Modeling land-use dynamics in Northern Mato Grosso, Brazilian Amazon

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1. Introduction

A first step in building a landscape change model consists in mapping the changes by using a change detection methodology. Consequently, the change function and vector of variables that affect the changes can be defined.

Northern Mato Grosso, an area of 19 000 km^2 (figure 1), is one of the most dynamic Amazonian regions due to its proximity to burgeoning population centers and soybean plantation in central Brazil. The region is crossed by the Cuiabá-Santarém road, which is planned to be a soybean-exporting corridor to Amazonian international ports. In addition, high flammability forests of this Amazonian border makes it very susceptible to rampant deforestation as a function of increasing ignition sources (Nepstad et al. 2001).

This study involved multitemporal analyses of satellite imagery time series, and it focused on the calculation of regional transition rates and the spatial transition probability maps, which depict the areas most favorable for each type of change, based on spatial variables stored in GIS.

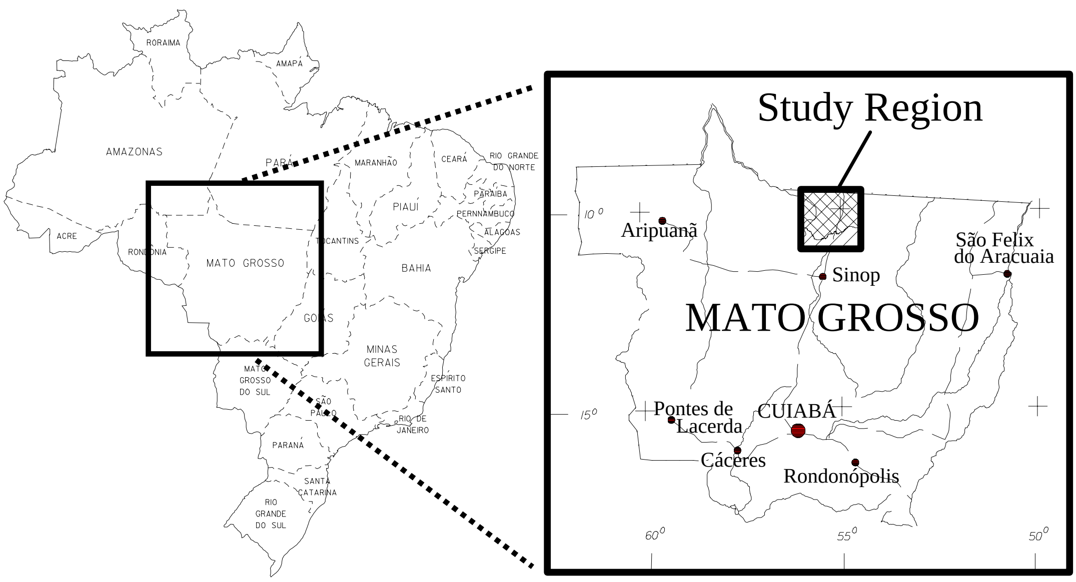


Fig. 1 – The Northern Mato Grosso study case area and its location with respect to Brazil.

2. Image processing methodology

The satellite images used were MSS of 1977 and Thematic Mapper of 1986, 1994, and 1999 (scenes 226/67 and 227/67). This time span allowed us to follow the colonization of this important Amazonian region from the beginning of its wide occupation almost up to the present time. Land-use and land-cover classes mapped were forest, deforestation, and regrowth. Good registering is crucial for multitemporal analysis, therefore, the TM image set of 1994 was first registered by using GPS ground control points, and subsequently all other image sets were co-registered to the 1994 image set.

The image processing methodology used in this work is summarized in figure 2. It consists of a hybrid algorithm that combines maximum likelihood classification, calibrated with field samples, and a deforestation mask, obtained by setting interactively a cutting-off threshold on bands TM 4 and TM 7 (figure 3). In this process, Cerrado areas are erased by using a vegetation map because they can be confounded with deforestation.

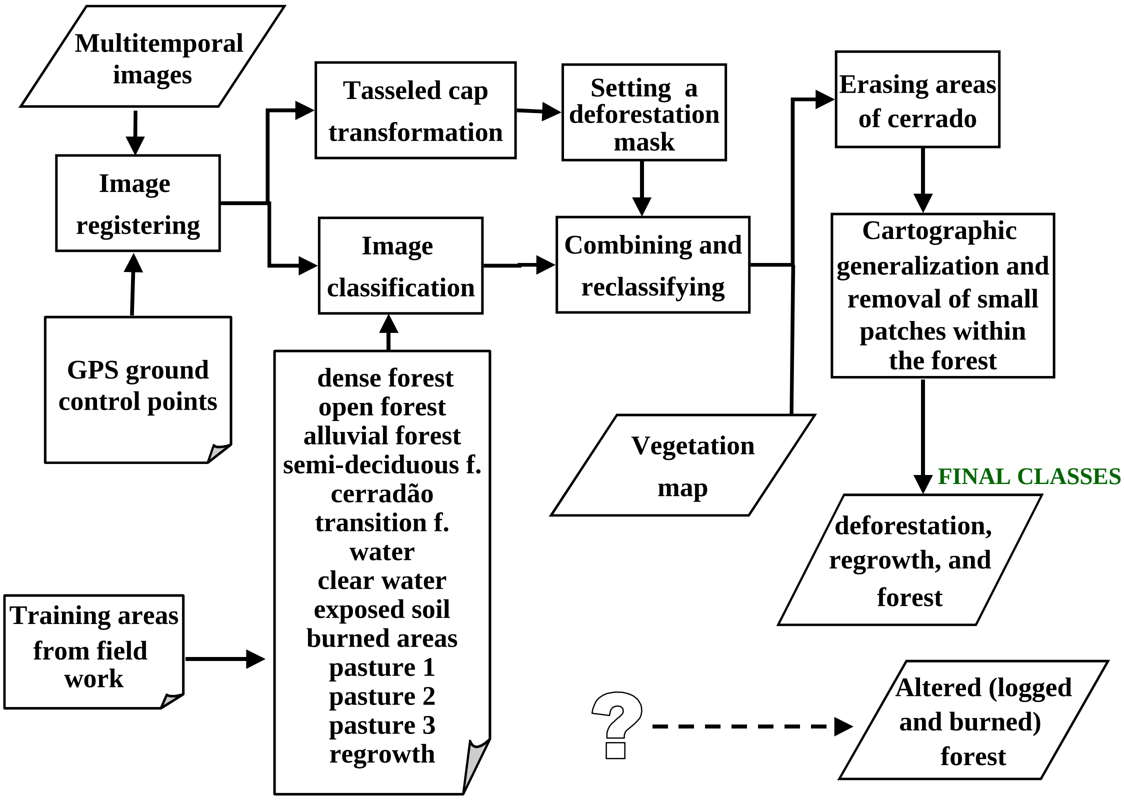


Fig. 2 – Flowchart of the image processing methodology.

