MINISTÉRIO DA CIÊNCIA, TECNOLOGIA, INOVAÇÃO E COMUNICAÇÕES
INSTITUTO NACIONAL DE PESQUISAS DA AMAZÔNIA
PROGRAMA DE PÓS-GRADUAÇÃO EM CIÊNCIAS DE FLORESTAS TROPICAIS

DEFORESTATION ACTORS: PATTERNS AND SIMULATION OF DEFORESTATION ON A CATTLE RANCHING FRONTIER IN THE STATE OF AMAZONAS

MANAUS-AM

2019

AURORA MIHO YANAI NASCIMENTO

DEFORESTATION ACTORS: PATTERNS AND SIMULATION OF DEFORESTATION ON A CATTLE RANCHING FRONTIER IN THE STATE OF AMAZONAS

Advisor: Dr. Philip Martin Fearnside

Co-advisors: Dr. Paulo Maurício Lima de Alencastro Graça

Dra. Maria Isabel Sobral Escada

Thesis presented to the graduate program in Tropical Forest Science of the National Institute of Amazonian Research (INPA) in partial fulfillment of the requirements for the degree of doctor in Tropical Forest Science.

MANAUS-AM

2020

INSTITUTO NACIONAL DE PESQUISAS DA AMAZÔNIA

MINISTÉRIO DA CIÊNCIA, TECNOLOGIA, INOVAÇÕES E COMUNICAÇÕES

PÁTRIA AMADA BRASIL GOVERNO FEDERAL

PROGRAMA DE PÓS-GRADUAÇÃO EM CIÊNCIAS DE FLORESTAS TROPICAIS

DEFESA PÚBLICA TESE / PPG-CFT - INPA

Ata da Defesa Pública da Tese de Doutorado de **AURORA MIHO YANAI NASCIMENTO,** aluno(a) do Programa de Pós-Graduação *Stricto Sensu* em CIÊNCIAS DE FLORESTAS TROPICAIS - CFT, realizada no dia 19 de dezembro de 2019.

Aos dezenove dias do mês de dezembro de 2019, às 14h, no Auditório da COCAP, Campus I, INPA-Aleixo, realizou-se a Defesa Pública da Tese de Doutorado intitulada: **"DEFORESTATION ACTORS: PATTERNS AND SIMULATION OF DEFORESTATION IN A CATTLE RANCHING FRONTIER IN THE STATE OF AMAZONAS"**, em conformidade com o Artigo 68 do Regimento Interno do PPG-CFT e Artigo 52 do Regimento Geral da Pós-Graduação do Instituto Nacional de Pesquisas da Amazônia (MCTIC-INPA) como parte final de seu trabalho para a obtenção do título de **DOUTOR (A) EM CIÊNCIAS DE FLORESTAS TROPICAIS.** A Banca Examinadora foi constituída pelos seguintes professores doutores: **HENRIQUE DOS SANTOS PEREIRA (UFAM), JOSÉ LUÍS CAMPANA CAMARGO (INPA), FRANCIS WAGNER SILVA CORREA (UEA), RITA DE CÁSSIA GUIMARÃES MESQUITA (INPA), MOACIR ALBERTO ASSIS CAMPOS (INPA).** O(a) Presidente da Banca Examinadora, Dr. Philip Martin Fearnside (Orientador), deu início à sessão convidando os senhores membros e o(a) doutorando(a) a tomarem seus lugares e informou sobre os procedimentos a serem observados para o prosseguimento do exame. A palavra foi, então, facultada ao(à) Doutorando(a) que apresentou uma síntese do seu estudo e respondeu às perguntas formuladas pelos membros da Banca Examinadora. Depois da apresentação e arguição, a referida Banca Examinadora se reuniu e decidiu por APROVAR.

A sessão foi encerrada às 17h e, para constar eu, Ana Serra Campos, Secretária do PPG-CFT lavrei a presente Ata, que depois de lida e aprovada foi assinada pelo Presidente e membros da Banca Examinadora.

Banca Examinadora:

Dr (a) HENRIQUE DOS SANTOS PEREIRA	[X] Aprovado(a)	[ ] Reprovado(a)	Henrique dos Santos Pereira
Dr (a) JOSÉ LUÍS CAMPANA CAMARGO	[X] Aprovado(a)	[ ] Reprovado(a)	[signature]
Dr (a) FRANCIS WAGNER SILVA CORREA	[X] Aprovado(a)	[ ] Reprovado(a)	[signature]
Dr (a) RITA DE CÁSSIA G. MESQUITA	[X] Aprovado(a)	[ ] Reprovado(a)	RCMesquita
Dr (a) MOACIR ALBERTO ASSIS CAMPOS	[X] Aprovado(a)	[ ] Reprovado(a)	Moacir Albert Assis Campos

Dr. Philip Martin Fearnside
Presidente da Banca/Orientador

Dr. Niro Higuchi
Coordenador do PPG-CFT
PO. N°242/2017

d Nascimento, Aurora Miho Yanai
Deforestation actors: patterns and simulation of deforestation in a cattle ranching frontier in the state of Amazonas / Aurora Miho Yanai Nascimento; orientador Philip Martin Fearnside Fearnside. -- Manaus:[s.l], 2020.
155 f.

Tese (Doutorado - Programa de Pós Graduação em Ciências de Florestas Tropicais) -- Coordenação do Programa de Pós-Graduação, INPA, 2020.

1. desmatamento. 2. fronteira agropecuária. 3. mudança de uso e cobertura da terra. 4. modelagem. 5. Amazônia. I. Fearnside, Philip Martin Fearnside, orient. II. Título.

CDD: 333.75

Sinopse:

Este estudo apresenta uma análise da dinâmica do desmatamento de diferentes atores em uma região de fronteira agropecuária no Amazonas. A partir da análise espaço-temporal do desmatamento na área ocupada por cada tipo de ator foi feita uma simulação do desmatamento até 2050 para estimar a contribuição desses atores na mudança de cobertura da terra.

Palavras-chaves: desmatamento, fronteira agropecuária, uso e cobertura da terra; modelagem; CAR; Amazônia.

AGRADECIMENTOS

Ao Senhor Deus.

Ao Instituto Nacional de Pesquisas da Amazônia (INPA) ao Programa de Pós-Graduação em Ciências de Florestas Tropicais pela oportunidade de formação.

Ao Instituto Nacional de Ciência e Tecnologia para os Serviços Ambientais da Amazônia (INCT-SERVAMB), ao Conselho Nacional de Desenvolvimento Científico e Tecnológico, a Fundação de Amparo à Pesquisa do Estado do Amazonas pelo apoio financeiro e logístico.

Ao Instituto Nacional de Pesquisas Espaciais (INPE) pelo apoio logístico durante o tempo em que estive lá processando e analisando parte dos dados.

Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) pela bolsa de doutorado.

Ao IDESAM (Instituto para a Conservação e o Desenvolvimento Sustentável da Amazônia), Gabriel pelas orientações para o trabalho de campo e a Ana Paula Rezende pela disposição em nos acompanhar em Santo Antônio do Matupi.

Ao INCRA (Instituto Nacional de Colonização e Reforma Agrária) que forneceu o conjunto de dados do assentamento de Matupi em 2011.

Sou especialmente grata ao Dr. Philip Fearnside pela orientação, paciência, revisões detalhadas dos manuscritos e ensinamentos sobre a Amazônia e seus desafios.

Sou especialmente grata ao Dr. Paulo Graça pelos ensinamentos sobre sensoriamento remoto, paciência, apoio e orientação durante o trabalho de campo e processamento dos dados.

Sou especialmente grata a Dra. Isabel Escada pela orientação na análise dos padrões de desmatamento, ensinamento sobre os atores da Amazônia, revisão dos manuscritos e apoio durante o período que estive no INPE.

Ao Dr. Reinaldo Barbosa pelos ensinamentos e ao Dr. Euler Nogueira pela parceria e conselhos mesmo de longe.

Ao Leonardo Ziccardi pela parceira e auxílio nas análises estatísticas com o R.

