Physical Landscape Correlates of the Expansion of Mechanized Agriculture in Mato Grosso, Brazil

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ABSTRACT: Mechanized agriculture is rapidly expanding in the state of Mato Grosso, Brazil. In the past five years, land area planted with soybeans, the state's principal crop, has increased at an average rate of 19.4% yr^{-1}. Drivers of this large-scale land-use conversion are principally economic and sociopolitical, but physical properties of the landscape make some areas more attractive than others for expansion of mechanized agriculture. The goal of this study is to evaluate several physical characteristics of land in Mato Grosso and to quantify their respective weights in determining the likelihood of land-use conversion to crop production. A 2003 land-cover classification at 250-m reso-

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lution was compared to maps of five physical landscape characteristics (surface slope, soil type, total November precipitation, distance from paved roads, and previous land-cover type based on a 2001 classification). A land-cover transition matrix was generated to inform analysis of the role of previous land-cover type, and statewide distributions of the other four landscape characteristics were examined across agricultural and nonagricultural land. Finally, logistic regressions were performed to quantify the respective correlations of these various characteristics with the probability of conversion to mechanized agriculture. Areas of new cropland in 2003 (converted since the 2001 classification) were nearly 3 times as likely to have been converted from pasture/cerrado as from all other land-cover types combined, but in terms of class original extent, bare soil was by far the most likely class to be converted to cropland, with 56% of its 2001 land area being converted by 2003. The physical landscape parameter found most highly correlated with conversion to mechanized agriculture between 2001 and 2003 was that of the previous land-cover type, followed by topographic slope and distance from paved roads. Soil type and total November precipitation were poorly correlated with mechanized agriculture. Findings from this study suggest that holistic, spatially explicit models of likelihood of conversion to mechanized agriculture should consider land cover, slope, and proximity to main roads in addition to political and economic parameters to generate realistic scenarios for sustainable land-use planning.

KEYWORDS: Mechanized agriculture; Soy; Land-use change; Logistic regression; Brazil

1. Introduction

In the three decades since soy production began in Brazil, soy has advanced to become the nation's principal crop, both in planted area and in quantity produced. Since 1990, the amount of land planted with soy in Brazil has doubled and production has quadrupled. Mechanization has been a key element in both the rapidity of expansion and the increase in yield. Researchers and farmers first introduced soy into the southern region of the country, and have since extended planting into the cerrado of central Brazil and even into some areas of Amazonia. Soy cultivation now encompasses more than 20×10^{-6} ha of Brazilian land and accounts for approximately 10% of the nation's trade revenue.

The center-west region is presently the hub of soy activity, producing over half of the nation's crop (Jaccoud et al. 2003). The state of Mato Grosso alone saw 5.15×10^6 ha of soy planted for the 2003–04 harvest, which represents about 6% of the state's total land area. Planted area in Mato Grosso has increased at an average rate of 19.4% yr^{-1} since 1999. Plans to further expand Mato Grosso's soy growing area can easily be realized if market demand and public policy continue to support growth. Few natural barriers are foreseen for expansion in this region. Brazilian and foreign agricultural experts agree that approximately 100×10^8 ha of cerrado land is technically viable for expansion of soy in Brazil (Schnepf et al. 2001; Dros 2003). The only obstacle at present appears to be inadequate transportation networks for distribution of products, equipment, fertilizer, etc., but infrastructure improvements are already being implemented (Laurance et al. 2004).

Mechanized agriculture in the center-west region is presently concentrated primarily in woodland and grassland savanna (cerrado) areas (Anderson et al. 2003). The Brazilian cerrado is thought to support the largest number of species of any type of savanna in the world (Klink et al. 1993; Myers et al. 2000; Fearnside 2001), but only 1.5% of this land is protected within federal reserves. Moreover, the transition zone between forest and cerrado, which contains more endemic plant species than either "pure" forest or cerrado, is even less protected than the cerrado biome (Fearnside and Ferraz 1995).

While economic and political drivers influence the establishment and success of agricultural plantations, physical aspects of the landscape also play a role in determining where they are established. Much crop production in Mato Grosso is highly mechanized, and physical landscape factors are likely to weigh heavily in decisions to invest in this type of agriculture. As with all agriculture, precipitation and soil type must be considered, as well as the relative difficulty of land preparation (mainly depending on the previous land-cover type). For mechanized agriculture, topography and proximity to adequate roads for transporting inputs and products are additional factors that influence the spatial distribution of cultivated land. Previous studies have demonstrated the impact of road access on land-use change (Stone et al. 1991; Wilkie et al. 2000; Laurance et al. 2002; Alves 2002).

How much land in Mato Grosso will ultimately be converted to mechanized agriculture depends on future economic, political, biophysical, and climatic conditions. However, current assessment of the likelihood of conversion to mechanized agriculture for different landscapes in Mato Grosso can inform land-use planning toward economic and ecological sustainability. The present study considers five physical landscape characteristics and seeks to quantify correlations between mechanized agriculture and these spatial factors. The objective of this study is to ascertain, through observations of land-use change patterns and through statistical analysis, the roles and respective importance of several key physical landscape factors in determining the likelihood of conversion to mechanized agriculture for land across Mato Grosso.

2. Methods

2.1. Study area

The study area comprises the entire state of Mato Grosso, Brazil, whose land area totals over 900 000 km^2. The state is part of the center-west region of Brazil, sharing its southwestern border with Bolivia (Figure 1). An extensive area of wetlands known as the Pantanal covers a large portion of southwestern Mato Grosso, the northern region is largely forested, and the rest of the state contains a mosaic of various types of savanna (cerrado) and transition forest types. Current agribusiness is primarily concentrated in the cerrado and transition forest zones.

2.2. Datasets

Five key physical landscape characteristics were selected for examination as potential correlates of mechanized agriculture expansion, following field observations in Mato Grosso's northern-central region, discussions with agriculturalists in