To map regrowth, a threshold was established to separate the several types of pastures (e.g. productive pastures, degraded pastures, abandoned pastures) from areas where regeneration processes have developed a shrublike vegetation. As regrowth can be misclassified with well-developed pastures, the lowest post-probability cells of regrowth class in the maximum likelihood classification were reclassified to other classes (Fig. 4). Since regrowth can not be mapped based solely on a single time of imagery acquisition, an algorithm for reclassifying land cover classes based on the multi-temporal series was developed (Fig. 5).

As a last step, the annual transition matrices were derived from the matrices obtained for the analyzed periods by using their Eigen vector and values. Henceforth, we can use the annual transition matrix to reproduce the past changes or project the future based on the past trends.

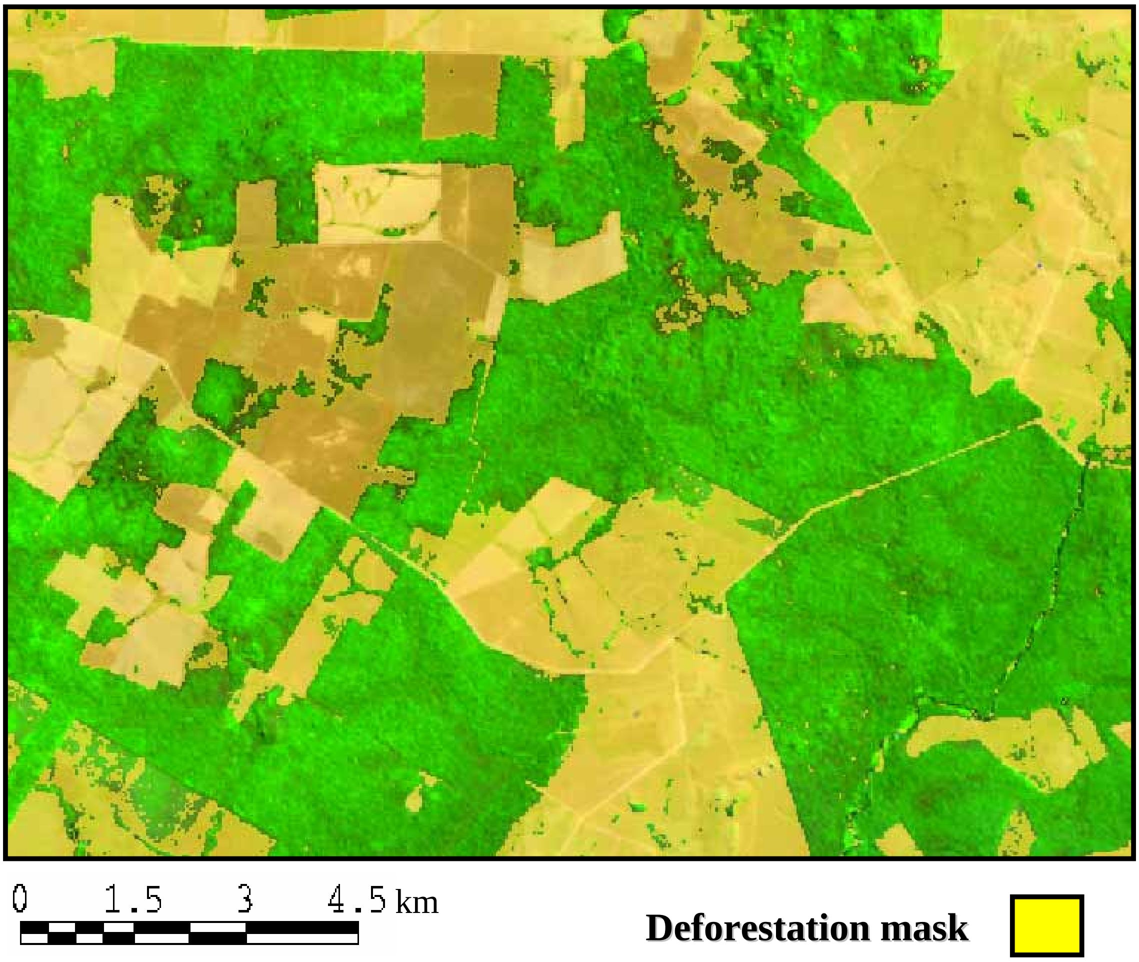


Fig. 3 – Deforestation mask obtained by setting interactively a cutting-off threshold on bands TM4 and TM7. Notice the burned pastures (in dark yellow) and the nearby affected forests (in dark green). Thematic Mapper color composite from July 1999.