Ao Zé Ribeiro pela ajuda no trabalho de campo em Matupi.

A Ruth, Raimundo e aos colegas do laboratório Agroeco pela amizade e convivência.

Ao meu marido Sadi Nascimento Jr., aos meus pais Chotoku e Sumiko Yanai, a minha irmã Angela Yanai, *obaachan* Fukiyo Iizuka e a família Nascimento: Sr. Sadi, D. Fátima e Felipe pelo apoio e carinho nesta jornada.

ABSTRACT

The recent increase in forest cover loss in Brazil's Amazon region has been causing substantial concern at the global level. By understanding the deforestation process in the past and in the present, we can better model the advance of deforestation. Here, we assessed the contributions of different types of actors to deforestation and land occupation in Santo Antônio do Matupi District located in the southern portion of Amazonas State, and we simulated the deforestation patterns of actors inside and outside of the Matupi settlement project through 2050. In the Matupi settlement, we assessed the actors with a focus on land-tenure concentration (i.e., lot concentration), and outside of settlement we assessed the actors based on the Rural Environmental Register or CAR (*Cadastro Ambiental Rural*). We also assessed deforestation in public land without destination, in an agro-extractivist settlement and in protected areas. Based on the information from this analysis, we created a map with all actors' landholdings and obtained parameters for the deforestation patch sizes for use as input data in a spatially explicit model to simulate the deforestation trajectory of each type of actor, using as an assumption the recent increasing trend in deforestation rates (2013-2018) and the weakening of command and control action. Two scenarios were constructed based on the same assumption, but with different approach to deforestation rates: (i) Business-as-usual scenario with absolute rates (BAU-SAR), where we used deforestation rates in terms of area cleared at each model time step and (ii) Business-as-usual scenario with relative rates (BAU-SRR), where we applied rates in terms of a percentage in relation to the remaining forest area in the landholdings and land categories. The results showed that, in the Matupi settlement, lot "concentrators" occupied 28% (9653 ha) of the settlement and 29% of the lots (152 lots); the numbers of lots concentrated ranged from two to ten; concentrators of two lots and non-concentrators were the predominant actors. Outside of the settlement, we found the following actor types: "small" (< 100 ha), "semi-small" (100 - 400 ha), "medium" (> 400 - 1500 ha) and "large" (> 1500 ha). Most of the total area in small (72%) and semi-small (49%) landholdings had been cleared by 2018, while the medium and large landholdings still had large areas of remaining forest. Only a small portion of the area occupied by these actors had been cleared (medium: 20%; large: 12%). Statistical analysis showed that the main predictors of deforestation were: landholding size, year of first clearing and the distance between the landholding and the Transamazon Highway (adj $R^2 = 0.507$). Most actors of all types were found in public land without destination, although some actors were also found in the agro-extractivist settlement (medium: 8%; large: 28%) and in conservation units (medium: 21%; large: 21%). Deforestation modeling indicated a substantial increase in clearing through 2050 in both scenarios, mainly in the Matupi settlement, in areas occupied outside of the settlement by small and semi-small landholdings and in public land without destination. In the BAU-SRR deforestation increased more gradually in than in the BAU-SAR. We verified that more than 50% of the forest in the lots of a family that concentrated 10 lots in the Matupi settlement, medium landholdings, and large landholdings and in protected areas remained by 2050. This study provides a better understanding of the actors on an Amazonian cattle-ranching frontier and of the spatial and temporal dynamics of their deforestation.

Key-words: deforestation patterns; rural settlement; deforestation modeling; Amazon forest; environmental policies.

RESUMO

A perda de cobertura florestal nos últimos anos tem causado grande preocupação a nível global. Entendendo como o desmatamento ocorreu no passado e atualmente, podemos modelar o avanço do desmatamento de forma mais precisa. Neste estudo, avaliamos a contribuição dos diferentes tipos de atores para o desmatamento e ocupação da terra na região do Distrito de Santo Antônio do Matupi localizado no sul do Amazonas, e simulamos os padrões de desmatamento dos atores dentro e fora do projeto de assentamento Matupi (PA Matupi) até 2050. Os atores no PA Matupi foram avaliados quanto à concentração de terras (i.e., concentração de lotes) e fora do assentamento com base nos dados de imóveis rurais do CAR (Cadastro Ambiental Rural). Além disso, analisamos o desmatamento nas categorias de terra (terras públicas não destinadas, assentamento agro-extrativista e áreas protegidas). A partir dessas análises foi criado um mapa com a área ocupada (i.e., *landholding*) por cada tipo de ator e obtidos parâmetros de tamanho das manchas de desmatamento por tipo de ator. Esses dados serviram de entrada no modelo espacialmente explícito para simular a trajetória de desmatamento dos atores usando como premissa a recente tendência de aumento nas taxas de desmatamento (2013-2018) e o enfraquecimento das ações de comando e controle. Dois cenários foram elaborados utilizando a mesma premissa, mas com abordagens diferentes com relação às taxas de desmatamento: (i) Cenário negócios como sempre com taxas absolutas, em que foram utilizadas as taxas anuais de desmatamento em termos de área e (ii) Cenário negócios como sempre com taxas relativas, em que foram utilizadas taxas anuais de desmatamento relativas aos remanescentes florestais dentro de cada área ocupada por cada tipo de ator e categorias de terra. Os resultados indicaram que no PA Matupi os “concentradores” de lotes ocupavam 28% (9.653 ha) da área total do assentamento e 29% dos lotes (152 lotes); o número de lotes concentrados foi de 2 a 10 lotes; concentradores de 2 lotes e não-concentradores foram os atores predominantes no assentamento. Em relação aos atores fora do assentamento, identificamos os seguintes atores (produtores rurais): pequenos (< 100 ha), semi-pequenos (100 – 400 ha), médios (> 400 – 1.500 ha) e grandes (> 1.500 ha). A maior parte da área ocupada pelos pequenos (72%) e semi-pequenos (49%) foi desmatada até 2018, enquanto as áreas ocupadas por médios e grandes apresentavam maior área de floresta remanescente e pequena porção de área desmatada (médios: 20%; grandes: 12%). A análise estatística realizada evidenciou os principais preditores do desmatamento e demonstrou que o desmatamento se relaciona mais fortemente com fatores tais como: o tamanho da área ocupada (imóvel); o ano do primeiro desmatamento e; com a distância entre a área ocupada e a rodovia Transamazônica (R^2 ajustado = 0.507). Destacamos que a maior parte dos atores analisados fora do PA Matupi estava em terras públicas não destinadas, porém, alguns deles foram encontrados no assentamento agro-extrativista (médios: 8%; grandes: 28%) e em unidades de conservação (médios: 21%; grandes: 21%). A modelagem do desmatamento demonstrou que nos dois cenários houve um incremento importante no desmatamento até 2050, principalmente no PA Matupi, em áreas ocupadas fora do assentamento por pequenos e semi-pequenos e em terras públicas não destinadas. No cenário negócios como sempre com taxas relativas, o incremento do desmatamento foi mais gradual em comparação ao cenário negócios como sempre com taxas absolutas. Observou-se que nas áreas ocupadas pela família que concentra 10 lotes no PA Matupi, médios e grandes fora do assentamento e em áreas protegidas mantiveram mais de 50% da cobertura florestal até 2050, em relação à cobertura florestal existente em 2019. Este estudo proporciona um melhor entendimento sobre os atores localizados em áreas de fronteira agropecuária na Amazônia e sobre a dinâmica de desmatamento espaço-temporal associada a esses atores.

Palavras-chave: padrões de desmatamento; assentamento rural; modelagem do desmatamento; Floresta Amazônica; políticas ambientais.