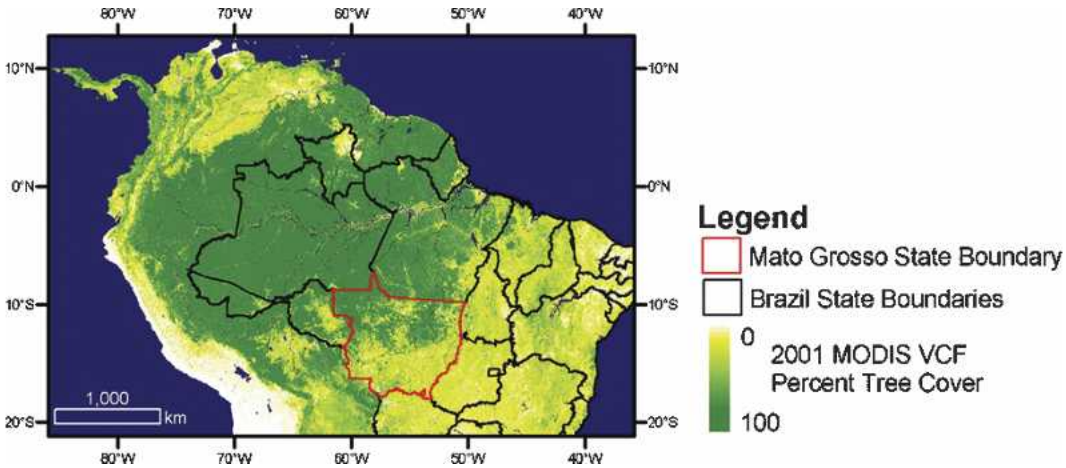

Figure 1. Location of Mato Grosso. MODIS 500-m vegetation continuous fields data product shows percent tree-cover estimates for the region for 2001 (Hansen et al. 2003). (Source: the Global Land-Cover Facility, College Park, MD.)

Brazil, and previous literature. These five factors are topographic slope of the land surface, soil type, total November precipitation, distance from paved roads, and land-cover type prior to conversion to mechanized agriculture. Spatial datasets of these variables were then combined using a geographic information system (GIS) and compared to a 2003 land-cover classification (Morton et al. 2005). Figures 2–6 show the data layers for Mato Grosso.

In addition, several spatially explicit datasets showing boundaries of state and federal protected lands, provided by the Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis (IBAMA), were incorporated. Three of these protected areas were masked out of the study area,[1] as they were determined to be under markedly different land-use policy regimes from those covering the majority of the state. The concern was that inclusion of these areas in the logistic regression might result in misleading probabilities of conversion for the land within their boundaries and might also skew results for other areas.

2.2.1. Land-cover classification

The 2003 land cover was classified using field-based observations from central Mato Grosso and phenological signatures from normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI) time series from the Moderate Resolution Imaging Spectroradiometer (MODIS) vegetation index (MOD13)

[1] Areas masked out include the Xingu Indigenous Park and surrounding indigenous lands (Capoto/Jarina, Wawi, and Batovi), which together compose a single polygon in the northeastern portion of the state; the Guariba/Roosevelt Extractive Reserve in the northwestern corner; and the Environmental Protection Area of the Rio Araguaia, along Mato Grosso's eastern border.

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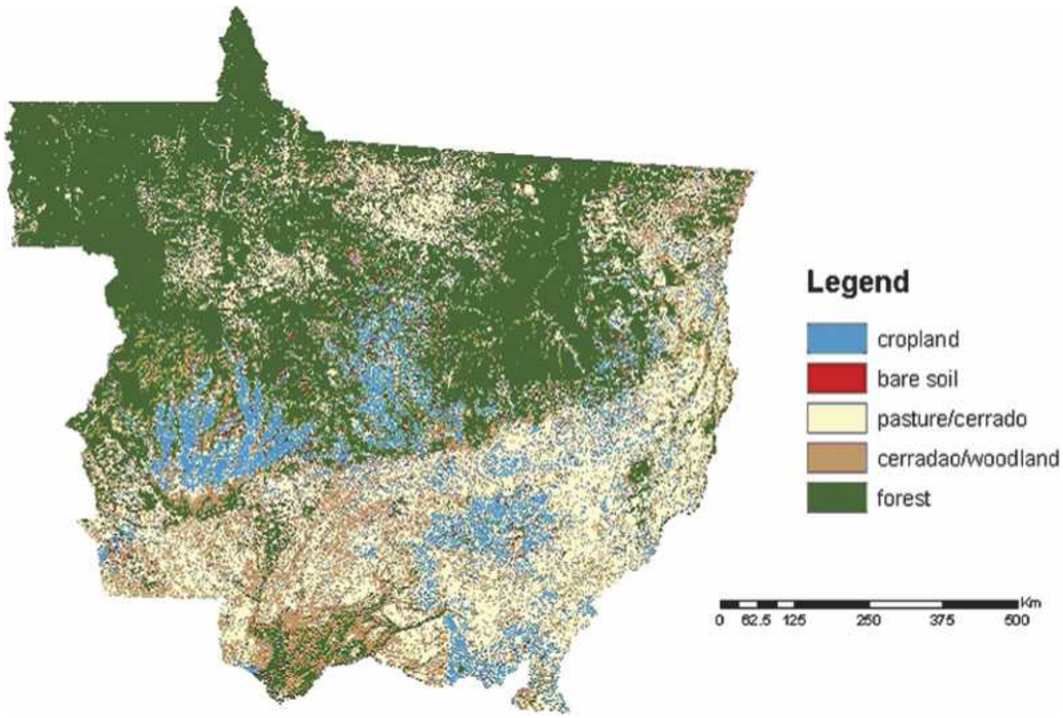

Figure 2. The 2003 land-cover classification for Mato Grosso based on annual phenological signatures in NDVI and EVI time series (Morton et al. 2005).

product (Huete et al. 1999). Field observations were scaled to 250-m resolution to identify training pixels in MODIS imagery using coincident Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) imagery at 15–90-m resolution and MODIS imagery at 250-m resolution. NDVI and EVI time series for each MODIS training pixel were assigned to land-cover classes using a decision tree classifier. Prior to classification, NDVI and EVI time series were adjusted based on quality assessment (QA) data layers in the MOD13 product; cloudy values in each pixel's time series were replaced with predicted values from a spline model. The resulting classification included five land-cover categories: cropland,[2] bare soil (including areas cleared in preparation for cattle or crops as well as fallow fields), pasture/cerrado, cerradão/woodland, and forest. To assess land cover in 2001, classification methods developed using 2003 field observations and coincident imagery were applied to NDVI and EVI time series from 2000 to 2001.

2.2.2. Topography

A 90-m digital elevation model was obtained from the 2000 National Aeronautics and Space Administration (NASA) Shuttle Radar Topography Mission (SRTM),

[2] Pixels classified as cropland are generally considered to represent areas of mechanized agriculture due to the large pixel size and the impracticality of cultivating such areas without the aid of mechanization.