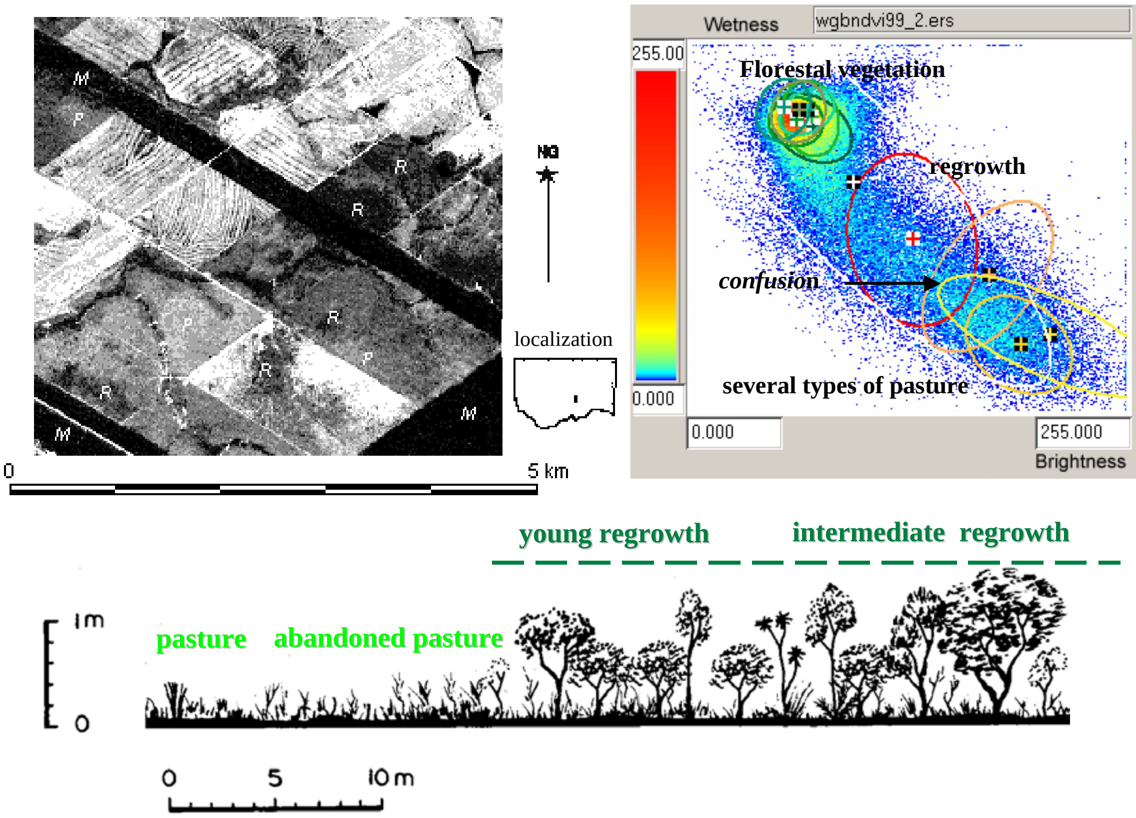
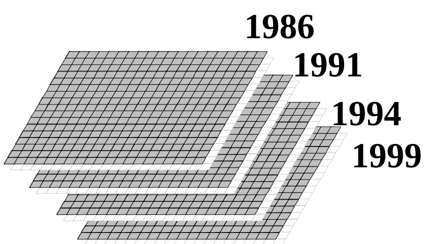


Fig. 4 – Spectral modeling of regrowth.



For T = 1986 to 1999 do:

"if (cell $_{t-1}$ = deforestation and cell $_{t}$ = forest) then cell $_{t}$ = regrowth else

if (cell $_{t-1}$ = forest and cell $_{t}$ = regrowth) then cell $_{t}$ = deforestation else cell $_{t}$ = cell $_{t}$"

Cross-tabulation of the time period landscape maps

91x94

	deforestation	regeneration	forest
deforestation	61.67	26.42	16.07
regeneration	38.33	73.58	0.00
forest	0.00	0.00	83.93

***P* is the annual transition matrix**

$$P^t = HV^tH^{-1}$$

***H and V* are *Eigen* values and *Eigen* vector matrices**

Fig 5 – Algorithm for reclassifying land cover classes based on the multi-temporal series, and for obtaining the annual transition matrix.

Results

As shown in figure 6, deforestation has deeply affected Northern Mato Grosso. The deforestation rate almost doubled in 1994-1999 period (Fig. 7). The region's forest is loosing about 500 km^2 of area per year, 200 km^2 more than the amount of prior periods. A forest loss that exceeds at the present time more than 8000 km^2, that is about 42% of the region's original forest. These results agree with the last data released on Amazonian deforestation, which showed that deforestation rate in Amazon has accelerated (e.g. INPE 1999).

Deforestation process can be seen as diffusion waves (observe in figure 6 the extinction of the forest remnants in the older colonization areas, while new colonization fronts are being opened). The multi-temporal analyses showed also that vast tracts of secondary forests are also being converted into pastures. As a result, regrowth is only evolving into a secondary forest in few areas.

In conclusion, two colonization models were implemented in this region: one in which the forest reserve was collective and the other in which each lot has its own forest reserve (50%). None of them was successful in preserving the forest within the colonization project. Thus, we can assert that whenever this model of occupation is installed, there are few hopes that large forest patches, which can contain unaltered forest core areas, will remain within a colonization region.

For projection purposes, figure 8 shows hypothetical landscape evolutions for Northern Mato Grosso. Notice the different dynamics trends, being the deforestation in the 1994-99 period much faster. If the recent dynamic trend prevails, we can expect a reduction of the original forest to one fifth within the next 25 years. Although, we cannot use past trends to project the future, the devastation of this rich biodiversity ecoregion can be predictable, unless drastic actions to hinder this rapid process be soon undertaken. Moreover, this phenomenon can be even accelerated due to “Avança Brasil” - the Brazilian Development plan for the Amazonian region. As new development centers are created or roads are paved, the deforestation wave moves into new regions, reproducing the patterns of devastation, and advancing into the last Amazonian frontier (Carvalho et al. 2001, Laurance et al. 2001).