TABLE OF CONTENTS

GENERAL INTRODUCTION 15

Chapter 1: Deforestation dynamics in Brazil's Amazonian settlements: Effects of land-tenure concentration

Abstract 17
1. Introduction 18
2. Materials and Methods 20
3. Results 28
4. Discussion 45
5. Conclusions 52
Acknowledgments 53
References 53

Chapter 2: Brazil's Amazonian deforestation actors: Clearing behavior on a cattle-ranching frontier

1. Introduction 59
2. Materials and Methods 62
3. Results 70
4. Discussion 82
5. Conclusions 87
Acknowledgments 87
References 88

Chapter 3: Simulating the deforestation patterns of actors on a cattle-ranching frontier

Abstract 92
1. Introduction 94
2. Materials and Methods 95
3. Results 108
4. Discussion 116
5. Conclusion 119
Acknowledgments 119
References 120

Chapter 4: Land-tenure concentration on a cattle-ranching frontier

Abstract 123

1. Why land-tenure concentration occurs? 123

2. Why is the percentage of clearing in small landholdings higher than in large landholdings? 124

3. How can land-tenure concentration be avoided? 125

References 126

GENERAL CONCLUSION 128

REFERENCES 130

ANEXOS: Documentos de solicitação e disponibilização de dados do INCRA do projeto de assentamento Matupi 132

SUPPLEMENTARY MATERIAL 135

Chapter 1: Deforestation dynamics in Brazil's Amazonian settlements: Effects of land-tenure concentration 135

Additional information on Materials and Methods 135

Chapter 2: Brazil's Amazonian deforestation actors: Clearing behavior on a cattle-ranching frontier 140

Additional Information on Materials and Methods 140

Chapter 3: Simulating the deforestation patterns of actors on a cattle-ranching frontier 145

LIST OF TABLES

Chapter 1:

Table 1. Deforestation patterns in the Matupi settlement. 25

Table 2. Actor-polygons found associated with classified deforestation patterns. Values in bold italics refer to polygon samples[1] used in the classification...35

Table 3. Types of concentration found in 2011 and numbers of lots concentrated in the Matupi settlement. 37

Table 4. Deforestation rate per lot from 1995 to 2011 in three groups of actors categories. ..39

Table 5. Total deforestation (~2011) and remaining forest (2011) considering the categories of actors and the percentage of remaining forest (2011) per lot (non-concentrators and concentrators of non-neighboring lots) and per landholding for concentrators. 44

Chapter 2:

Table 1. Actor types and the landholding sizes based on the fiscal module (1 fiscal module in our study area = 100 ha). 64

Table 2. Characteristics of landholdings by actor type. 71

Table 3. Estimates of deforestation through 2018 and of remaining forest in hectares per actor type. *Estimated from 1995 to 2018 (24 years), only including landholdings with total clearing ≥ 1 ha. 71

Table 4. Patch size estimated in six-year intervals from 1995 to 2018 for each actor type. ...75

Table 5. Distribution of actor types in different land categories. 80

Chapter 3:

Table 1. Variables used in the model. 99

Table 2. Deforestation rates for each category in the model. 103

Table 3. Variables for which weights-of-evidence coefficients were used in the model for each actor type and land category. The blank boxes indicate that the variable was excluded because it showed a correlation with another variable. 104

Table 4. Parameters of deforestation patches used the model. 106

Table 5. BAU scenario with absolute rates (BAU-SAR): remaining forest in hectares and in percentages in relation to 2019 for actors in the Matupi settlement. 111

Table 6. BAU scenario with relative rates (BAU-SRR): remaining forest in hectares and in percentages in relation to 2019 for actors in the Matupi settlement. 111

Table 7. BAU scenario with absolute rates (BAU-SAR): remaining forest in hectares and in percentages relative to 2019 for actors outside the Matupi settlement. 113

Table 8. BAU scenario with relative rates (BAU-SRR): remaining forest in hectares and in percentages relative to 2019 for actors outside the Matupi settlement. 114

Table 9. BAU scenario with absolute rates (BAU-SAR): remaining forest in hectares and in percentages relative to 2019 in the different land categories. 115

Table 10. BAU scenario with relative rates (BAU-SRR): remaining forest in hectares and in percentages relative to 2019 in the different land categories. 115

Supplementary Material - Chapter 1:

Table S1. Confusion matrix for classification from ~1994 to 1999. Values refer to numbers of samples (polygons) in training step and in the validation step. Total number of samples shown in bold. 136

Table S2. Confusion matrix for classification from 2000 to 2016. Values refer to numbers of samples in the training step and the validation step. Total number of samples shown in bold.136

Table S3. Deforestation rate per lot from 1995 to 2011 for each actor category. 137

Table S4. P-values in pairwise tests in comparing actor categories. Values in bold indicate significant differences ($p < 0.05$). FC: Family concentrator; FCs: Families concentrators and ICs: Individual concentrators..138

Supplementary Material - Chapter 2:

Table S1. Hydrography (water courses) and non-forest vegetation in the landholdings of each actor type...144

Table S2. Coefficients estimated for deforestation models (Equations 1 and 2). 144

Supplementary Material - Chapter 3:

Table S1. Values of minimum similarity for each region using *absolute rates* in the Matupi model and in the null model. Values ≥ 50% in the Matupi model are indicated in green and in the null model in orange. 153

Table S2. Values of minimum similarity for each region using *relative rates* in the Matupi model and in the null model. Values ≥ 50% in the Matupi model are indicated in green and in the null model in orange...154

Table S3. Comparison between observed and simulated deforestation in the calibration phase. 157

LIST OF FIGURES

Chapter 1:

Fig. 1. Location of the study area. Landsat-8 OLI image (2016): R (6), G (5), B (4). 21

Fig. 2. Total area cleared per year mapped in the Matupi settlement. 29

Fig. 3. Numbers of patches (polygons) of different sizes and in different periods of time. 29

Fig. 4. Results of decision-tree classifications for the first (~1994-1999) and second (2000-2016) classification periods. 30

Fig. 5. Deforestation pattern classification in the Matupi settlement (2016). 31

Fig. 6. Percentage of each deforestation pattern in relation to total deforestation. 32

Fig. 7. Distribution of patch areas for each deforestation pattern. 33

Fig. 8. Mean area cleared per year divided into time intervals and deforestation patterns. 34

Fig. 9. Boundaries of landholdings updated to 2011 and deforestation patterns (1995 - 2011). The “Individual concentration (Independent lots)” is the same as “concentrators of non-neighboring lots” mentioned in the text. 36

Fig. 10. Distribution of mean clearing per landholding from 1995 to 2011 separated into three groups: non-concentrators (n = 364 landholders), concentrators of 2 lots (n = 47 landholders) and concentrators of ≥ 3 lots (n = 13 landholders). 38

Fig. 11. Total area cleared per landholding from 1995 to 2011 (n = number of landholders per category). 40

Fig. 12. Proportion of total clearing in each lot and landholding through 2016 (n = number of landholders per category). 41

Fig. 13. Total area cleared in the period from 1995 to 2011 by type of actor (n = 17 years). .42

Fig. 14. Trajectory of deforestation through time per area occupied by each type of landholder. Proportion of clearing represents the proportion of clearing in relation to the total area occupied by the category. 43

Chapter 2:

Fig. 1. Location of the study area. 62

Fig. 2. Percentage of forest remaining per landholding in 2018 by actor type. The black line dividing each gray box is the median of the data (middle quartile); gray box: interquartile range (IQR) = Q1 (first quartile or 25th percentile) – Q3 (third quartile or 75th percentile); dashed lines (whiskers) represent the range of data outside the middle 50%. 72

Fig. 3. Cumulative deforestation from ~1994 to 2018 for each actor type. The percentages shown for the initial (~1994) and final (2018) years analyzed indicate the total area cleared in relation to the area occupied by the actors. 73

Fig. 4. Distribution of mean annual clearing from 1995 to 2018 per landholding of the different actor types. The black line dividing each box is the median of the data (middle quartile); gray box: interquartile range (IQR) = Q1 (first quartile or 25th percentile) = Q3 (third quartile or 75th percentile); dashed lines (whiskers) represent the range of data outside the middle 50%; circles represent outliers. 74

Fig. 5. Distribution of actors in relation to the Transamazon Highway (BR-230). The black line dividing each box is the median of the data (middle quartile); gray box: interquartile range (IQR) = Q1 (first quartile or 25th percentile) – Q3 (third quartile or 75th percentile); dashed lines (whiskers) represent the range of data outside the middle 50%; circles represent outliers. 76