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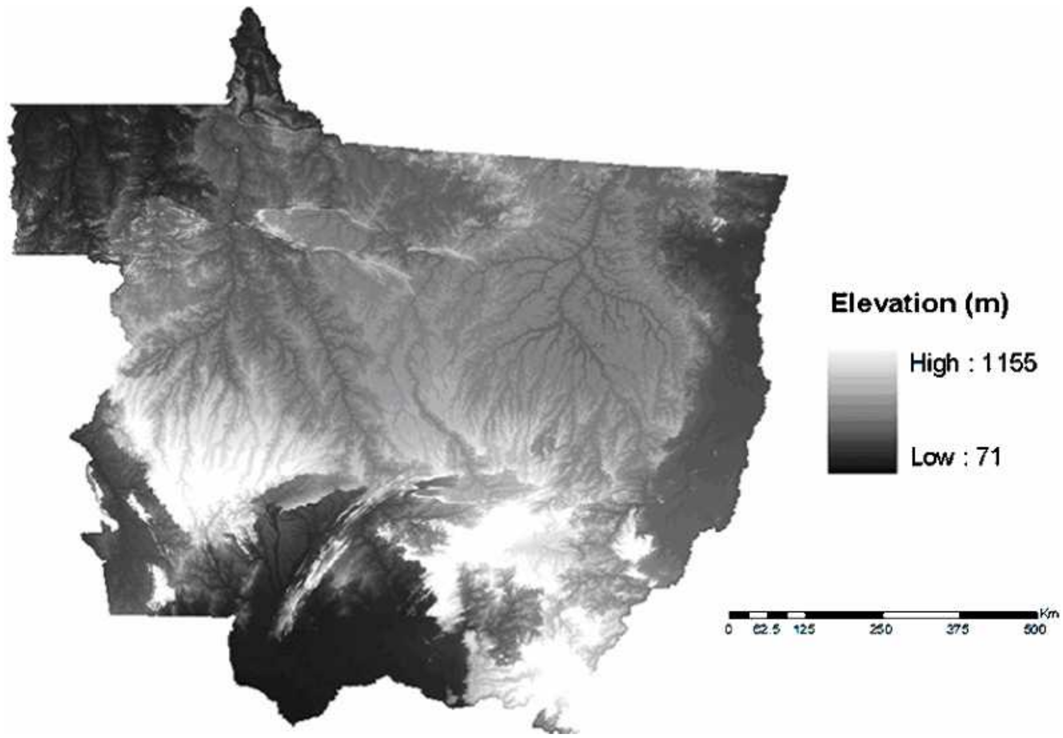

Figure 3. Elevation map of Mato Grosso. (Source: NASA Shuttle Radar Topography Mission 90-m digital elevation model.)

for the state of Mato Grosso. The "forest effect" (Sun et al. 2003) was noted as a problem because elevation estimates changed suddenly and significantly along straight lines at forest edges due to incomplete penetration of the canopy by C- and X-band radar data. Forest edges thus appear as cliffs in the image. To correct this problem, mean slopes were calculated for each 90-m pixel, and a new data layer was generated using these values. Slopes of pixels affected by forest edges were then identified, and these pixels were reassigned neighborhood mean slope values in order to smooth forest edge "cliffs" without significantly altering the rest of the dataset. Within-canopy slope values were not considered a problem, because changes in vegetation structure within these forested areas are gradual, unlike the sharp changes at forest edges, and because slope is the parameter of interest for the present study rather than absolute elevation.[3] The procedure was repeated, and the three resulting slope maps were compared statistically to ensure reliability of the output. The final corrected 90-m data layer was resampled to 250 m to enable cross analysis with the land-cover map and other data layers. The resampled values were deemed sufficiently reliable for the purposes of the present study. Kellndorfer et

[3] Mato Grosso has a relatively small range of elevation (50–1200 m), such that elevation itself does not bear greatly upon the viability of vegetation types from one area of the state to another. Thus, slope is the parameter of interest here due to its effect on the ease/viability of mechanized agriculture, and elevation itself is not considered in the analysis.

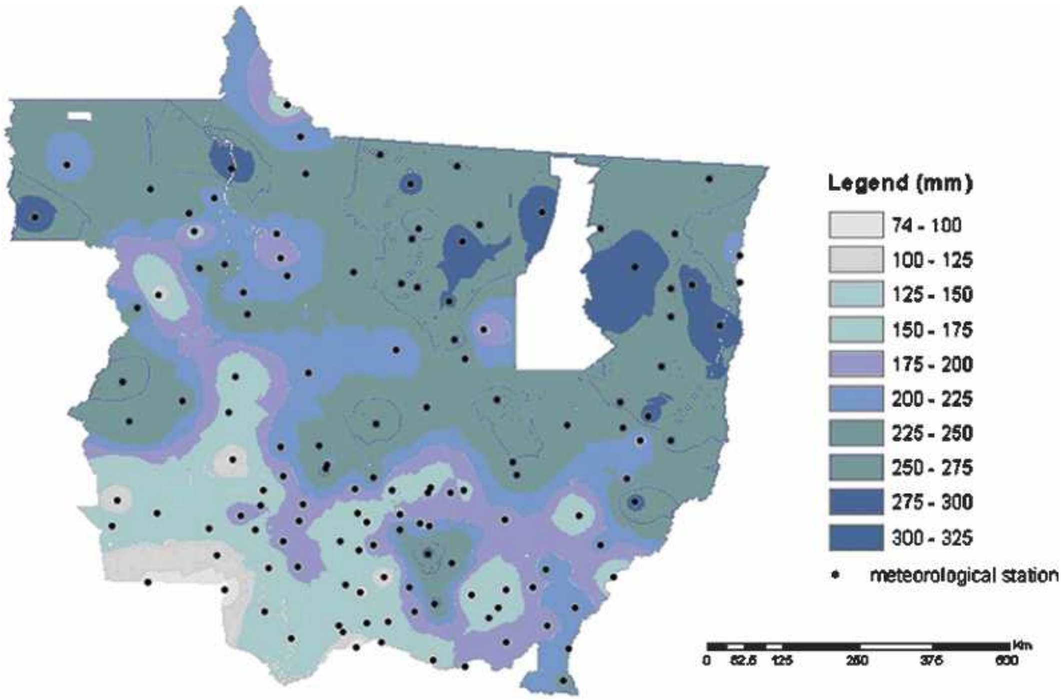

Figure 4. Interpolated measurements of mean total Nov precipitation for Mato Grosso, 1999–2002, based on meteorological station data. Station locations are indicated. Protected areas are masked out as described earlier in paper. (Source: ANEEL.)

al. (Kellndorfer et al. 2004) demonstrate that SRTM's relative vertical error can be corrected through sample averaging and the results considered reliable, even for estimates of absolute elevation, given a minimum mapping unit of 1.8 ha (significantly smaller than the 250-m grid cells used here).