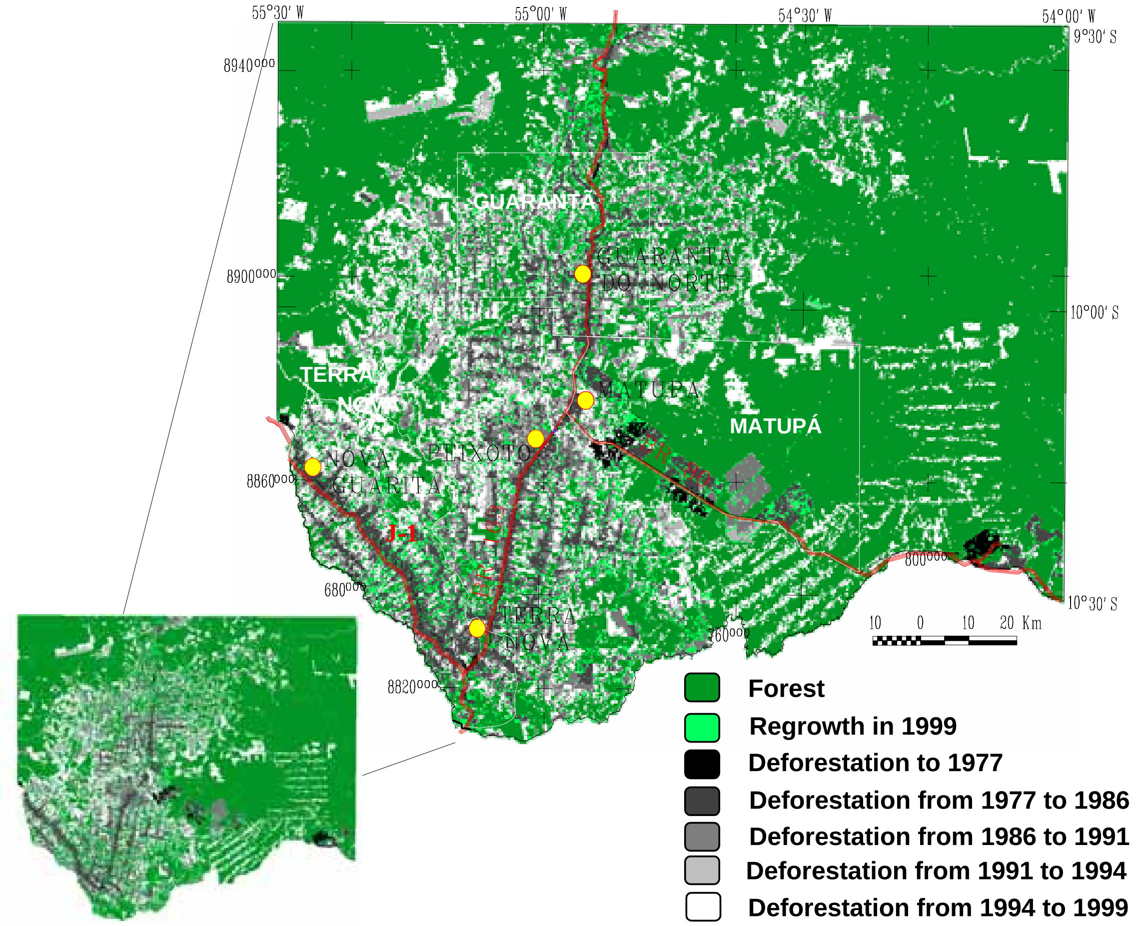


Fig. 6 – Landscape dynamics in Northern Mato Grosso (Brazil)

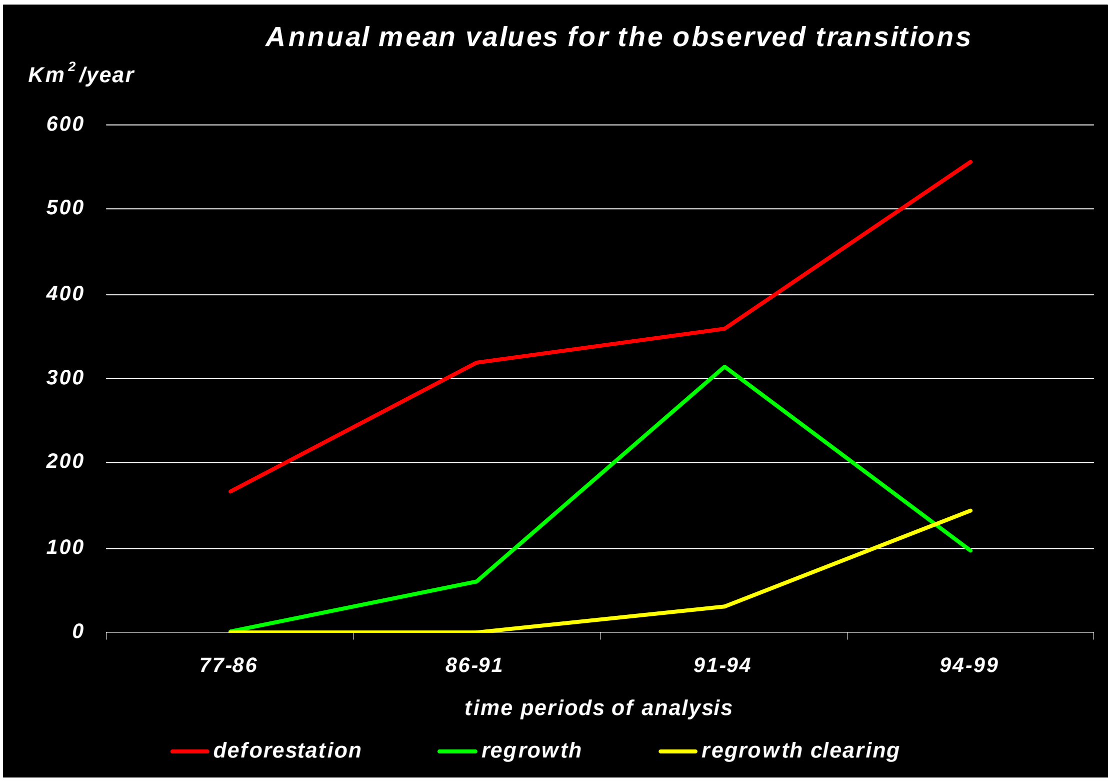


Fig. 7 – Annual mean values of landscape changes in Northern Mato Grosso study case area.