Fig. 6. Relation of landholding size to deforestation in terms of area (above) and percentage (below) according to the time of occupation. 78

Fig. 7. Relation between real and predicted deforestation in terms of area (left) and in terms of percentage (right). Symbols indicate landholding size (values are continuous: larger sizes have larger circles), and the time of first clearing is shown by the color scale from gray (old) to blue (recent). A square frame outlined with dotted line is a zoomed view.. 79

Fig. 8. Distribution of landholdings, roads in 2018 and land categories. 81

Fig. 9. Distribution of large and medium landholdings. Medium and large landholdings with clearing and unofficial roads can be observed inside conservation units (A and B). A medium landholding is located in an Indigenous land (C). Large landholdings are often found at the ends of access roads (D). 83

Chapter 3:

Fig. 1. Study area. 96

Fig. 2. Framework describing steps of the modeling for each actor type and land category. . 97

Fig. 3. Spatial distribution of actors landholdings and of land categories: (A) actors in the Matupi settlement based on the lots concentration. We excluded lots for which we have no information. (B) actors located outside of the settlement and (C) unknown actors located in the different land category types. 98

Fig. 4. Modeling framework based on the deforestation actors in Dinamica-EGO. 101

Fig. 5. Minimum similarity in the Matupi model and the null model using absolute rates and relative rates. 107

Fig. 6. Deforestation in 2019 (real) and 2050 in simulated scenarios for (A) the study area as a whole, (B) the Matupi settlement, (C) smallholders and (D) semi-smallholders. 109

Fig. 7. Deforestation in 2019 (real) and 2050 in simulated scenarios for (A) public land without destination, (B) medium landholders and (C) largeholders. 110

Fig. 8. Cumulative deforestation from 2019 to 2050 in simulated scenarios for each actor type in the Matupi settlement. 112

Fig. 9. Cumulative deforestation from 2019 to 2050 in the scenarios simulated in the landholdings outside of the Matupi settlement. 114

Fig. 10. Cumulative deforestation from 2019 to 2050 in simulated scenarios in the different land categories. 116

Supplementary Material - Chapter 1:

Fig. S1. Lots and access roads in the Matupi settlement, showing deforested areas and dates of deforestation...139

Fig. S2. The Matupi settlement indicating 30 lots held by non-concentrators that had portions of large geometric deforestation patches spanning more than one lot in 2011. This suggests fragmentation of previously concentrated landholdings...139

Supplementary Material - Chapter 2:

Fig. S1. Distribution of protected areas, landholdings and deforestation in the study area...142

Fig. S2. Correlation matrix of dependent and predictor variables. The dependent variables are in bold. 142

Fig. S3. Distribution of polygon sizes (≥ 1 ha) in year intervals for each actor type. 143

Fig. S4. Pearson residuals of predicted deforestation in terms of total area cleared (left) and in percentage of clearing (right)...143

Supplementary Material - Chapter 3:

Fig. S1. Cumulative deforestation through 1994 and annual deforestation from 1995 to 2019 for the study area as a whole. 145

Fig. S2. Cumulative deforestation through 1994 and annual deforestation from 1995 to 2018 for the Matupi settlement...147

Fig. S3. Cumulative deforestation through 1994 and annual deforestation from 1995 to 2018 for landholdings outside the settlement. 149

Fig. S4. Cumulative deforestation through 1994 and annual deforestation from 1995 to 2018 for different land categories. 152

GENERAL INTRODUCTION

The construction of Transamazon Highway (BR-230) (Brazil, PR 1970) and the incentives for land occupation through settlement projects in areas surrounding this highway were important drivers of deforestation in the history of Brazil's Amazon forest. This region is characterized by the presence of settlement projects, road networks, cattle-ranching activity and is known as "arc of deforestation" (Becker, 2005; Kirby et al., 2006; Laurance et al., 2002). The roads that provide access to the forest facilitate, illegal extraction of timber occurred followed by the illegal land occupation and subsequent conversion of forest to agriculture or pasture (Souza Jr. et al., 2013).

Despite Brazil's efforts to reduce annual rates of Amazon deforestation the decline rates from 27,772 km^2 in 2004 to 4571 km^2 in 2012, since 2013 deforestation rates have increased due the weakness of deforestation control (Nepstad et al., 2014; Brazil, INPE, 2019; Carvalho et al., 2019). Deforestation has substantial influence on regional climate, since it causes changes in the region's water balance and increases carbon emission (Coe et al., 2013; Nogueira et al., 2015). In addition, the remaining forest in southern and eastern Amazonia are hotspots of ecosystem services with high biodiversity (Strand et al., 2018).

On the cattle-ranching frontier, although the main land cover change (i.e., primary forest being converted to pasture) is similar among the different actor types (e.g., actors in the settlement project and outside of the settlement), the contribution of each actor type to deforestation is different. This is because the clearing behavior among the actors is different and the spatial configuration of deforestation patches (size, form and spatial distribution of the patches) can be vary through the time. Deforestation patches that can be identified on satellite images help in assessing the dynamics of deforestation patterns for these actors (Zipperer, 1993; Geist e Lambin, 2001; dos Santos Silva et al., 2008). We can use this information to better understand how governance policies, such as command-and-control operations, influence the dynamics of deforestation in the region. In addition, by better understanding the actors' clearing behavior, parameters can be obtained for use in deforestation models to project the contribution of each actor type to future deforestation. Despite deforestation models being simplified representations of reality, we can capture and reproduce certain pattern in the deforestation process to indicate possible deforestation trajectories.

The aim of this study was to assess the contribution of the different actor types to deforestation and to simulate the deforestation patterns of actors through 2050. The study was done in the southern portion of Amazonas State, specifically in Santo Antônio do Matupi District (henceforth “Matupi District”).

This thesis was divided into the following chapters:

1. Deforestation dynamics in Brazil’s Amazonian settlements: Effects of land-tenure concentration.
2. Brazil’s Amazonian deforestation actors: Clearing behavior on a cattle-ranching frontier.
3. Simulating the deforestation patterns of actors on a cattle-ranching frontier.
4. Land-tenure concentration on a cattle-ranching frontier

In Chapter 1 we focused on actors located in the Matupi settlement. We identified actors who concentrated lots and assessed the deforestation dynamics in relation to land concentration by these actors.

In Chapter 2 we focused on the actors located outside of the settlement (smallholders, semi-smallholders, medium landholders and largeholders). These actors occupy land spontaneously in areas of public land without destination, in protected areas and in an Agro-Extractivist settlement.

In Chapter 3 we used a spatially explicit modeling to simulate the deforestation patterns of actors identified in the previous chapters. The deforestation dynamics of each actor type is represented in terms of the area cleared per year, the size and shape of deforestation patches and by the drivers of deforestation identified as indicating how deforestation will spread through the years in landholdings occupied by these actors.

In Chapter 4 we synthesize our findings from field observations and contribute to discussions on the issues surrounding land-tenure concentration. This research contributes to the better understanding of the deforestation behavior of actors, which could help to improve the effectiveness of the present command-and-control actions on cattle-ranching frontiers and to develop better policies for the different actor types with the aim of reducing the spread of deforestation and maintaining the remaining forest resource.

Chapter 1

Deforestation dynamics in Brazil's Amazonian settlements: Effects of land-tenure concentration*

Aurora Miho Yanai[1], Paulo Maurício Lima de Alencastro Graça[1,3], Maria Isabel Sobral Escada[2], Leonardo Guimarães Ziccardi[1], Philip Martin Fearnside[1,3,4]

[1]Department of Environmental Dynamics, National Institute for Research in Amazonia (INPA), Av. André Araújo n° 2936, CEP 69067-375, Manaus, Amazonas, Brazil.

[2]Department of Image Processing, National Institute for Space Research (INPE), Av. Astronautas, n° 1758, CEP 12227-010, São José dos Campos, São Paulo, Brazil

[3]Brazilian Research Network on Climate Change (RedeClima)

[4]Corresponding author

Email addresses: yanai@inpa.gov.br; pmlag@inpa.gov.br; isabel@dpi.inpe.br; leonardo.g.ziccardi@gmail.com; pmfearn@inpa.gov.br

Manuscript in review on Journal of Environmental Management. Submitted on 5 February 2019.