2.2.3. Precipitation

The Agência Nacional de Energia Elétrica (ANEEL) provided daily and monthly precipitation totals from 125 meteorological stations in Mato Grosso. These point data were plotted spatially, and monthly total values were interpolated using a four-step inverse distance-weighted algorithm. November was identified as a key month of crop sensitivity to precipitation for the wet season cycle according to discussions with producers in the region and information provided by M. del Carmen Vera Diaz of the Instituto de Pesquisa Ambiental da Amazônia, so total November precipitation was set as the specific variable of interest. Values were recorded from 1999, 2000, 2001, and 2002, and their means were calculated and used as the precipitation parameter in statistical analyses.

2.2.4. Soil type

The Empresa Brasileira de Pesquisa Agropecuária/Instituto Brasileiro de Geografia e Estatística (Embrapa/IBGE 1981) produced a map of soil types at a spatial

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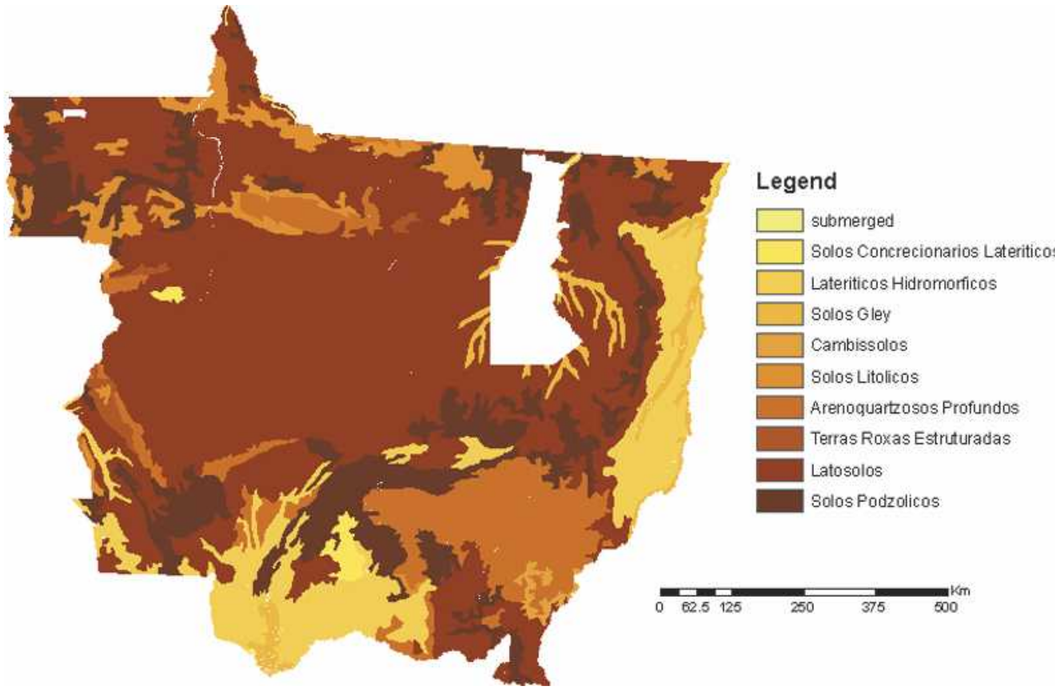

Figure 5. Map of soil types, ranked by suitability for agriculture (darker colors indicating greater suitability). (Embrapa/IBGE 1981; digitized by the USGS).

resolution of 1:5 000 000 from a 1981 survey, which was subsequently digitized and made available by the United States Geological Survey (USGS). Soil types have been divided here into 10 general categories ranked according to suitability for agriculture.

2.2.5. Road networks

The Fundação Estadual do Meio Ambiente de Mato Grosso (FEMA) provided a dataset showing all intercity roads in the state, made from a 2001 survey. We selected all paved roads adequate for truck transport from this dataset, and calculated Euclidean distances from every pixel in the state map to the nearest point on any of these roads. Resulting values were employed as inputs for statistical analyses, measured in units of 1 km.

2.3. Analysis

2.3.1. Transition matrix

A matrix was generated to display vectors of land-cover change between 2001 and 2003 according to the classification maps used throughout the study. The purpose of this step was to establish an initial sense of the influence of land-cover type on the potential for conversion to mechanized agriculture by giving attention to the

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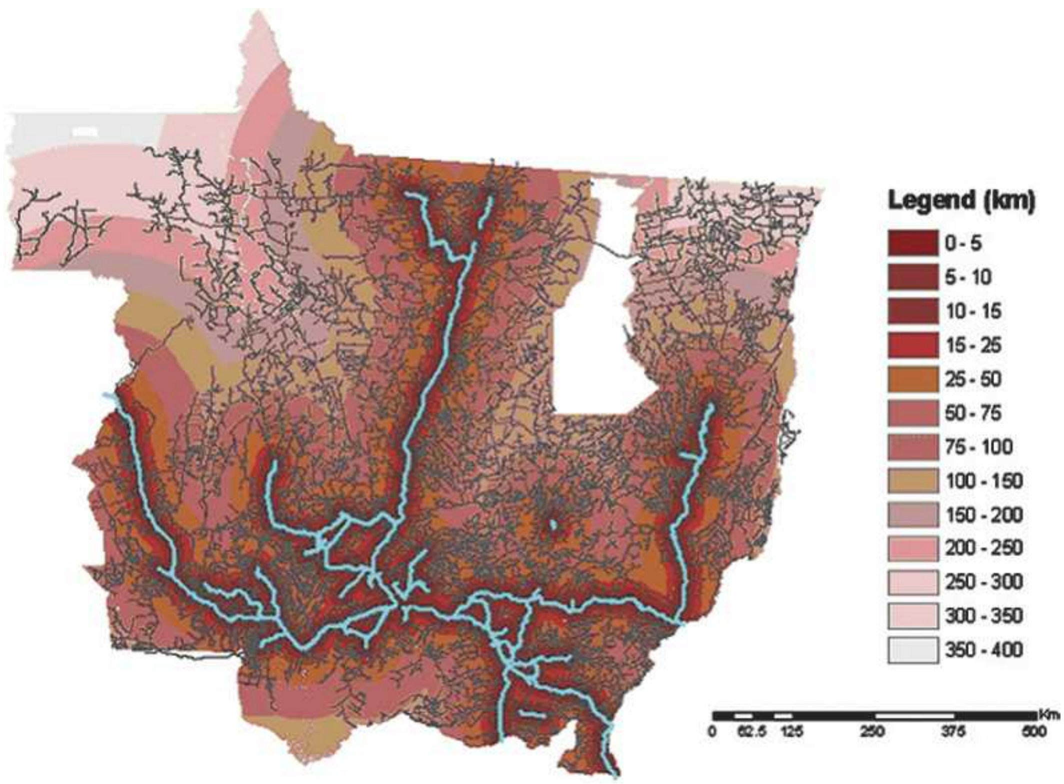

Figure 6. Distance to nearest paved road, for all pixels (250 m) in Mato Grosso. Overlay includes all intercity roads, with paved roads highlighted in blue. (Source: FEMA, Mato Grosso survey.)

magnitudes and directions of change among the various land-cover classes. Pixels where land was converted to agriculture between 2001 and 2003 were then plotted spatially, colored according to original class.

