disturbance for the year 2026 is 1.02% of the study area, up from 0.59% in 2000.

Second, in order to estimate how well the land-change model will place the location of this disturbance in the future, we decay the Klocation statistic to the year 2026. We assume that the behavior of the model during the validation phase indicates the behavior during the extrapolation phase. Klocation is assumed to be 1 for the year that the extrapolation begins, because we know the location of disturbance for this initial point in time. The further the model predicts into the future, the more the model will place the location of grid cells at incorrect locations, thus Klocation will decay to 0 over time (Pontius and Spencer, in preparation).

Based on equation 2, the estimation of Klocation for the year 2026 allows us to be able to estimate the probability that a grid cell will be disturbed in the future, given that the model says it will be disturbed (Pontius et al. 2003).

The method also allows us to state the probability that a pixel will be disturbed given that the model says it will be undisturbed in 2026. In order to quantify the uncertainty of the simulated landscape, three assumptions are made. We assume that: 1) the estimated kappa is correct, 2) the extrapolated quantities of disturbed and undisturbed are accurate; and 3) the grid cells of the 2026 reference map are crisp categories.

$$\begin{aligned}
 P(j|M_k) &= Q_j + [K_{location} * (1-Q_j)] && \text{if } j = k \\
 &= Q_j * (1 - K_{location}) && \text{if } j \neq k
 \end{aligned}
 \tag{equation (2)}$$

where

j = category index in reference image for 2000 = disturbed, undisturbed

k = category index in predicted image for 2026 = disturbed, undisturbed

P(j|M<sub>k</sub>) = the probability that a cell is category j given that the model says it is category k in 2026

Q<sub>j</sub> = proportion of category j in the predicted image for 2000

K<sub>location</sub> = the best guess at the model run's grid cell-level certainty, which ranges from 0 to 1

### 2.5 Calculation of Carbon Credits

In order to estimate the amount of carbon released to the atmosphere after anthropogenic land use changes, we use data provided by Winrock International specifying the amount of carbon stored for each land cover type per unit of area. If a land cover is disturbed, we estimate that 50% of stored carbon would be released to the atmosphere. To isolate the land cover areas and types that were disturbed between 2000 and 2026, we overlay the 2026 predicted landscape image with a land cover image. The area of land cover is multiplied by the amount of carbon per unit of area and then divided by 2, giving us the amount of carbon that would be released into the atmosphere if there were no conservation project.

### 3 Results

Our analysis estimates that 577,000 metric tons of carbon would be released to the atmosphere, assuming that no conservation projects were to exist. Currently, carbon credits are valued at \$0.98 per metric ton, this means that we expect that carbon credits worth approximately \$0.6 Million would be awarded to the investors of the Noel Kempff Mercado Forestry Project between 2000 and 2026.

Any estimation of carbon credits awarded must be made in conjunction with validation statements of the land use change prediction. We use three validation methods to make statements about our trust in the modeled business-as-usual landscape. First, a visual validation provides an intuitive assessment at how well a model extrapolation represents the year 2000 (Figure 3). One can see that the model was good at simulating future disturbance near existing cities, however, the model failed to simulate a large portion of disturbance along the Paragua River. After applying the visual validation method to the entire predicted landscape image, it is apparent that the model made more errors than not for the locations that changed.

