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Effects of roads, topography, and land use on forest cover dynamics in the Brazilian Atlantic Forest

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ABSTRACT

Roads and topography can determine patterns of land use and distribution of forest cover, particularly in tropical regions. We evaluated how road density, land use, and topography affected forest fragmentation, deforestation and forest regrowth in a Brazilian Atlantic Forest region near the city of São Paulo. We mapped roads and land use/land cover for three years (1962, 1981 and 2000) from historical aerial photographs, and summarized the distribution of roads, land use/land cover and topography within a grid of 94 non-overlapping 100 ha squares. We used generalized least squares regression models for data analysis. Our models showed that forest fragmentation and deforestation depended on topography, land use and road density, whereas forest regrowth depended primarily on land use. However, the relationships between these variables and forest dynamics changed in the two studied periods; land use and slope were the strongest predictors from 1962 to 1981, and past (1962) road density and land use were the strongest predictors for the following period (1981–2000). Roads had the strongest relationship with deforestation and forest fragmentation when the expansions of agriculture and buildings were limited to already deforested areas, and when there was a rapid expansion of development, under influence of São Paulo city. Furthermore, the past (1962) road network was more important than the recent road network (1981) when explaining forest dynamics between 1981 and 2000, suggesting a long-term effect of roads. Roads are permanent scars on the landscape and

Introdução

Brazilian Atlantic Forest has a **long land use history**

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Past patterns of **land use** have an **important role** in cycles of **deforestation, fragmentation, and reforestation**

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Steep slopes and poor soils → remain forested

Demand for agricultural products create new land use demands and influence rates of deforestation

Roads → improve land access and allow new land uses

Objetivo

Evaluate the relationships of:

Topography

Land use

Roads

Forest fragmentation

Deforestation

Forest regrowth

Plateau of Ibiúna, a Pre-Cambrian formation situated 50 km from the city of São Paulo

Materiais e Métodos

Topography

Land use

Roads

Slope map were generated from topographic maps - IGC 1979

Forest fragmentation

Deforestation

Forest regrowth

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Uso ou cobertura?

Forest fragmentation

Deforestation

Forest regrowth

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Aerial photographs: 1962, 1981, 2000

visual photo interpretation

(stereoscopic device)

Forest fragmentation

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agriculture, forest, **buildings**

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Forest fragmentation

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Forest dynamics

Measured for the two time spans

(1962–1981 and 1981–2000)

Materiais e Métodos

Landscape modifications

Grid → 94 non-overlapping squares of 100ha

Materiais e Métodos

Landscape modifications

Grid → 94 non-overlapping squares of 100ha

Each square and in each year: **road distribution** (road length/square area), **land-use and land-cover proportions** (class area/square area; agriculture, forest, and buildings), **forest fragmentation** (forest patch density, which was the number of forest patches in each square), **slope variation** (slope standard deviation to represent the relief variation), and **distance** from the city of São Paulo

Materiais e Métodos

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Centro do município?

Limite geográfico?

Desenvolvimento do Modelo

Forest fragmentation was transformed to a normal distribution using logarithm transformation

Desenvolvimento do Modelo

Forest fragmentation **was transformed to a normal distribution** using logarithm transformation

Não testou a normalidade:

Histograma

***Skewness* (simetria da distribuição)**

Testes como K-S e S-W

Q-Q Plot

Desenvolvimento do Modelo

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Não testou a normalidade:

Histograma

***Skewness* (simetria da distribuição)**

Testes como K-S e S-W

Q-Q Plot

Não apresentou metodologias semelhantes

Transformação dos dados pode comprometer a interpretabilidade

Desenvolvimento do Modelo

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Método dos mínimos quadrados generalizados – explorar as relações entre:

Desenvolvimento do Modelo

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Método dos mínimos quadrados generalizados – explorar as relações entre:

Forest fragmentation

Deforestation

Forest regrowth

road density

agriculture cover

buildings cover

standard deviation of slope

distance from the city of SP

Desenvolvimento do Modelo

Forest fragmentation was transformed to a normal distribution using logarithm transformation

Método dos mínimos quadrados generalizados[1] – explorar as relações entre:

Forest fragmentation

Deforestation

Forest regrowth

road density

agriculture cover

O método GLS é aplicado quando a variância dos erros não é a mesma (heteroscedasticidade), ou quando há certa correlação entre os resíduos