2.3.2. Distributions of physical landscape properties for cropland versus other classes

The remaining four physical landscape characteristics—slope, soil type, precipitation, and distance from paved roads—were examined in terms of their distributions across pixels classified as cropland in 2003, and then across all other pixels within Mato Grosso. Like the transition matrix, this was a preliminary analysis meant to provide a baseline understanding of any general patterns that may exist between these physical landscape characteristics and the presence or absence of mechanized agriculture. A 10 000-point random sample was used for the analysis due to the unwieldiness of the large datasets covering all land in the state. Soil types were assigned integer values from 0 to 9 according to their rankings of agricultural suitability, 0 indicating soils unsuitable for agriculture (submerged) and 9 indicating those most suitable (solos podzolicos). Medians and quartiles are used to describe the data rather than means and standard deviations since all four landscape attributes under examination have nonnormal distributions.

2.3.3. Multiple logistic regressions

Two multiple logistic regressions (MLRs) were performed using SAS statistical software in order to determine relationships between the selected physical variables and probabilities of conversion to mechanized agriculture. Logistic regression was chosen for its utility in analyses with dichotomous dependent variables. Previous studies have demonstrated its usefulness for examining causes as well as effects of land-use and land-cover change (Ludeke et al. 1990; Osborne et al. 2001; Serneels and Lambin 2001).

Logistic models are constructed such that

$$\text{logit}(p) = \log[p/1 - p] = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n, \tag{1}$$

for n-independent variables, where α is the intercept, β values are slope coefficients for the independent variables, and p is the probability of the outcome $Y = 1$ as opposed to 0, of the two outcome possibilities (i.e., presence versus absence of a selected entity or quality). In applying the model, the β coefficients indicate both the direction and intensity of a given correlate's role in affecting the outcome, such that increases in variables with positive coefficients correspond with increased probability of a $Y = 1$ outcome, and increases in variables with negative coefficients likewise correspond to decreased probability that $Y = 1$. Specifically, the value of the β coefficient represents the change in the log odds ratio of the probability that $Y = 1$ for each unit change in the independent variable. In the present study, the five physical landscape properties are set as independent variables, and the presence or absence of mechanized agriculture is set as the dependent variable such that a $Y = 1$ outcome refers to a pixel classified as cropland, and $Y = 0$ indicates a different land-cover class.

Two logistic regressions were conducted. The first was a "snapshot" analysis for understanding how physical landscape characteristics are correlated with the general spatial distribution of mechanized agriculture as shown in the 2003 land-cover classification. The second was an analysis to examine how conversions to mechanized agriculture that occurred between 2001 and 2003 may have been correlated with those same characteristics. Essentially, these two regressions are assessments of the impacts of the selected physical factors on 1) where mechanized agriculture *is*, and 2) where it *is expanding*. In this paper the two regressions are referred to as "agricultural area" and "agricultural expansion" for clarity.

The two regressions employed a single stratified sample. Points were selected randomly within each land-cover class, with sample sizes proportional to the area in each class such that the full sample contained a total of 7108 points statewide (1/2000 of the total number of pixels in each data layer). All sample points were included in the agricultural area regression, but for the agricultural expansion regression all pixels classified as cropland in 2001 were removed so as to examine only those areas of recent expansion (between 2001 and 2003).

The dependent variable in each case was the dichotomous outcome of "cropland" versus "other land-cover type" (1–0) based on the 2003 classification map.

Table 1. Regression variables.

Dependent variable	Type	Unit
Cropland vs all other land-cover classes in 2003	Binary	1–0
Independent variables	Type	Unit
Mean slope within pixel	Continuous	°
Soil type	Categorical	1–0 (binary dummy variables for each category)
Euclidean distance from nearest point on a paved road	Continuous	km
Mean total Nov precipitation, 1999–2002	Continuous	mm
Land-cover type in 2001 (second regression only)	Categorical	1–0 (binary dummy variables for each category)

Independent variables included slope, soil type, distance from paved roads, and mean total November precipitation (1999–2002). Previous land-cover type was included as an additional independent variable in the agricultural expansion regression (Table 1).

Prior to building the regression models, input data were transformed as necessary in order to meet assumptions of parametric analysis.[4] All independent variables were also tested for collinearity. Both regressions used a forward approach and a maximum likelihood decision scheme. Afterward, regression coefficients were standardized using the equation

$$b^* = (b)(S_X)(R)/S_{\mathrm{logit}(\hat{Y})}, \tag{2}$$

where b^* is the standardized regression coefficient, b is the unstandardized coefficient, S_X is the standard deviation of the independent variable, R is the square root of SSR/SST (where SSR = regression sum of squares and SST = total sum of squares), and $S_{\mathrm{logit}(\hat{Y})}$ is the standard deviation of the log odds ratio of the predicted probability of the outcome $Y = 1$ for the dependent variable Y. This standardization enabled all coefficients to be compared with each other and used together in building the final probability model.

2.3.4. Spatial map of model results

The spatial map of conversion probability was developed using results from the agricultural expansion regression, since that model maximizes input of relevant physical landscape data and since current expansion dynamics tell more about the probability of future conversion than static snapshots of the spatial distribution of mechanized agriculture. Variables not found to be statistically significant were excluded from the model. For the independent variable of previous land cover, 2003 land-cover classes were used as input data since these now form the basis for future conversion probabilities.

The regression model was applied to the entire state with the exception of 1) the protected areas that were masked out earlier and 2) all pixels classified as cropland

[4] Square root transformations were performed on data for slope, precipitation, and distance from roads, and dummy variables (1–0) were created for each category of soil type (10 categories) and previous land-cover class (4 categories).

in 2003. The resulting map shows relative probabilities of conversion for all yet-unconverted land in Mato Grosso that is not protected within the excluded land reserves. These probability estimates are based solely on the physical landscape factors as constructed in the regression model, and do not consider economic and political drivers.