Abstract

Brazil's Amazon deforestation is a major global and national environmental concern, and the ability to model and project both its course and the effect of different policy options depends on understanding how this process occurs at present and how it might change in the future. The present paper addresses one key factor in Amazon deforestation: land-tenure concentration in settlements. Brazil's policies for establishing and regulating settlement projects represent critical government decisions shaping the landscape in the 5×10^6 km^2 Legal Amazonia region. We used remote-sensing data and data mining to evaluate the effect of land-tenure concentration in a settlement project (*Projeto de Assentamento*) located in a frontier area where cattle ranching is expanding. We identified the actors and their deforestation patterns in the Matupi settlement in the southern part of Brazil's state of Amazonas. We spatially identified actors who concentrated "lots" (the parcels of land distributed to individual settlers) in 2011 and assessed whether the concentration was done by individual landholders or by "families" (where members merged their lots and the clearing was done together). Deforestation rates (1995-2011) were estimated for each type of actor and the trajectory of deforestation in the settlement (~1994-2016) was also analyzed. Concentrators occupied 28% (9653 ha) of the settlement and 29% of the lots (152 lots) analyzed; the numbers of lots concentrated ranged from two to ten. Concentrators of two lots and non-concentrators were the predominant actors in the settlement. The mean annual clearing per landholding for concentrators of two lots (families: 4.1 ± 2.8 ha; individuals: 5.1 ± 4.6 ha) was greater than for non-concentrators (1.7 ± 1.2 ha), despite their patterns being similar (small geometric and small irregular). Concentrators of three or more lots had mean annual clearing per landholding between 6.2 ± 12.2 ha and 23.9 ± 38.7 ha and, the large-geometric pattern (patches >34 ha per year) was predominant. The deforestation rate per lot was clearly higher among concentrators as compared to non-concentrators, showing that lot concentration speeds deforestation. Non-concentrators and concentrators of non-neighboring lots also had similar rates. Analysis of deforestation patterns helps to better understand the process of lot concentration by spatially identifying the predominant patterns of each type of actor. The approach used in our study could assist authorities in identifying and monitoring land-tenure concentration in settlements. Agrarian-reform policymakers need to monitor this process, since it speeds deforestation in Amazonian settlement projects, as well as undermining the social objectives of the agrarian-reform program.

Keywords: Agrarian reform; Settlement project; Colonization; Deforestation pattern; Amazon forest; Land concentration

Highlights:

- Deforestation in Brazilian Amazonia is increased by land-tenure concentration.
- Settlers receive 1 lot per family, but newcomers buy out the original settlers.
- “Concentrators” in settlements establish ranches of 2-10 lots (~200-1000 ha).
- In the Matupi settlement 29% of the lots had been concentrated after 16 years.
- Concentrators with ≥ 3 lots typically clear in large patches (>34 ha per year).

1. Introduction

Brazil’s Amazonian settlements have an important role in the region’s land-use dynamics. Direct and indirect vectors of deforestation (e.g., extensive cattle ranching and illegal occupation of several lots by a single landholder) contribute to increasing deforestation rates in settlements (Alencar et al., 2016). Because most settlements are located near major roads (e.g., the Transamazon Highway), deforestation pressure in these areas tends to be intense (Godar et al., 2012a). Deforestation results in the loss of important environmental services provided by the forest, such as maintenance of water cycling, carbon stocks and biodiversity (Fearnside, 1997, 2008a).

Settlements contributed 17% (160,410 km^2) of the total clearing (clearcutting of both forest and non-forest vegetation) through 2013 in Brazil’s 5 × 10^6 km^2 administrative region denominated “Legal Amazonia” (Yanai et al., 2017). This represents 20% (2.6 Pg C) of the total carbon lost in Legal Amazonia through 2013 (13.1 Pg C, Nogueira et al., 2015). “Federal settlement project” (PA = *Projeto de Assentamento Federal*) is the category with the largest number of settlements and encompasses 72% (115,634 km^2) of the total clearing in settlements

(Yanai et al., 2017). Federal settlement projects are established by Brazil's National Institute for Colonization and Agrarian Reform (INCRA), which distributes parcels of land called "lots" (*lotes*) with one lot for a single person or family. When a settlement begins, all or almost all lots are held by individual families (i.e., "non-concentrators"), but as time passes many original settlers sell their lots to wealthier neighbors or to newcomers who "concentrate" several lots to manage the area as a larger property, even though the lots are held under different names. When the original settlers sell their lots to wealthier newcomers, this creates a new wave of landless migrants, leading to a continued cycle of land invasion and subsequent legalization and/or resettlement in new INCRA projects (Fearnside, 2001).

In 2017, Law 13.465 (formerly MP-759), popularly known as the "land-thieves law" or "*lei da grilagem,"* was passed allowing illegal land claims up to 2500 ha to be legalized (Brazil, PR, 2017, Art. 6). This law also specifies that illegally occupied lots in settlement projects can be legalized after only two years of occupation (Art. 26B) and that lots can be sold after 10 years of legal occupation (Arts. 18, §1 & 22, §1). In addition, the law specifies (Art. 17, §6) that settlements be considered "consolidated" 15 years after they were founded (thereby allowing lots to be sold). A particularly pernicious effect for settlements is ending a provision that allows settlers to start paying installments owed to the government for the original purchase of the lot only after adequate infrastructure (access roads, etc.) has been installed (see: Branford and Torres, 2017). These debts can now be called for immediate payment, and this can be demanded independent of the adequacy of infrastructure (Art. 17, §8). All of these provisions can be expected to result in the less-wealthy settlers, who have only one lot, selling their land to wealthier neighbors or to newcomers. Irrespective of the effect of lot concentration in speeding deforestation, newcomers who buy lots in settlement areas have been found to clear forest at a substantially faster rate per lot than the original occupants (Fearnside, 1987).

Land concentration is an important issue in Amazonian rural settlements because it violates the principles of Brazil's agrarian reform program, which is intended to distribute land to landless families. In addition, concentration of lots transforms settlements into large cleared areas used mainly for cattle pasture. For cattle ranchers, one of the main motivations for land concentration is expansion of pasture. Because law enforcement is currently not sufficient to control this process, concentration of lots is a typical feature of settlement projects.

The present study addresses the question of whether the effect of lot concentration results in distinct patterns and rates of deforestation between concentrators (either families or individuals) and non-concentrators. We answer the question by (1) spatially identifying concentrators and non-concentrators and whether concentration is done by “individuals” (i.e., several lots identified by INCRA as occupied by a single person) or “families” (i.e., a family with lots in the names of several family members), (2) defining typologies of deforestation based on the types of actors, remote-sensing data and data-mining techniques and (3) evaluating the rates and trajectories of deforestation through the time in each type of land-tenure concentration.

The term “deforestation pattern” refers to a spatial configuration of patches of deforestation with similarities in size, shape and location that can be mapped from satellite imagery (Zipperer, 1993; Geist and Lambin, 2001; dos Santos Silva et al., 2008). The term “actors” refers to landholders (either individuals or families), whether or not they were settled by INCRA.

The property size is the most important variable used in many studies to separate different types of actor: however, identifying the thresholds to use in differentiating small and large landholders is complex because these criteria should consider the local dynamics of land-cover change for each type of actor (Godar et al., 2012b). Hence, a spatial and temporal analysis at the polygon level can provide data at the patch scale in order to evaluate and understand changes resulting from human action in space and through time (Lu et al., 2013). Identifying the actors and the deforestation patterns associated with these actors can improve our comprehension of how carbon stocks have been lost by the different actor categories and how deforestation might proceed in the future as the process of land concentration continues. Understanding the deforestation behavior of different actor types is essential if the future course of land-use change is to be predicted and appropriate measures taken to avoid unfavorable outcomes.