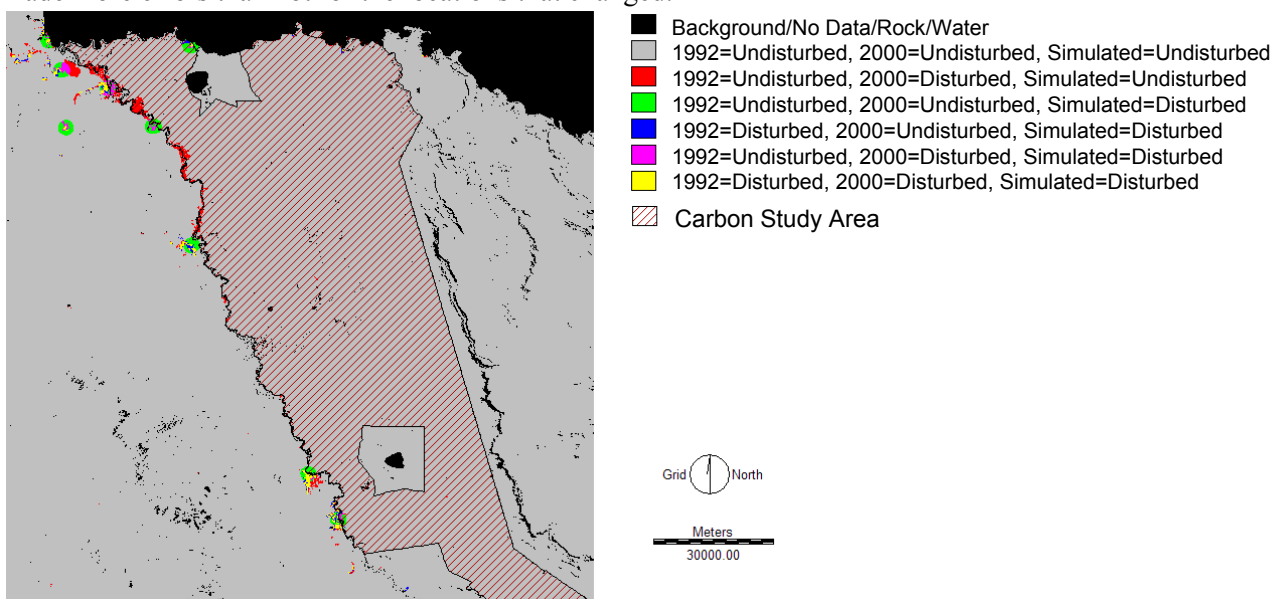


Figure 3. Comparison of predicted versus true LUC from 1992 to 2000.

Second, to quantify the validation statements, the ROC statistic shows that the suitability image, created after combining the major town and Paragua River drivers, has a goodness-of-fit of 0.965 with a Boolean image of anthropogenic land cover disturbance between 1992 and 2000. This shows us how well the suitability map portrays the location of land that was disturbed between 1992 and 2000.

Third, we rely on the Klocation statistic to quantify the validation of land-use change model. Figure 4 shows the results of the model runs, expressed with Klocation. The best simulation of a 2000 landscape utilized major towns and the Paragua River driver maps, which had a Klocation of 0.223 after controlling for persistence of disturbance, and using the correct quantity of disturbance for 2000.

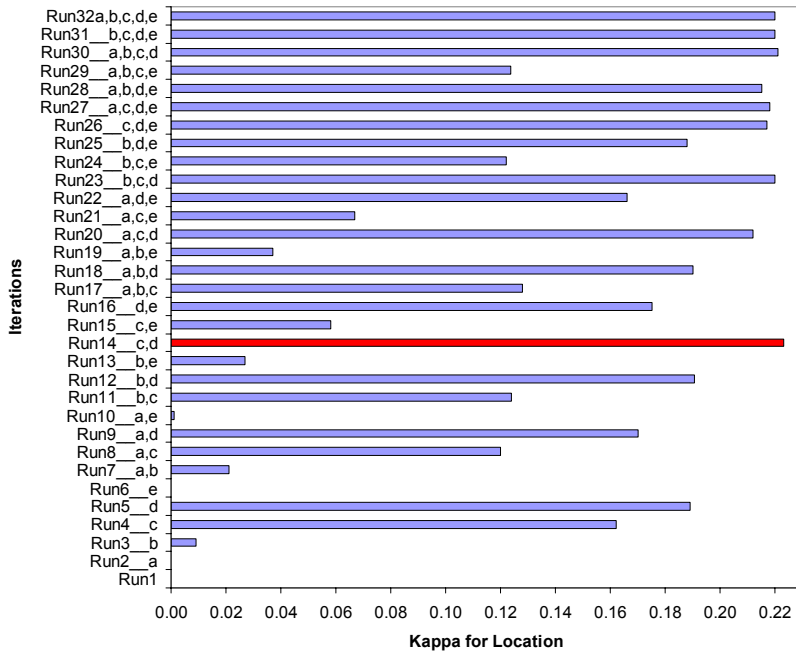


Figure 4. The results of the model runs, expressed with Klocation. The best simulation of a 2000 landscape utilized major towns and the Paragua River driver maps, which had a Klocation of 0.223 after controlling for persistence of disturbance. Letters a-e denote the images of Figure 3 that were included in the simulation run from 1992 to 2000.