3. Results and discussion

3.1. Transition matrix

The transition matrices below (Tables 2a,b) show vectors of land-cover conversion in Mato Grosso between 2001 and 2003 according to the respective land-cover classifications (Morton et al. 2005) that were used throughout the study. Considering land area converted to cropland, clearly most comes from the 2001 pasture/cerrado class. 72% of the land classified as new cropland in 2003 came from areas previously classified as pasture/cerrado, almost 3 times the area converted from all other classes combined: 17.5% had been classified as bare soil in 2001, 7% as cerrãdo/woodland and 3% from forest. However, when considered as proportions of the total original extent of each class in 2001 (Table 2b), over 56% of the area classified as bare soil in 2001 was converted to mechanized agriculture by 2003, whereas only 9% of pasture/cerrado land was converted during this period and very small percentages of cerrãdo/woodland and forest classes. This observation dramatically affects expectations regarding conversion probabilities from the different land-cover types to mechanized agriculture. Although some

Table 2a. Transition matrix showing pixel counts by land-cover type in 2001 and how those same pixels were classified in 2003.

		2003 Land cover					
	Pixel counts	Cropland	Bare soil	Pasture/ cerrado	Cerrãdo/ woodland	Forest	Total 2001 pixels
2001 Land cover	Cropland	688 322	27 773	352 565	19 452	2277	1 090 389
	Bare soil	90 664	10 256	44 098	13 953	2848	161 819
	Pasture/cerrado	372 341	49 924	2 778 147	827 399	73 193	4 101 004
	Cerrãdo/woodland	36 603	30 704	905 476	1 362 198	250 836	2 585 817
	Forest	17 479	48 558	303 374	415 561	5 490 667	6 275 639

Table 2b. Transition figures as percentages of 2001 class extent.

		2003 Land cover				
	Percent of 2001 land area	Cropland	Bare soil	Pasture/ cerrado	Cerrãdo/ woodland	Forest
2001 Land cover	Cropland	63.13	2.55	32.33	1.78	0.21
	Bare soil	56.03	6.34	27.25	8.62	1.76
	Pasture/cerrado	9.08	1.22	67.74	20.18	1.78
	Cerrãdo/woodland	1.42	1.19	35.02	52.68	9.70
	Forest	0.28	0.77	4.83	6.62	87.49

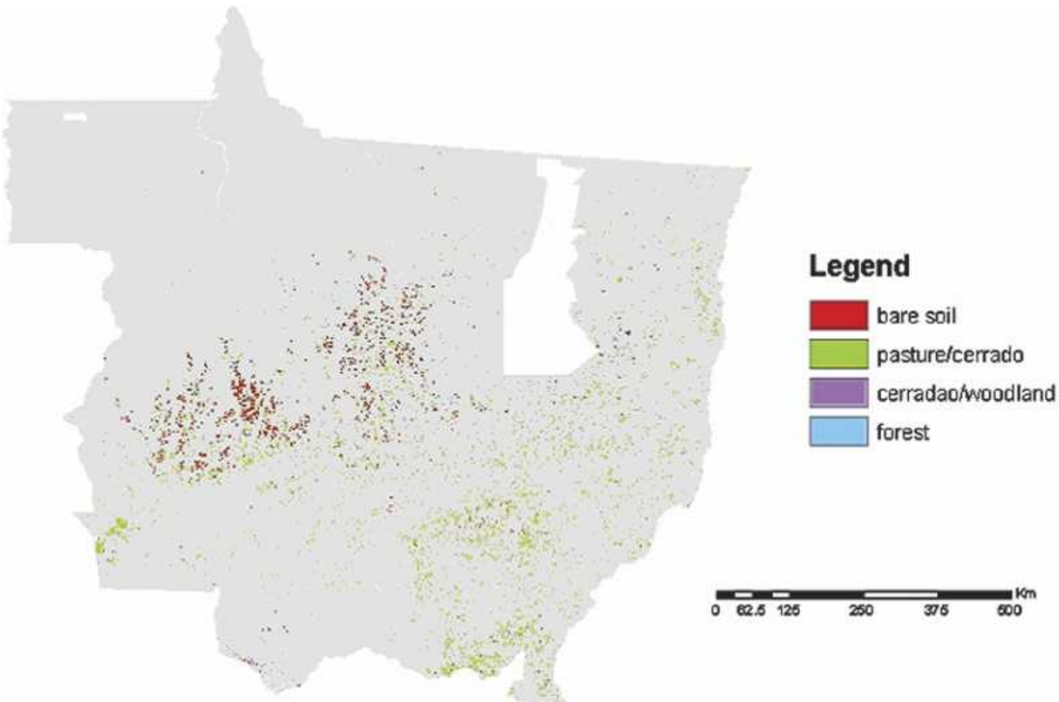

Figure 7. The 2001 land-cover classes of pixels subsequently converted to cropland by 2003.

degree of classification error must be acknowledged in considering the numbers in these tables due to "shifting borders" and other difficulties, the general trends are clear. Figure 7 shows the spatial distribution of the various 2001 land-cover classes in the locations where they were converted to mechanized agriculture by 2003.

3.2. Distributions of physical landscape properties for cropland versus other classes

In the comparison of physical landscape properties between cropland and other land-cover classes in Mato Grosso, notable differences were found between the two categories with respect to topography as well as distance from roads: Slope values and paved-road distances were both quite a bit lower for cropland areas than for other areas of the state. Trends were less clear with precipitation and soil type: Precipitation values show a slightly broader distribution in noncrop areas than in cropland, but the values are generally slightly higher in noncrop areas with the exception of the minimum values. Soil suitability values are nearly identical between the two categories (Table 3).

This analysis is intended to provide a preliminary idea of the similarities and differences between crop and noncrop landscapes in terms of these physical properties. Results shown here are quite general and are elaborated in the multiple regression analysis.

Fig. 7 live 4/C

Table 3. Distributions of physical landscape properties, compared between cropland and other land-cover classes within Mato Grosso.

		Min	First quartile	Median	Third quartile	Max	Std error
Distance from paved roads (km)	Cropland	0	16	37.5	65	227	1.6
	Other classes	0	27	72	153	406	1.2
Mean total Nov precipitation, 1999–2002 (mm)	Cropland	103	188	218	242	306	1.8
	Other classes	81	189	230	253	311	0.6
Soil suitability for agriculture (integer ranking, 0 = low, 9 = high)	Cropland	0	6	8	8	9	0.1
	Other classes	0	6	8	8	8	0.03
Mean slope within pixel (°)	Cropland	0	0	0	1	8	0.04
	Other classes	0	0	1	2	34	0.04

3.3. Logistic regressions

Collinearity among variables was low, with absolute values ranging from 0.005 to 0.223 for the agricultural area regression and between 0.001 and 0.248 for the agricultural expansion regression. These values are all well below the tolerated maximum of 0.80 (Menard 2002), so all variables were included in the regressions. Additionally, the Hosmer and Lemeshow (Hosmer and Lemeshow 1989) goodness-of-fit test yielded an X^2 value of 11.8108 and a p value of 0.1598 for the agricultural area regression and $X^2 = 8.512$, $p = 0.3851$ for the expansion regression, indicating that the input data sufficiently met all assumptions for logistic regression.