2. Materials and Methods

2.1. Study area

The present study was carried out in the Matupi Federal Settlement Project in Matupi District. A “district” is an administrative unit within a municipality (county), in this case the municipality of Manicoré in the state of Amazonas, Brazil. The Matupi settlement is located in the southern part of Amazonas state near the Transamazon Highway (BR-230), which provides a road connection to the state of Rondônia (a major source of migration) via the BR-319 Highway, which connects Porto Velho (Rondônia) with Manaus (Amazonas) (Fig. 1).

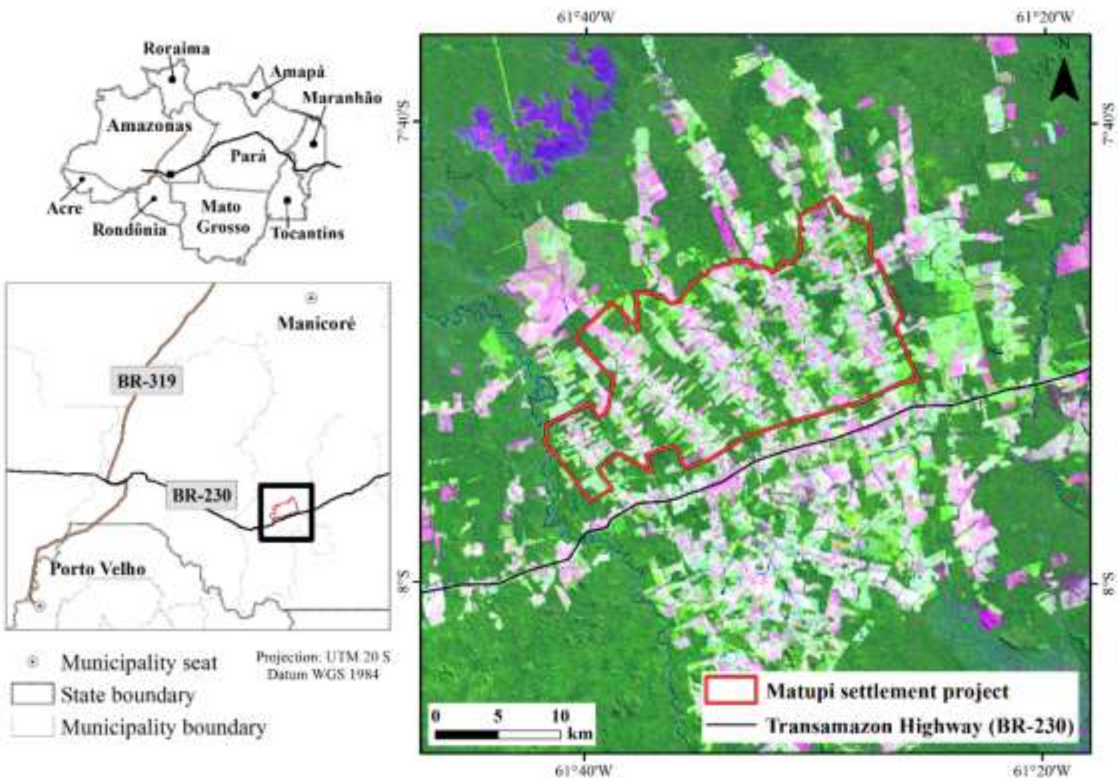


Fig. 1. Location of the study area. Landsat-8 OLI image (2016): R (6), G (5), B (4).

Most actors in Amazonian settlements originate from locations near the settlement or from the southern and southeastern regions of Brazil (Fujisaka et al., 1996; Fearnside, 2008b; Caviglia-Harris et al., 2013). Land prices are low in settlements in frontier expansion areas such as Matupi, which attracts farmers from consolidated frontiers (e.g., Rondônia) where the farmers can sell their land and use the proceeds to buy a larger area in a new frontier settlement (Carrero and Fearnside, 2011).

Matupi District (formerly known as “km 180”) is an area characterized by expansion of logging and cattle ranching. This general area was indicated as having a very high density of forest loss (>10 km^2 per 100 km^2 of land area) from 2001 to 2014 (Kalamandeen et al., 2018). Carbon loss in the Matupi settlement through 2013 was estimated at 3,389,406 Mg C (18,168 ha of area cleared), while estimated carbon stock in the remaining forest in 2013 (16,762 ha) was 3,129,204 Mg C (Yanai et al., 2017).

The Matupi settlement was officially created on 20 July 1992, initially with 465 lots covering 30,810 ha. However, the occupation process in the Matupi settlement only began in 1995 with the establishment of 91 families (da Silva et al., 2011). In 1997 the settlement area officially increased to 34,345 ha (decree n° 24 of August 1997) and the total number of lots increased to 537, with area of each lot between 25 and 135 ha (mean lot size = 64 ha). The Matupi settlement has nine access roads (known as "*ramais*"): Nova Vida, Bela Vista, Matupi, Matupiri, Santa Luzia, Boa Esperança, Maravilha, Triunfo and Bom Futuro (Supplementary Material, Fig. S1). The total area of the Matupi settlement is 34,938 ha, based on a vector map of the settlement's boundary.

2.2. Mapping deforestation through 2016 in the Matupi settlement

Cleared areas were mapped at 1:20,000 scale using Landsat-5 TM (1994 to 2011), ResourceSat-1 LISS-3 (2012) and Landsat-8 OLI images (2013 to 2016) (path: 231; row: 65) with spatial resolution of 30 m. The color composition used was the false color composition: shortwave infrared (Red), near infrared (Green), and red (Blue). We used images from the U.S. Geological Survey (USGS), and for each year we chose the image with the least cloud cover. We performed an atmospheric correction using the FLAASH (Fast Line-of-sight Atmospheric Analysis of Hypercubes) tool in Envi software to better differentiate land-cover change and to compare cleared areas in different years when necessary. We manually mapped cleared areas from 1994 to 2016 in the Matupi settlement by visual interpretation. Thus, cleared areas mapped in a given year (e.g., 2000) were used as a mask for mapping cleared areas in the next year (e.g., 2001). The area of each polygon was then calculated and areas < 1 ha were excluded to reduce noise caused by small polygons.

Polygons (i.e., patches) of clearing for each year were delimited based on the spectral response of cleared areas. For example, if one area was cleared by slash-and-burn and a nearby area had exposed soil, with the boundaries of both areas being visible, then each area was mapped as a distinct polygon for the year in question. We used this approach since the clearing process could help distinguish the actions of different actors. We only mapped areas cleared by clearcut and areas of forest loss with severe fire where the spectral response was that of clearing. Areas degraded by logging or by non-severe fire were not mapped because the boundaries of these patches are not as clear as in clearcut areas.

Because the occupation process in the Matupi settlement started in 1995, we began mapping clearing using the 1994 Landsat image as a reference. The polygons of cleared areas mapped for 1994 therefore represent cumulative areas and those from 1995 to 2016 represent annual clearing.

The minimum area considered in our study was 1 ha. Each polygon in the vector map was identified with the year that the deforestation was mapped, and the area in hectares was calculated.

Data from PRODES (Project for Monitoring Amazonian Deforestation) were used to assist our mapping when doubts arose concerning specific areas and to verify the agreement between our mapping and the PRODES dataset as a whole (Brazil, INPE, 2018a). PRODES is the Brazilian government's program of annual deforestation monitoring carried out by the National Institute for Space Research (INPE). We did not use the PRODES vector map because PRODES does not have annual deforestation mapping before 2000 for the Matupi settlement area and because the deforestation dataset from 2015 onwards had a spatial adjustment of the vector mask (i.e., cumulative deforestation from previous years) (Brazil, INPE, 2015). This spatial adjustment makes it difficult to use PRODES data for our spatial-temporal analysis in the Matupi settlement.