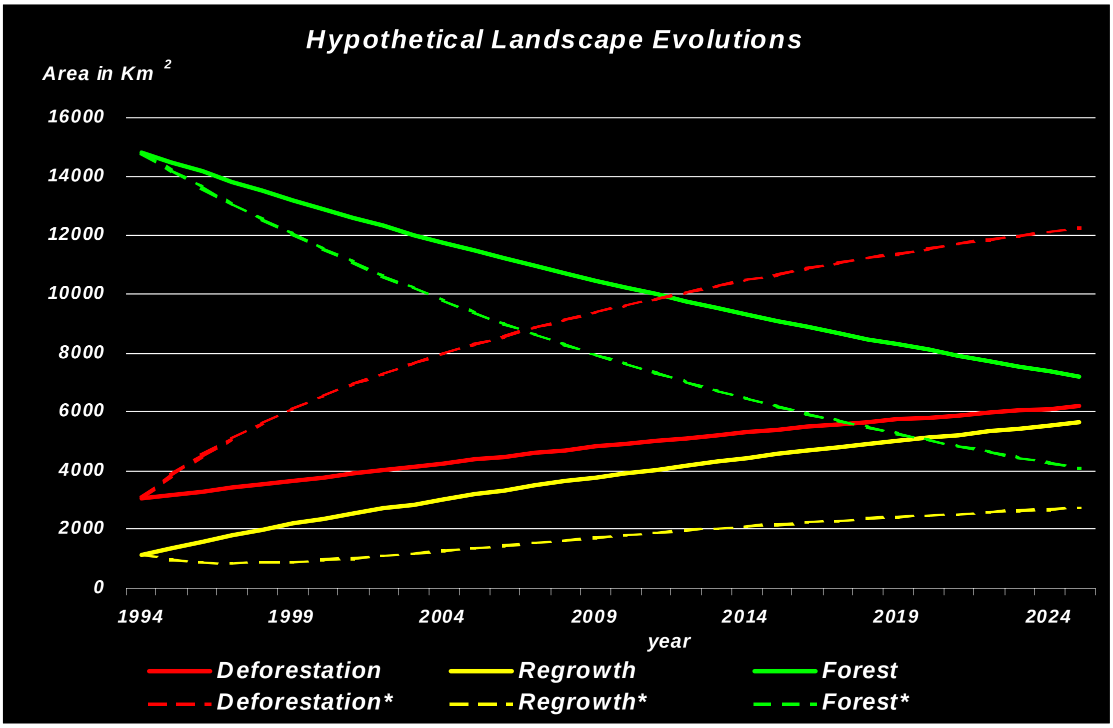


Fig. 8 – Hypothetical landscape evolutions for Northern Mato Grosso, considering 1991-1994 (solid lines) and 1994-1999 (dashed lines) transition matrices.

Deforestation in the Brazilian Amazonia can be at a great extend explained as a result of the lack of social and economic opportunities in other regions of Brazil, which leads a diversity of agents to occupy and explore the new lands opened from the forest. This context partially accounts for the faster late nineties dynamics of Northern Mato Grosso, due to the land pressure exerted by the MST (the Brazilian Movement of Landless People) and as a counter-effect of the agrarian reform, which induced farmers to deforest more land, since forest must be cleared to assure land tenure in Amazon (Fearnside 1985). The expectation of paving of northern track of Cuiabá-Santarém road and the initial economic boon produced by "Plano Real" – the Brazilian economic plan - should also be considered influencing this faster dynamics.

Due to the decline of gold mining within the region at the beginning of the nineties, a host of ex-*garimpeiros*, the Brazilian word for pan miner, sought land to be settled in. By opening roads throughout the region's forest, the local administrations supported this claim for land, as a way to solve the urban problems caused by high rates of unemployment. New colonization projects were founded and even new towns emerged as a consequence of this semi-spontaneous settlement process (Fig. 9). As a result, big companies' forest reserves were occupied and large tracts of forest, previously held by few pioneer squatters, were exposed to this second wave of invasion, which was led by community leaders and local politicians.

Higher influx of financial assistance provided by the Brazilian Government to support colonization projects, such as PRONAF fund, has contributed to this process by attracting a mixture of people, composed of rural workers, ex-colonists who abandoned their previous plots, and indigents from urban centers, from the surrounding municipalities and even as far as the Goias state to the new settlement areas, which are being created with the help of federal and state governmental agencies (Figs. 10 and 11). Because few areas remain unoccupied in the region, this movement for land is shifting towards the wilderness of Southern Para.

On the other hand, the deforestation and its impacts have started being mitigated by a coordinated effort carried out by local community organizations, state institutions, and non-governmental conservation and humanitarian agencies present in the region. Protected areas are being created within the region, such as *Serra do Cachimbo* natural reserve and *Iriri* indigenous reserve, campaigns against fire were undertaken by federal agencies and NGOs, laws against burning, illegal deforestation, and logging are being enforced through IBAMA and SEMA - the Mato Grosso environmental agency -, still at a timid stage due to the lack of resources. Only IBAMA has a sole officer permanently located within the region, at Guarantã. But, in many places, this conservation action has come too late to protect large tracts of undisturbed forest, leaving the regional communities only with the option of restoring their degraded environment.

Fig. 9. A town semi-spontaneously emerged: *Leonisiolândia* on BR-80 road, named after the Peixoto de Azevedo' mayor.

Fig. 10. People waiting to be settled in, *Nhandu* River in Municipality of Novo Mundo.

Fig. 11 – Burning practice used by settler to clear land for cultivation. Novo Mundo municipality.