→ Fatores não foram analisados/justificados

1. Generalized Least Squares (GLS)

Modelos Similares – Explorar mudanças

Time period	Dependent variable	Independent variables
1962–1981	Fragmentation Deforestation Regrowth	Road62, agriculture62, buildings62, SPdist and slope
	Agriculture expansion	Road62, forest62, buildings62, SPdist and slope
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All variables with 60% or more of correlation were not included

A ausência de multicolinearidade[1] é uma das premissas para estabelecer um modelo de regressão múltipla correto

1. variáveis independentes possuem relações lineares exatas ou aproximadamente exatas

Modelos Similares – Explorar mudanças

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Visando simplificar as equações, foi selecionado uma abordagem de *Backward elimination* (*equal chance of affecting forest variables*) → todos os preditores são inclusos no modelos e de acordo com o p-valor são removidos

Seleção de Modelos

Bayesian information criterion (BIC) – Critério de seleção de modelos dentro de um conjunto finito de modelos (introduz uma penalidade no número de parâmetros utilizados)

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> ment was measured using Bayesian Information Criterion (BIC) values, which is more conservative than Akaike's Information Criterion (AIC) (Burnham and Anderson, 2002). We calculated BIC

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ment wa
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Criterion

The Basics of Financial Econometrics: Tools, Concepts, and Asset Management Applications.
Frank J. Fabozzi, Sergio M. Focardi, Svetlozar T. Rachev and Bala G. Arshanapalli.

APPENDIX E

Model Selection Criterion: AIC and BIC

In several chapters we have discussed goodness-of-fit tests to assess the performance of a model with respect to how well it explains the data. However, suppose we want to select from among several candidate models. What criterion can be used to select the best model? In choosing a criterion for model selection, one accepts the fact that models only approximate reality. Given a set of data, the objective is to determine which of the candidate models best approximates the data. This involves trying to minimize the loss of information. Because the field of information theory is used to quan-

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Justificativa fraca

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Próximas etapas

Variables selection → examination of model residuals to validate the assumptions (normally distributed errors, constant variance, and independent observations)

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Ecological phenomena are NOT spatially and temporally independent

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Variables selection → examination of model residuals to validate the assumptions (normally distributed errors, constant variance, and **independent observations**)

Ecological phenomena are NOT spatially and temporally independent

Tests → if spatial autocorrelation was detected additional models with the same variables and correlation structures were included

Atenuando o efeito da autocorrelação espacial

By including spatial autocorrelation structures in the final models, the aim was **to nullify the effects of spatial autocorrelation** on the significance of regression coefficients and reduce the chance of Type I errors (incorrect rejection of null hypotheses)

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Significance of the spatial correlation - ANOVA

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regression models should be more robust

Resultados

(A)		1981					
		Rural buildings or urban areas	Agricultural fields	Pine and eucalyptus plantations	Vegetation in early stages of regrowth	Native forest	Total
1962	Rural buildings or urban areas	5.13	20.92	0.85	6.39	11.61	44.90
	Agricultural fields	64.71	1500.46	66.87	337.36	734.22	2703.62
	Pine and eucalyptus plantations	0.58	47.41	22.09	11.07	84.33	165.48
	Vegetation in early stages of regrowth	12.42	393.70	21.04	117.40	735.77	1280.33
	Native forest	27.47	852.82	113.38	238.81	2034.45	3266.93
	Total	110.31	2815.31	224.23	711.00	3600.38	7461.00

(B)		2000					
		Rural buildings or urban areas	Agricultural fields	Pine and eucalyptus plantations	Vegetation in early stages of regrowth	Native forest	Total
1981	Rural buildings or urban areas	80.35	20.27	3.08	2.05	4.57	110.32
	Agricultural fields	602.35	1702.01	185.31	112.18	213.46	2815.31
	Pine and eucalyptus plantations	27.63	56.65	120.15	6.50	13.30	224.23
	Vegetation in early stages of regrowth	129.98	258.10	41.69	87.95	193.32	711.04
	Native forest	395.26	635.49	153.85	359.1	2056.68	3600.38
	Total	1235.57	2672.52	504.08	567.78	2481.33	7461.00

Resultados são pautados na mudança da cobertura entre os períodos: *Most deforestation was caused by agriculture*

Não há análise intermediária (19 anos não analisados)