2.3. Identifying actors and linking actors to deforestation patches

Identification of the actors and their clearing (i.e., polygons of deforestation) was done based on the dataset for the Matupi settlement provided to us by the Amazonas office of INCRA in Manaus. This dataset consisted of (i) a vector map of lot boundaries (n = 537 lots), (ii) occupation survey (*Levantamento Ocupacional*) data on families in the Matupi settlement collected in October 2011 in 526 lots, and (iii) data on property diagnoses collected by INCRA in 164 lots from 2014 to 2016. Datasets (ii) and (iii) were obtained during *in loco* visits to the lots by an INCRA officer. In our analysis, we used information on the landholder and the beginning date of occupation for the lot. We also used data obtained during our fieldwork in

2016, which consisted of GPS points of the lot boundaries on the six access roads we visited (Matupi, Matupiri, Maravilha, Triunfo, Bom Futuro and Nova Vida; See Supplementary Material, Fig. S1).

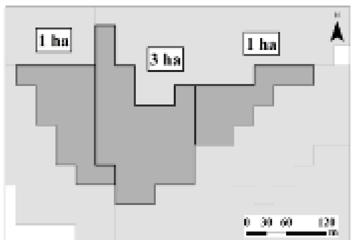
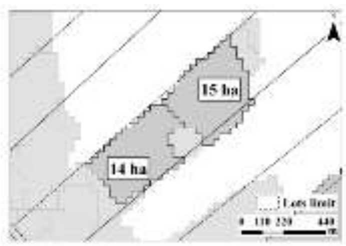
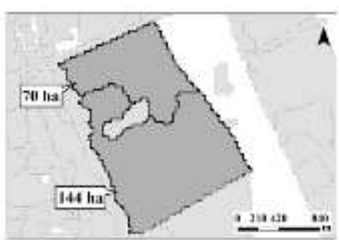
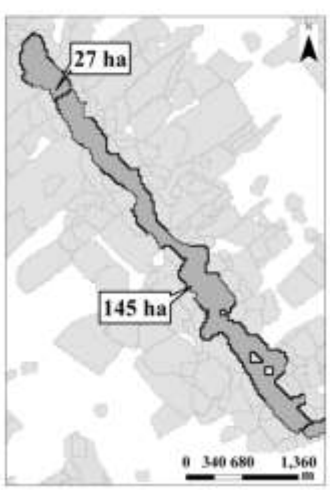
All of these data assisted us in identifying and spatially locating the landholders and their polygons of deforestation. Thus, for example, if data in INCRA’s 2011 occupation survey indicated that a landholder had occupied a given lot since 2004, then the polygons of deforestation from 2004 to 2011 were attributed to that landholder. In addition, if the same landholder occupied the lot in 2016, then any 2012-2016 deforestation polygons were also attributed to the landholder. When the year of occupation was not mentioned, only polygons of deforestation from 2011 were attributed to the landholder.

We used this approach to be sure of correctly associating the actor and his or her clearing in the lot because the polygons of deforestation in a lot could be made by different actors who occupied the lot at different times. Out of a total of 2551 polygons of deforestation mapped in the Matupi settlement, we could identify the actors in 887 polygons (35%). We used 178 of the identified polygons as the dataset that was divided between training and validation samples for classification of the deforestation pattern in the subsequent steps.

2.4. Classification of deforestation patterns

The method used to classify deforestation patterns was based on the landscape object (i.e., deforestation polygons mapped in the previous step). We used the GeoDMA (Geographic Data Mining Analyst) plugin (Körting et al., 2013) in Terra View software to classify the patterns of deforestation. The classification steps consisted of (i) feature extraction based on deforestation patches (i.e., polygons) and (ii) classification of deforestation-patterns based on the reference set of patches identified previously. In the feature-extraction step, landscape metrics at patch level were calculated for each polygon of deforestation based on spatial and contextual information (Körting, 2012). Polygons where the actors were known were selected for each deforestation pattern considering the spatial-pattern typologies of deforestation defined in Table 1.

Table 1. Deforestation patterns in the Matupi settlement.

Deforestation pattern	Actors associated with the pattern	Description
Small irregular 	The initial premise is that this is the predominant pattern for landholders who do not concentrate lots;	**Main activity:** cattle ranching and agriculture; Small patches (either grouped or isolated) indicate a small clearing each year inside of the lot. Cleared areas are for pasture or agriculture.
Small geometric 	The initial premise is that this is more common in landholders who do not concentrate lots. The cleared areas are small and respect the boundary of the lot.	**Main activity:** cattle ranching and agriculture; Patches can be isolated, which could be associated with the new pasture areas or grouped with older patches that could indicate the expansion of pasture.
Large geometric 	The initial premise is that large geometric clearings are predominantly in landholdings of individual and family landholders who have concentrated lots.	**Main activity:** cattle ranching Large areas cleared in one year by actors who concentrate lots.
Large irregular 	We assumed that this pattern is mainly associated with the first families or individuals who occupied the settlement, each receiving a single lot from INCRA.	**Main activity:** cattle ranching and agriculture; This pattern represents the beginning of the occupation process along of the access roads in the Matupi settlement. The occupation is characterized by clearing at the front of the lots, which can have the effect of indicating land tenure.

We separated the classification into two periods: (i) ~1994 to 1999 and (ii) 2000 to 2016. This was done because the initial process of ocupation in the Matupi settlement resulted in large polygons of deforestation that could be confused with similar polygons deforested in recent years. The separation into these periods results in better distinguishing the process of deforestation and the types of actors. The large areas cleared along access roads in the first years are the result of the first landholders who occupied the lots each clearing the front of the lot to indicate land tenure. We could not differentiate the clearing done by these landholders in the satellite images. In contrast, the large polygons cleared in recent years are attributed to lot concentration when the polygons span several lots.

In total, 239 polygons were used to assist the classifications. Out of this total, in 178 polygons the actors who cleared them were known, and for 61 polygons we have no information about the actors (these polygons were used only for the first classification period).

In the first classification period (~1994-1999) we considered the “large irregular,” “small geometric” and “small irregular” patterns. For the second classification period (2000-2016) we considered the “small irregular,” “small geometric” and “large geometric” patterns. The “small irregular” (n = 62) and “small geometric” (n = 66) patterns were in areas with the non-concentrating actor type. The “large geometric” cases (n = 22) were in areas of lot concentration.

For each classification, 40% of the total samples selected were chosen randomly by an automatic process for use in the validation step. Decision-tree classification was performed using the training samples, which represented 60% of the samples. Decision-tree classification reports the landscape metric and the thresholds that best discriminate each type of pattern. In the validation step, a confusion matrix and Kappa statistic were used to evaluate the classification.

2.5. Estimation of lot concentration in 2011 and deforestation rates by landholders

Since the data from the 2011 occupation survey of families covered most of the lots in the Matupi settlement, we used these data to classify the vector map of lot limits for each actor type. The actors were divided into two major groups: non-concentrators and concentrators, the latter group including both individual and family actor types. When concentration in neighboring lots was found, we merged these lots into one. The merged lots represent the landholding of a concentrator. In the case of non-concentrators, the landholding and the lot area are the same. We use the term “landholding” to refer to the area occupied by a single actor (individual or family); the area may be one or several lots and the occupation may or may not be legal.

The criterion used to identify concentration by families was if the members of the same family occupied neighboring lots and one of the family members resided in the neighboring lot (e.g., a parent living in his or her child’s lot). We also considered as concentration by a family the cases where both (i) lots are occupied by people with the same surname and (ii) the polygons of deforestation they made, which were identified by the period that the landholders occupied the lots, span these two or more lots.

We also considered a type of concentration of non-neighboring lots. This refers to concentrators of neighboring lots who also occupied one nearby lot in same access road. We found three concentrators in this category; two were individual landholders who concentrated four neighboring lots and each also had one non-neighboring lot, and in the third case one family landholder occupied two lots, one in front of other, with one of the lots neighboring his parents’ lot. We placed these non-neighboring lots cases in a separate category as “concentrators of non-neighboring lots” with the aim of comparing the dynamics of clearing in these lots with those of non-concentrators. In addition, the two landholders who concentrated four neighboring lots were analyzed in the category of individual landholdings with four lots, and the other landholder was placed in the category for family concentration of two lots because the landholder lived with the parent in the parent’s lot.