The agreement due to random chance shown in figure 5a illustrates that the model has a 50% chance to correctly place the location of a disturbed cell because the images have two categories. When comparing the simulated image to the reference image the additional agreement due to quantity is over 49%. The agreement due to location is just over 0.1%, and error due to location is 0.5%, and the error due to quantity is less than 0.1% (Figure 5b).

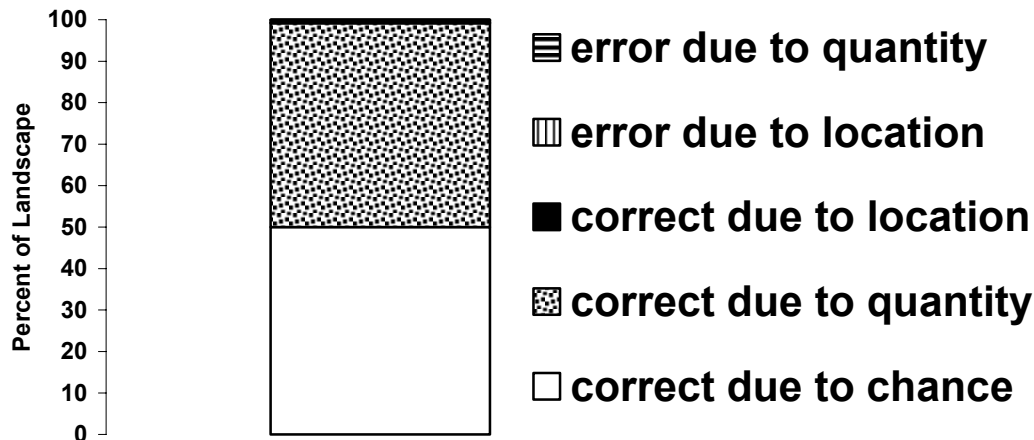


Figure 5a. Components of agreement and disagreement between images of simulated 2000 and a 2000 reference image



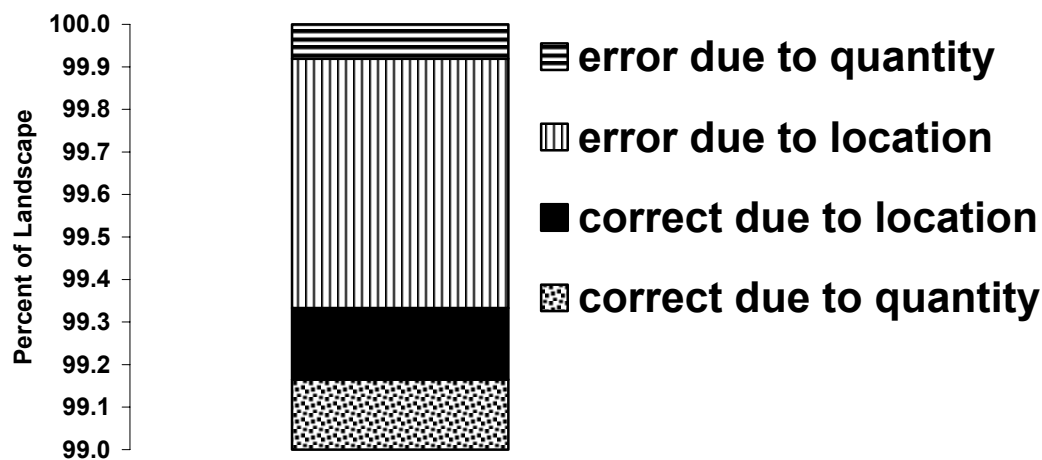


Figure 5b. Components of agreement and disagreement between images of simulated 2000 and a 2000 reference image.

After the certainty in the model is understood at a known point in time, i.e. 2000, the model is unleashed to simulate the landscape of 2026. Figure 6 is the model's best guess at the 2026 landscape. Validation information to a known point in time is utilized to project the certainty of the models' simulation into the future. In doing so, we predict that Klocation will be 0.008 in 2026. The Klocation of 0.008 is smaller than the Klocation of 0.223 observed in the validation, because the extrapolation interval of 26 years is much larger than the validation interval of 8 years.