Resultados

Time period	Dependent variable	Independent variables	BIC	Weight	Evidence	RSE
1962–1981	Fragmentation	+Buildings62	126.89	0.926	1.0	0.433
	Deforestation	+Slope	274.20	0.969	1.0	0.941
	Regrowth	−Buildings62	142.62	0.996	1.0	0.472
	Agriculture expansion	+Slope	198.35	0.995	1.0	0.623
	Buildings expansion	+Agricult62	503.83	0.825	1.0	3.211
	Road expansion	+Slope	238.04	0.990	1.0	0.773
1981–2000	Fragmentation	+Road62	86.47	0.965	1.0	0.343
	Deforestation	+Road62	273.49	0.963	1.0	0.947
	Regrowth	−Agricult62	233.81	0.548	1.0	0.740
		−Agricult62 +DistSP	234.74	0.344	1.6	0.709
	Agriculture expansion	−Forest62 −DistSP	190.30	0.912	1.0	0.556
	Buildings expansion	−Forest62	289.30	0.676	1.0	1.001
		−Forest62 +Road62	290.84	0.313	2.2	0.978
	Road expansion	−DistSP	244.75	0.968	1.0	0.801

The smaller the residual standard deviation, the closer is the fit to the data. When the Residual Standard Error (RSE) is exactly 0 then the model fits the data perfectly

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First Period: buildings and slope variation were the main factor affecting forest cover dynamics

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First Period: Buildings were positively related with fragmentation, and negatively related with forest regrowth

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	Agriculture expansion	−Forest62				
		−DistSP	190.30	0.912	1.0	0.556
	Buildings expansion	−Forest62	289.30	0.676	1.0	1.001
		−Forest62				
		+Road62	290.84	0.313	2.2	0.978
	Road expansion	−DistSP	244.75	0.968	1.0	0.801

Between 1981 and 2000, forest dynamics were strongly affected by 1962 road density

Não há resultados mais detalhados com base no RSE

Discussões

Paralelos com realidades internacionais ou de outras regiões do Brasil:

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Paralelos com realidades internacionais ou de outras regiões do Brasil: In regions where land use has occured for centuries, for example Southeastern Brazil and Northern Wiscon-sin (USA), **it is difficult to assign a direct causality**. Nevertheless, remote areas in the North of Brazil could be used to evaluate the landscape changes caused by a new road

Percepções Gerais

- Metodologias coerentes, embora pouco justificadas

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The parameters were estimated by generalized least squares (GLS) to account for spatial autocorrelation and heteroskedasticity (unequal variance) of the residual, which was present especially in the equations for recruitment and mortality. The

Liang, J., Buongiorno, J., Monserud, R. A., Kruger, E. L., & Zhou, M. (2007). Effects of diversity of tree species and size on forest basal area growth, recruitment, and mortality. *Forest Ecology and Management*, 243(1), 116-127.

Percepções Gerais

- Metodologias coerentes, embora pouco justificadas

(Mac Nally, 1996). The HP method helps to identify the most influential predictor variables by capturing their independent and joint contribution to the goodness-of-fit of recruitment (Chevan and Sutherland, 1991, Mac Nally, 2000). In our analysis, the

Young, B., Liang, J., & Chapin III, F. S. (2011). Effects of species and tree size diversity on recruitment in the Alaskan boreal forest: a geospatial approach. *Forest ecology and management*, 262(8), 1608-1617.

Percepções Gerais

- Metodologias coerentes, embora pouco justificadas
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Time period	Dependent variable	Independent variables	BIC	Weight	Evidence	RSE
1962–1981	Fragmentation	+Buildings62	126.89	0.926	1.0	0.433
	Deforestation	+Slope	274.20	0.969	1.0	0.941
	Regrowth	−Buildings62	142.62	0.996	1.0	0.472
	Agriculture expansion	+Slope	198.35	0.995	1.0	0.623
	Buildings expansion	+Agricult62	503.83	0.825	1.0	3.211
	Road expansion	+Slope	238.04	0.990	1.0	0.773
1981–2000	Fragmentation	+Road62	86.47	0.965	1.0	0.343
	Deforestation	+Road62	273.49	0.963	1.0	0.947
	Regrowth	−Agricult62	233.81	0.548	1.0	0.740
		−Agricult62 +DistSP	234.74	0.344	1.6	0.709
	Agriculture expansion	−Forest62 −DistSP	190.30	0.912	1.0	0.556
	Buildings expansion	−Forest62	289.30	0.676	1.0	1.001
		−Forest62 +Road62	290.84	0.313	2.2	0.978
	Road expansion	−DistSP	244.75	0.968	1.0	0.801

Obrigada!