Regression results indicate that land surface slope and distance from paved roads were significantly correlated with mechanized agriculture in both the agricultural area analysis and the agricultural expansion analysis. Topography proved more strongly correlated than road distance in both regressions (see Table 4 for coefficients and p values of significance). The negative coefficients for the variable of topographic slope suggest that flat terrain is more conducive to mechanized agriculture than are high-relief landscapes. For distance from paved roads, the negative coefficients support the generally held notion that mechanized agriculture

Table 4. Regression coefficients for independent variables.

Variable	Standardized regression coef	Standard error of coef	Wald X^2 statistic	Pr > X^2
Agricultural area regression				
Intercept	0.38	0.143	7.04	0.0080
Slope	−0.34	0.024	188.12	<0.0001
Distance from paved roads	−0.25	0.019	166.94	<0.0001
Agricultural expansion regression				
Intercept	−1.45	0.247	34.37	<0.0001
Previous land cover				
Bare soil	2.45	0.204	143.63	<0.0001
Pasture/cerrado	0.94	0.133	50.26	<0.0001
Cerrãdo/woodland	−0.82	0.194	17.83	<0.0001
Slope	−0.39	0.051	58.13	<0.0001
Distance from paved roads	−0.13	0.044	9.21	0.0024

is more likely to be found close to paved roads rather than far away from them. Mean total November precipitation and soil type were not significantly correlated in either analysis.[5]

The agricultural expansion regression indicates that the most important correlate of land-use conversion to mechanized agriculture among the parameters examined in this study is previous land-cover type ($0.82 < |\beta| < 2.45$, $p < 0.0001$). Of the different land-cover types, bare soil was most strongly correlated, followed by pasture/cerrado. Cerrãdo/woodland was negatively correlated, suggesting that such a classification in 2001 served in effect as a deterrent to conversion to agriculture by 2003. Forest was the only class not found to be significantly correlated with conversion to mechanized agriculture.

Precipitation and soil type showed no significant correlation with the presence or absence of mechanized agriculture for the range of values observed in Mato Grosso during this time period. Precipitation data from ANEEL show that even relatively low-rain years in Mato Grosso offer plenty of rain for a crop to produce (>70 mm month^{-1} during the wet season). Regarding soil type, nonsignificant correlation in the regression models may suggest that poor soils are not viewed as a particular deterrent by farmers. Brazilian soybean strains have been cultivated specifically to thrive in relatively poor soils, and soil enhancement through fertilization, lime, etc., is well documented (Sfredo and Panizzi 1990; Maehler et al. 2003). However, it is quite possible that precipitation and soils datasets with higher spatial resolution could present different results.

The models produced by these regressions present good fits with the data. For the agricultural area regression, the association of predicted and observed responses yielded a ratio of 77.8% concordant to 21.7% discordant. For the expansion regression, the ratio was 88.0% concordant to 11.3% discordant.

3.4. Spatial map of model results

The probability map (Figure 8) generated from the agricultural expansion logistic regression model shows the relative likelihood of conversion to mechanized agriculture for land across the state of Mato Grosso. This product is based on the physical landscape variables that demonstrated significant correlation with this type of land-use conversion. Coefficients of those variables were inserted into Equation (1) from section 2.3, along with the intercept value, and the model was applied to pixels across the state.

Areas already classified as mechanized agriculture are masked out, as well as land within the reserves that were excluded from earlier analyses. The remaining areas are colored according to their likelihood of conversion, from low to high relative probability. The results suggest that future expansion of mechanized agriculture in the western and northeastern portions of Mato Grosso may be limited by the physical landscape features examined in this study. Continued expansion in current centers of mechanized agricultural production in central, eastern, and southern Mato Grosso appears somewhat less limited by these factors.

[5] The SAS logistic regression procedure excludes any independent variables not found to be significant, so coefficient estimates of these are not provided.

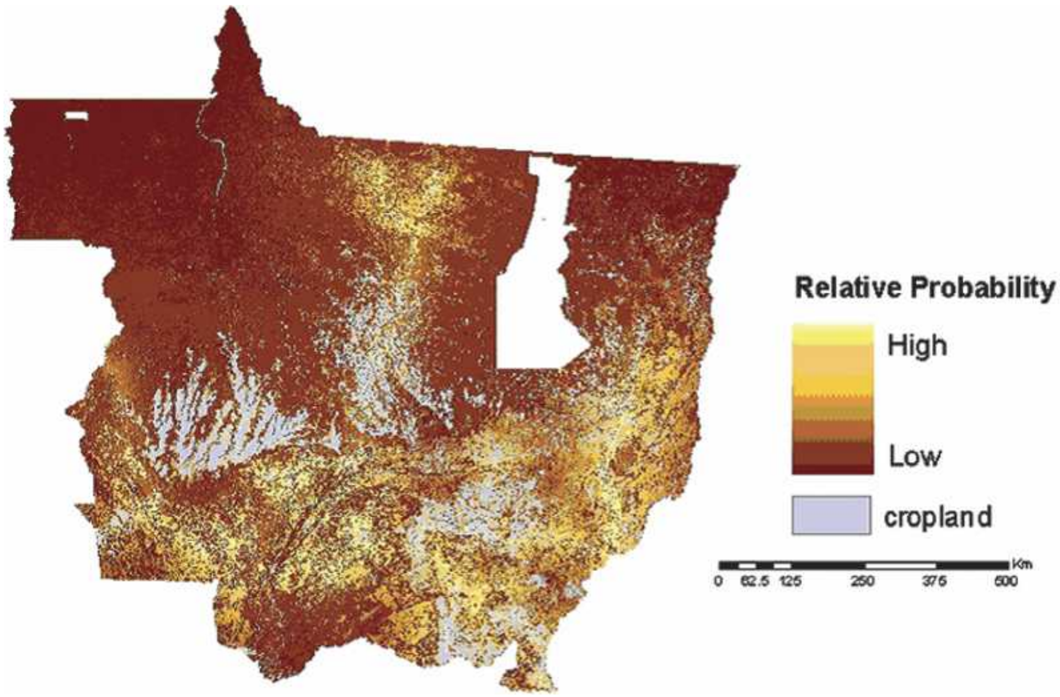

Figure 8. Probability of conversion to mechanized agriculture, based on logistic regression model of physical variables. White polygons are reserve lands excluded from the analysis, and blue pixels are those already classified as cropland as of 2003.

4. Conclusions

Analysis results indicate that of the physical landscape correlates considered in this study, previous land-cover type is the most highly correlated with land-use conversion to mechanized agriculture in the state of Mato Grosso between the years 2001 and 2003. Topographic slope and proximity to paved roads are also significantly correlated with this type of conversion. Soil type and November precipitation failed to demonstrate significant correlations with mechanized agriculture.