3. Weights of Evidence for calculating spatial transition probabilities

"Weights of Evidence" is a baysean method traditionally used by geologists to point out areas favorable for geologic phenomena, such as mineralization and seismicity (Goodacre et al. 1993, Bonham-Carter 1994,). Weights of Evidence method was adapted by us to calculate the empirical relationships of selected spatial variables, represented by gray-tone maps, with respect to the changes: deforestation, land-abandonment, and regrowth clearance. The weights represent each variable influence on the spatial probability of a transition $i \Rightarrow j$ and are calculated as follows.

$$O\left\{D/B\right\} = O\{D\}\frac{P\{B/D\}}{P\{B/\bar{D}\}}$$

$$logit\left\{D/B\right\} = logit\{D\} + W^{+}$$

Where W^{+} is the weight of evidence of occurring event D, given a spatial pattern B. The spatial post-probability of a transition $i \Rightarrow j$, given a set of spatial data, is expressed by the following equation:

$$P(i \Rightarrow j(x,y)/V) = \frac{e^{\sum W i \Rightarrow j(V)}}{1 + \sum_{i}^{j} e^{\sum W i \Rightarrow j(V)}}$$

Where *V* is a vector of *k* spatial variables, measured at location *x*,*y* and represented by its weights W^{+}_{1xy}, W^{+}_{2xy}, ..., W^{+}_{kxy}.

As advantages of Weights of Evidence over other parametric statistical methods, such as *Logist Regression* - which is the original parameterization method of DINAMICA(Soares-Filho et al., 2001) -, it is mentioned that this method is not constrained by the classical assumptions of parametric methods, which spatial data often violate. Furthermore, this method is easily calculated by using map cross-tabulation and additional formulae implemented in spreadsheet program, such as Excel. Therefore, it is not necessary the utilization of sophisticated statistical programs. The effect of each spatial variable can be calculated independently of a combined solution. The only assumption of this method is that the input maps be spatially independent. This can be assessed by using Crammer's V coefficient (Fig. 12), which is a correlation coefficient that ranges from 0.0, indicating no correlation, to 1.0, indicating perfect correlation (Bonham-Carter 1994). Thereby, correlated variables are eliminated from the integrated model.

As a consequence, the application of Weights of Evidence aims at selecting the most important variables needed for the change analysis as well as quantifying its weights on each type of change. Weights of evidence are assigned for each range of a variable represented by its cartographic layer. The maps resulting from the integration of the weights provide a knowledge of the areas most favorable for each type of change, thus they can be interpreted as maps of the spatial transition probability. Subsequently, the spatial relationships calculated by Weights of Evidence can be used to parameterize and calibrate the macro-dynamics simulation model.

For the Northern Mato Grosso study area, analyzed variables were soil, vegetation, distance to rivers, distance to main roads, distance to secondary roads, altitude, slope, distance to forest, distance to deforested land, distance to regrowth, and distance to urban centers.

Results

Figure 13 and 14 show the spatial relationships of analyzed variables with respect to deforestation and land-abandonment derived from the multi-temporal maps of Northern Mato Grosso. The spatial relationships, such as percentage of deforestation in relation to distance to main roads, can vary in function of time. Thus, these varying relationships can be used to characterize the distinct phases of the deforestation process and consequently be treated as dynamic coefficients.

	altitude	dis_secroads	dis_hidro	slope	soil	vegetation	urban	dis_deforest
dist_mainroads	0.2953	0.3667	0.2283	0.3745	0.3376	0.281	0.4183	0.257
altitude		0.32	0.2527	0.2015	0.303	0.251	0.2686	0.1448
dis_secroads			0.207	0.2909	0.2989	0.2149	0.4035	0.3111
dis_hidro				0.2595	0.2426	0.1786	0.1755	0.1173
slope					0.3366	0.2239	0.1841	0.2394
soil						0.7011	0.2941	0.3556
vegetation							0.1169	0.1868
urban								0.2761

Fig. 12 – Crammer's V coefficients showing correlation between maps used to calculate the spatial transition probabilities.

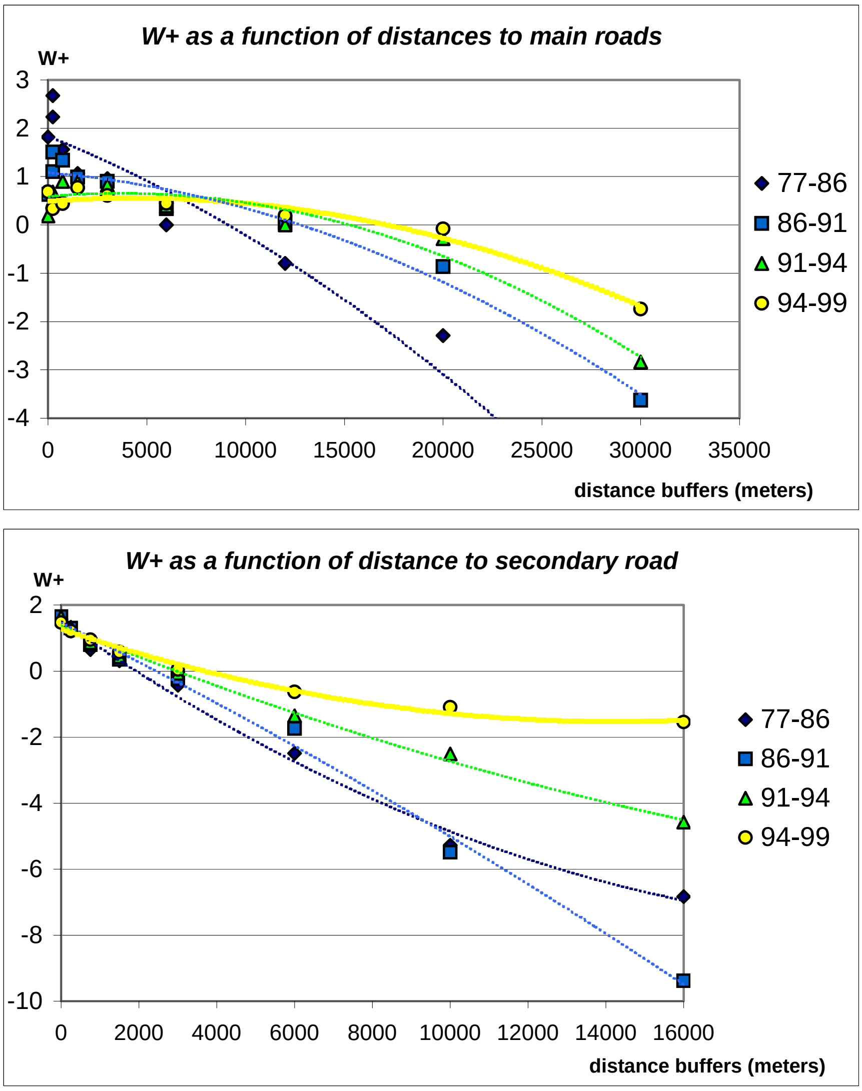


Fig. 13 – Effects of spatial variables on deforestation, as shown by *Weights of Evidence*. The trend lines represent adjusted second order polynomials.