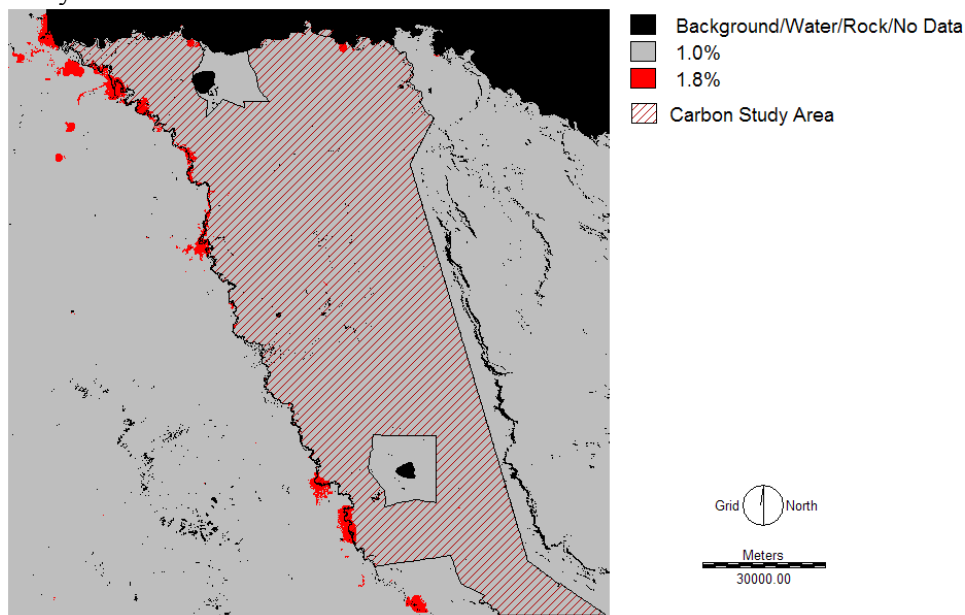


Figure 6. The model's best guess at the 2026 landscape, which shows the probability of disturbance, given the LUCC model extrapolation.

Equation 2 implies that the probability that a grid cell is disturbed land in the year 2026 is 1.8%, given that the model says it is disturbed. The probability that a grid cell is disturbed given that the model says it was undisturbed is 1.0%.

## 4 Discussion

### 4.1 Uncertainty of Quantity

There is tremendous need for future research in the uncertainty in extrapolating quantities of deforestation. If the land-change modeler predicts an exaggerated amount of deforestation, had there been no conservation project,

then an exaggerated amount of credits will be awarded. For example, if the entire carbon area were predicted to be deforested, then approximately 45.3 million tons of carbon would be saved. At \$0.98 per metric ton, credits worth \$44.3 million could be awarded. This is a stark contrast to our estimate of \$0.6 million. Considering this large difference in money, the uncertainty in the quantity of deforestation needs to be expressed.

#### **4.2 Effect of Arbitrary Extent**

No guidelines exist which specify the study area extent that should be used for spatial model baseline extrapolations. The method to quantify uncertainty of the 2026 landscape uses proportions of disturbance in the study area. Therefore, further analysis was performed to get an understanding of the effect that extent has on the 2026 landscape uncertainty. For example, if the study area was drastically reduced from approximately 2 million hectares to approximately 761,000 hectares, the probability that a grid cell is disturbed land in the year 2026, given that the model says it is disturbed, is 3.5% as opposed to 1.8%. The probability that a grid cell is disturbed given that the model says it was undisturbed is 2.7%, as opposed to 1.0%.

#### **4.3 Importance of Uncertainty**

Even if the project is successful, the LUC model could not show success, due to the expressed uncertainty of the LUC model prediction. Conversely, the LUC model would not detect project failure due to the uncertainty of the LUC model prediction.

#### **5 Conclusion**

In this analysis we found that the uncertainty of the prediction of deforestation in the Noel Kempff Mercado Carbon Project is high. In order for conservation projects to be profitable, the risk of deforestation needs to be high. In the Noel Kempff area, the predicted deforestation is low, resulting in a low value of anticipated carbon credits.

We hope that researchers adopt the statistical techniques illustrated in this paper. Currently, land-change modelers are not being held accountable for their predictions of future landscapes. Most land-change modelers fail to validate models and fail to state the uncertainty in future prediction. Consequently, policy makers and the general public develop opinions based on misleading research that fails to give them the appropriate interpretations required to make informed decisions. Validation efforts to a known point in time are necessary to make an estimate of the uncertainty for the extrapolation to an unknown point in time. Given the very large sum of money associated with land-use change forestry projects, we see the importance of stating the uncertainty in the location of predicted deforestation. We offer the methods of this paper as a means to improve techniques of policy relevant LUC modeling.