Understanding common physical and spatial characteristics of land converted to mechanized agriculture is a critical first step in projecting the likelihood of land-use conversion in other areas. In this study, we assess several such characteristics as being correlated with expansion of mechanized agriculture. Future studies should include land-cover type, topography, and distance to major transportation avenues in addition to political and socioeconomic parameters in holistic spatial models of land-use conversion. Practical land-use change scenarios generated through interdisciplinary efforts can inform sustainable land-use planning in Mato Grosso and potentially other regions as well.

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References

Alves, D. S., 2002: Space-time dynamics of deforestation in Brazilian Amazonia. *Int. J. Remote Sens.,* **23,** 2903–2908.

Anderson, L. O., E. H. M. Rojas, and Y. E. Shimabukuro, 2003: Avanço da soja sobre os ecossistemas *cerrado* e floresta no estado do Mato Grosso. *Anais XI Simpósio Brasileiro de Sensoriamento Remoto (SBSR)*, Belo Horizonte, Brazil, Instituto Nacional de Pesquisas Espaciais, 19–25.

Dros, J. M., 2003: Accommodating growth: Two scenarios for soybean production growth. WWF, Advice and Research for Development and Environment, Amsterdam, 10 pp.

Embrapa/IBGE, 1981: Mapa de Solos do Brasil. Servio Nacional de Levantamento e Conservação de Solos, Rio de Janeiro.

Fearnside, P. M., 2001: Soybean cultivation as a threat to the environment in Brazil. *Environ. Conserv.,* **28,** 23–38.

——, and J. Ferraz, 1995: A conservation gap analysis of Brazil's Amazonian vegetation. *Conserv. Biol.,* **9,** 1134–1147.

Hansen, M., R. DeFries, J. R. Townshend, M. Carroll, C. Dimiceli, and R. Sohlberg, 2003: 500-m MODIS vegetation continuous fields. Global Land Cover Facility, College Park, MD.

Hosmer, D. W., and S. Lemeshow, 1989: *Applied Logistic Regression*. Wiley Series in Probability and Mathematical Statistics, John Wiley and Sons, 307 pp.

Huete, A. R., C. Justice, and W. Van Leeuwen, 1999: MODIS vegetation index (MOD13). Algorithm theoretical basis document (ATBD), 122 pp. [Available online at http://modis-land.gsfc.nasa.gov/pdfs/atbd_mod13.pdf.]

Jaccoud, D., R. L. Sá, and S. Richardson, 2003: Sustainability assessment of export-led growth in soy production in Brazil. WWF, Sustainability Assessment Project, 20 pp.

Kellndorfer, J., W. Walker, L. Pierce, C. Dobson, J. Fites, C. Hunsaker, J. Vona, and M. Clutter, 2004: Vegetation height estimation from shuttle radar topography mission and national elevation datasets. *Remote Sens. Environ.,* **93,** 339–358.

Klink, C. A., A. G. Moreira, and O. T. Solbrig, 1993: Ecological impacts of agricultural development in Brazilian cerrados. *The World's Savannas: Economic Driving Forces, Ecological Constraints, and Policy Options for Sustainable Land Use*, M. D. Young and O. T. Solbrig, Eds., Man and the Biosphere Series, Vol. 12, UNESCO, 259–282.

Laurance, W. F., A. K. M. Albernaz, G. Schroth, P. M. Fearnside, S. Bergen, E. M. Ventincinque, and C. Da Costa, 2002: Predictors of deforestation in the Brazilian Amazon. *J. Biogeogr.,* **29,** 737–748.

Laurance, W. H., A. K. M. Albernaz, P. M. Fearnside, H. L. Vasconcelos, and L. V. Ferreira, 2004: Deforestation in Amazonia. *Science,* **304,** 1109.

Ludeke, A. K., R. C. Maggio, and L. M. Reid, 1990: An analysis of anthropogenic deforestation using logistic regression and GIS. *J. Environ. Manage.,* **31,** 247–259.

Maehler, A. R., J. A. Costa, J. L. F. Pires, and L. Rambo, 2003: Qualidade de grãos de duas cultivares de soja em função da disponibilidade de água no solo e arranjo de plantas. *Ciência Rural Santa Maria,* **33,** 213–218.

Menard, S., 2002: *Applied Logistic Regression Analysis*. 2d ed. Quantitative Applications in the Social Sciences Series, Vol. 106, Sage Publications, 111 pp.

Morton, D. C., R. S. DeFries, and Y. E. Shimabukuro, 2005: Quantifying cropland expansion in cerrado and transition forest ecosystems with Modis satellite image time series. *Proc. Symp. on Cerrado Land-Use and Conservation: Assessing Trade-Offs Between Human and Ecological Needs,* Brasília, Brazil, Society for Conservation Biology, in press.

Myers, N., R. A. Mittermeier, C. G. Mittermeier, G. A. B. da Fonseca, and J. Kent, 2000: Biodiversity hotspots for conservation priorities. *Nature,* **403,** 853–858.

Osborne, P. E., J. C. Alonso, and R. G. Bryant, 2001: Modelling landscape-scale habitat use using GIS and remote sensing: A case study with great bustards. *J. Appl. Ecol.,* **38,** 458–471.

Schnepf, R. D., E. Dohlman, and C. Bolling, 2001: Agriculture in Brazil and Argentina: Developments and prospects for major field crops. Agriculture and Trade Rep. WRS-01-3, Market and Trade Economics Division, Economic Research Service, U.S. Department of Agriculture, 80 pp.

Serneels, S., and E. F. Lambin, 2001: Proximate causes of land-use change in Narok District, Kenya: A spatial statistical model. *Agric. Ecosyst. Environ.,* **85,** 65–81.

Sfredo, G. J., and M. C. Panizzi, 1990: Importância da adubação e da nutrição na qualidade da soja. Embrapa-CNPSo, Documentos 40, Londrina, PA, Brazil, 57 pp.

Stone, T. A., I. F. Brown, and G. M. Woodwell, 1991: Estimation, by remote sensing, of deforestation in central Rondonia, Brazil. *For. Ecol. Manage.,* **38,** 291–304.

Sun, G., K. J. Ranson, V. I. Kharuk, and K. Kovacs, 2003: Validation of surface height from shuttle radar topography mission using shuttle laser altimeter. *Remote Sens. Environ.,* **88,** 401–411.

Wilkie, D., E. Shaw, F. Rotberg, G. Morelli, and P. Auzel, 2000: Roads, development, and conservation in the Congo basin. *Conserv. Biol.,* **14,** 1614–1622.