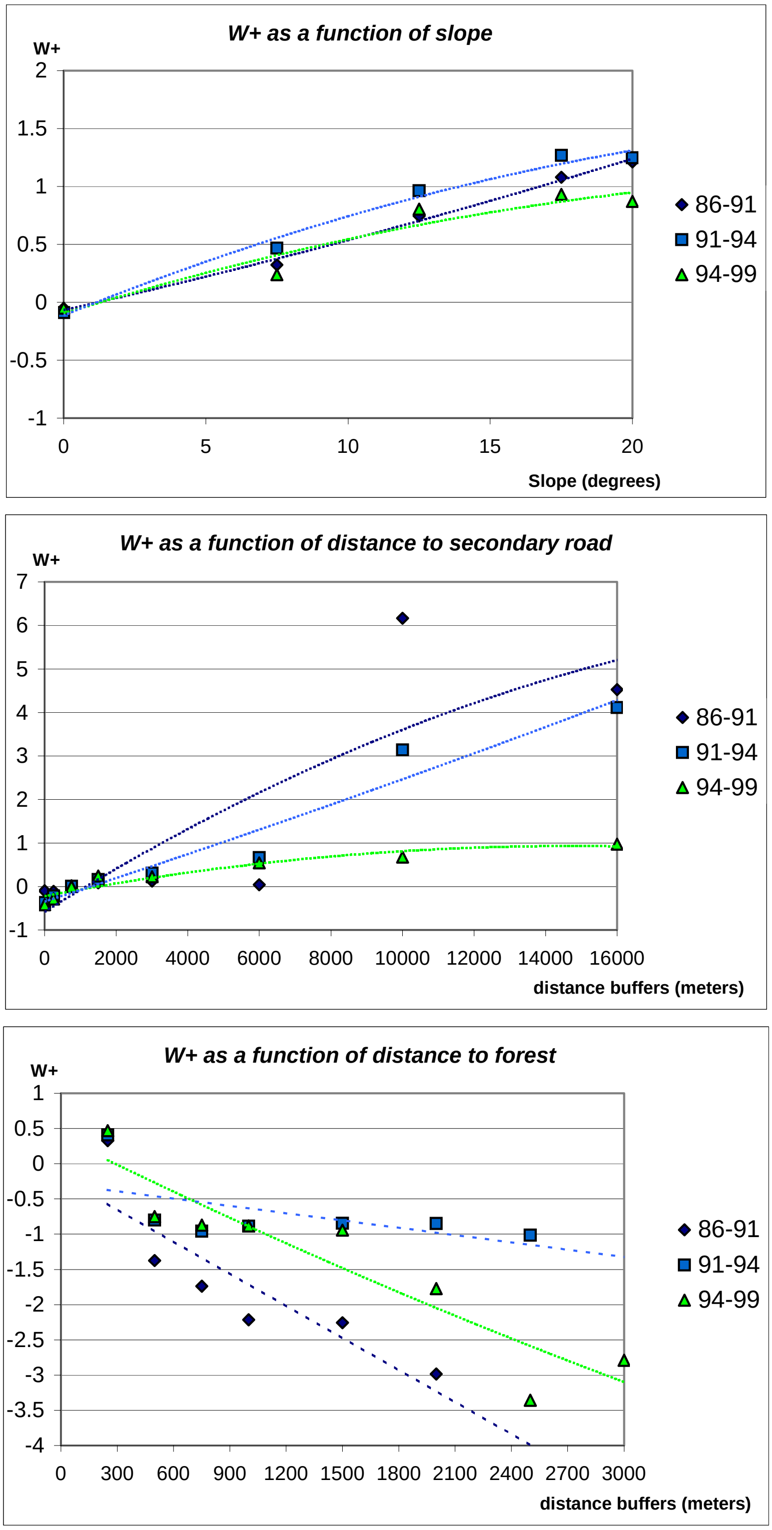


Fig. 14 – Effects of spatial variables on regrowth, as shown by *Weights of Evidence*. The trend lines represent adjusted second order polynomials.

As a result, these empirical functions can be extended to other Amazonian areas, such as the entire Cuiabá-Santarém corridor, or can be easily recalculated for other study case areas, as long as multi-temporal land-use maps and cartographic ancillary data (in digital format) are available.

4. Simulations developed for Northern Mato Grosso, Brazil

For macro-scale validation, DINAMICA was run for the entire Northern Mato Grosso area. This area comprises 19 000 Km^2, and it is represented by a raster map composed of 1400 by 1600 cells of 1 hectare resolution. The simulated landscape was divided into three classes: deforestation, regrowth, and forest, but the program has no restriction on the number of classes and transitions.

To run the simulations, DINAMICA was fed with a set of data: 1) a initial landscape map, 2) a static map set, which stores the unchanged characteristics of the region, 3) a text file with coefficients representing the weights of influence of each variable that affects the changes, 4) a map that stores the sojourn time of each landscape cell, 5) the transition matrix that sets the desired percentage of each class to be changed. Figure 17 shows DINAMICA architecture. First the software calculates the dynamic variables, which are represented by the distance between each landscape class cell and the nearest cell of a different class. These data are used together with the static maps to calculate the transition probability of each landscape map cell. At the end of each iteration, the landscape and sojourn maps are updated and saved together with the probability and distance maps; the entire process is then reinitiated (Fig. 18).