In the Noel Kempff Mercado project, assessment of uncertainty shows that there is a low level of certainty in the prediction of the 2026 landscape. If forestry project investors require a high level of certainty in landscape predictions, then the current state of LUC modeling is an unreliable method to assess carbon credits.

#### **Acknowledgements**

We thank Joe Spencer and our GIS colleagues for pushing the level of our work higher, also Elizabeth C. Smith for editing, advice, and support. Special thanks to Aaron Dushku and Winrock International, for providing data, and permission to perform this analysis. Also, we thank Clark Labs for the development of analytical tools that are in the GIS software IDRISI.

#### **References**

- Brown, S., I. Swingland, R. Hanbury-Tenison, G. Prance, N. Meyers, 2002. Changes in the use and management of forests for abating carbon emissions: issues and challenges under the Kyoto Protocol. *The Royal Society London*. 360, 1-13.
- Chicago Climate Exchange/Program. <http://www.chicagoclimatex.com/about/program.html>. Viewed November 18, 2003.
- Chen, J., P. Gong, C. He, W. Luo, M. Tamura, P. Shi 2002. Assessment of the Urban Development Plan of Beijing by Using a CA-Based Urban Growth Model. *Photogrammetric Engineering & Remote Sensing*, 68(10): 1041-1049.

- Kaimowitz, D. & Angelsen, A. 1998. Economic models of tropical deforestation: a review. Bogor, Indonesia: Center for International Forestry Research.
- Killeen, T.J., and T.S. Schulenberg (Editors). 1998. A biological assessment of Parque Nacional Noel Kempff Mercado, Bolivia. *RAP Working Papers 10*, conservation International, Washington, D.C.
- Kyoto Protocol 1997 United Nations Framework Convention on Climate Change. Kyoto, Japan. December 11, 1997. (Available from <http://unfccc.int/resource/docs/convkp/kpeng.html>).
- Lambin, E.F., Baulies, X., Bockstael, N., Fischer, G., Krug, T., Leemans, R., Moran, E.F., Rindfuss, R.R., Sato, Y., Skole, D., Turner II, B.L. and Vogel, C., 1999. Land-use and land-cover change implementation strategy. *Royal Swedish Academy of Sciences*, Stockholm, Sweden.
- Lo, C.P., and X. Yang 2002. Drivers of Land-Use/Land-Cover Changes and Dynamic Modeling for the Atlanta, Georgia Metropolitan Area. *Photogrammetric Engineering & Remote Sensing*, 68(10): 1041-1049.
- Pontius, R.G. 2000. Quantification error versus location error in comparison of categorical maps. *Photogrammetric Engineering & Remote Sensing*, 66(8) p. 1011-1016.
- Pontius, R.G. 2002. Statistical Methods to Partition Effects of Quantity and Location During Comparison of categorical Maps at Multiple Resolutions. *Photogrammetric Engineering & Remote Sensing*, 68(10): 1041-1049.
- Pontius, R. G., A. Agrawal, and D. Huffaker 2003. Estimating the Uncertainty of Land-Cover Extrapolations while Constructing a Raster Map from Tabular Data. *Journal of Geographical Systems* 5(3) p. 253-273.
- Pontius Jr, R., J Cornell and C Hall. 2001. Modeling the spatial pattern of land-use change with GEOMOD2: application and validation for Costa Rica. *Agriculture, Ecosystems & Environment* 85(1-3) p. 191-203.
- Pontius, R. G. Jr. and L. Schneider. 2001. Land-use change model validation by a ROC method for the Ipswich watershed, Massachusetts, USA. *Agriculture, Ecosystems & Environment* 85(1-3) p. 239-248
- Pontius, R. G. Jr. and J. Spencer. In preparation. Uncertainty in Extrapolations of Predictive Land-change Models.
- UNFCCC 2001 United Nations Framework Convention on Climate Change agenda items 4 and 7. In Proc. Conference of the Parties, 6th Session, Part 2, Bonn, 16-27 July 2001. (Available from <http://www.climnet.org/cop7/FCCCCP2001L.7.pdf>).
- University of Maryland Global Land Cover Facility. <http://glcf.umiacs.umd.edu>. Downloaded September 3, 2003.
- USGS The National Map Seamless Data Distribution System. <http://seamless.usgs.gov>. Downloaded September 7, 2003.