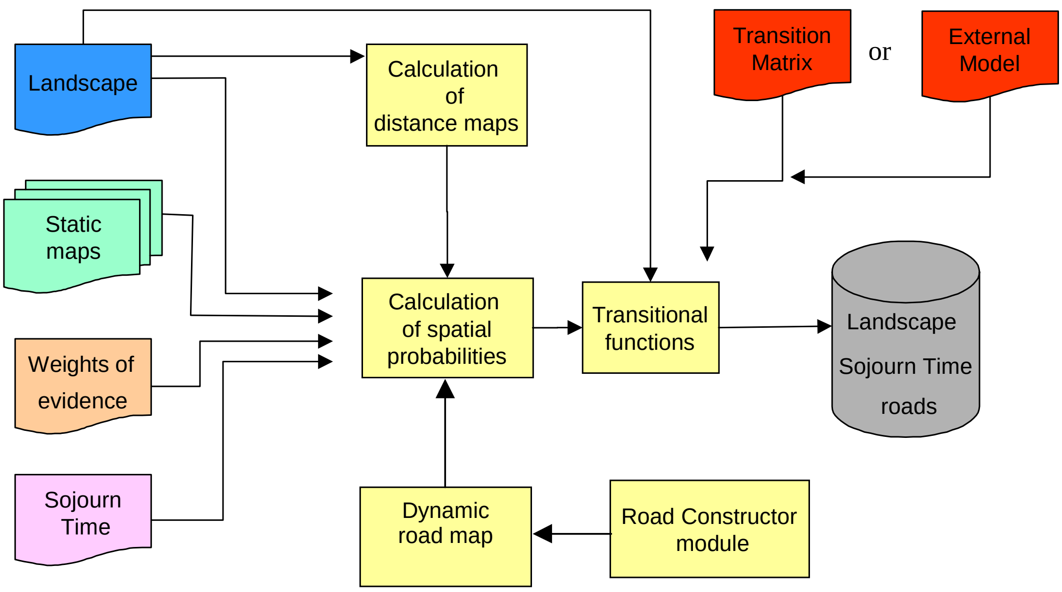


Fig. 17 – DINAMICA software architecture

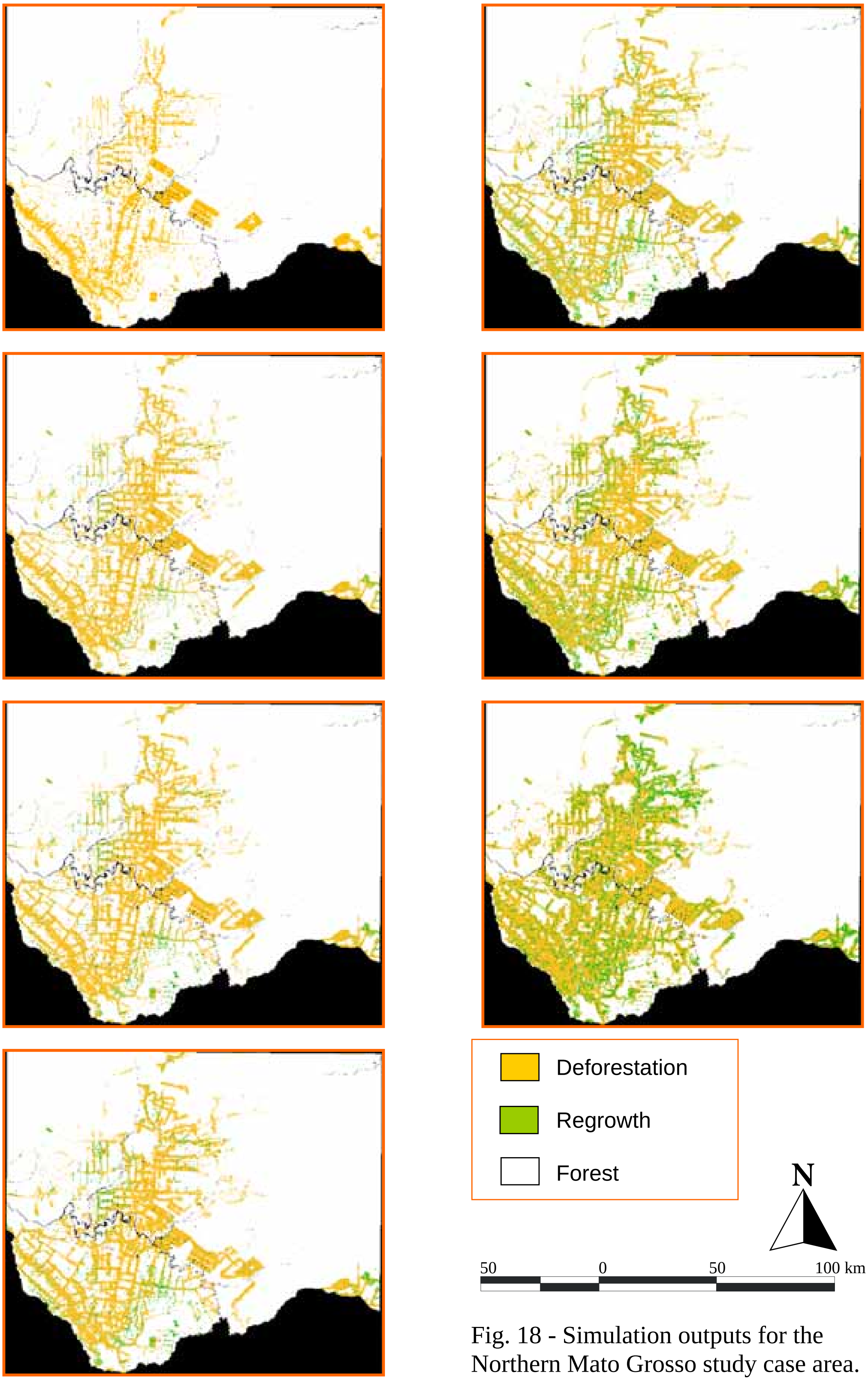


Fig. 18 - Simulation outputs for the Northern Mato Grosso study case area. Simulation was run using 8 steps and the 1991-1994 transition matrix

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