Lots excluded from our analyses (n = 21 lots) were those with unknown actors (4 lots), lots that were not visited by an INCRA officer due to inaccessibility in the Santa Luzia access road (10 lots) and “community” lots (7 lots). The “community” lot refers to a lot allocated by INCRA to construct infrastructure such as a school, church and space for recreational activities (e.g., a soccer field). The clearing in the community lot is therefore not associated with a specific actor. In most cases there is one community lot per access road. On one of the access roads (Boa Esperança) the community lot was occupied by a landholder, and it was included in our analysis. We then performed an intersection between the vector map of lot boundaries updated to 2011 and the vector map of deforestation patterns classified to estimate 1995-2011 deforestation rates per landholder (i.e., clearing per year in the area occupied by each landholder).

Although we are aware that deforestation in the lot could be done by different actors who occupy the lot at different times, we consider that it is important to establish the deforestation trajectories and rates of deforestation in areas where it was known whether or not the lot was occupied by concentrators in 2011. Landholders who were identified in this analysis as occupying the lot or area (in the case of concentrators of neighboring lots) in 2011 had inherited clearing done by previous landholders. To estimate the remaining forest in 2011, deforestation from 2012 to 2016 was considered to have been forest in 2011, and this total was summed with the forest in 2011. Because our dataset lacked normality, a non-parametric statistical test (Mann-Whitney U) was performed.

Additional information on methods is available in the Supplementary Material.

3. Results

3.1. Spatial and temporal dynamics of deforestation

The total area cleared through 2016 in the Matupi settlement was 22,945 ha (66% of the 34,938-ha settlement area), and the mean clearing per year (1995-2016) was 1026 ha. Peaks of deforestation occurred in 1997 and 2005 (9% and 10% of the total deforestation, respectively). In 2011 and 2016, high rates of deforestation were observed again, each of these years representing 8% of the total deforestation. In contrast, substantial reductions in deforestation were observed in 2006 (with a decrease of 1622 ha in relation to 2005) and in 2012 (with a decrease of 1199 ha in relation to 2011). The largest deforestation increment (1891 ha) occurred when the settlement area was officially expanded in 1997 (Fig. 2 and Supplementary Material, Fig. S1).

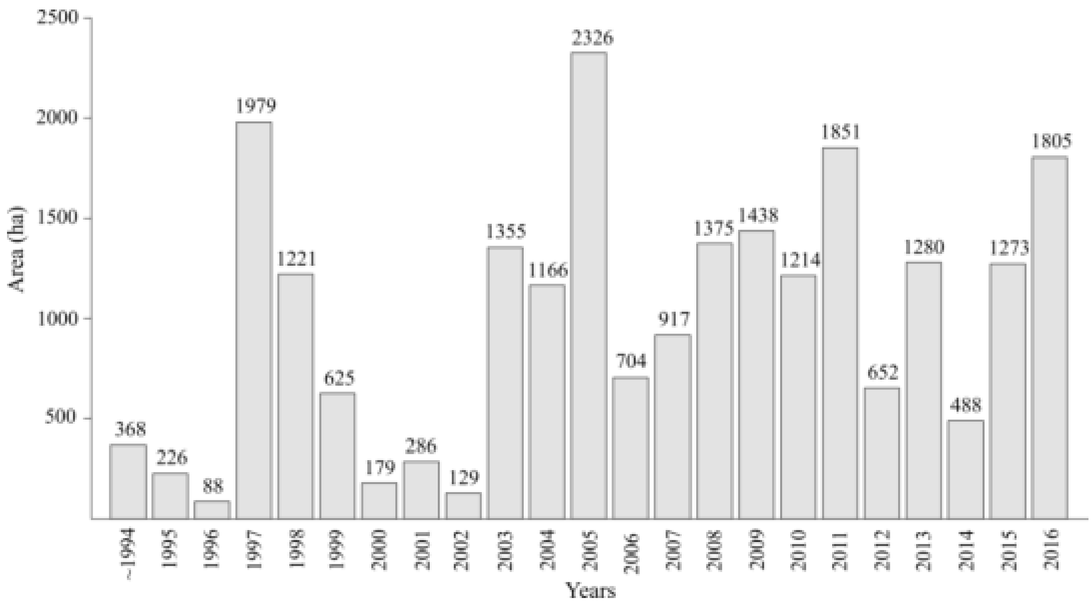


Fig. 2. Total area cleared per year mapped in the Matupi settlement.

We mapped a total of 2551 polygons (i.e., patches) with sizes ranging from 1 ha (minimum area considered) to 167 ha. In general, as patch size increased the numbers of polygons decreased for all periods analyzed. Most patches (74% or 1892 polygons) were in the < 5 and 5 - 10 ha size ranges (Fig. 3).

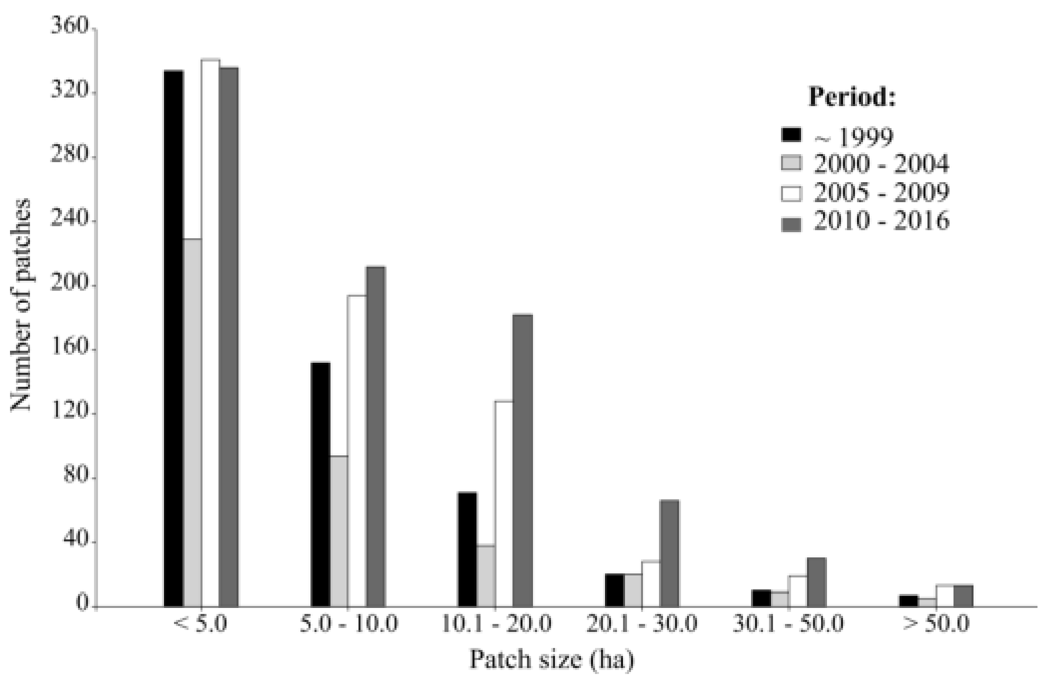


Fig. 3. Numbers of patches (polygons) of different sizes and in different periods of time.

The 2000-2004 period had the lowest number of patches in comparison with other periods for the three first classes (< 5, 5 - 10 and 10.1 - 20 ha) (Fig. 3). Deforestation in the settlement underwent a slowdown in this interval, mainly from 2000 to 2002 (see Fig. 2). In contrast, the 2010-2016 period had a greater number of patches for most sizes analyzed (5 - 10, 10.1 - 20, 20.1 - 30 and 30.1 - 50 ha) in comparison with other periods (Fig. 3).

3.2. Classification of deforestation patterns by actor type

A decision tree for the first classification (~1994 – 1999) identified compacity and normalized perimeter as the best landscape metrics for separating the deforestation patterns. The normalized perimeter metric transformed values between the minimum and maximum perimeters into values in the interval between 0 and 1. In the second classification (2000 – 2016), compacity and area best differentiated the patterns (Fig. 4). "Compacity" (which was used in both classifications), is a metric of patch shape (Eq. 1).

$$Compacity = (perimeter/area)/\sqrt{area} \qquad (1)$$

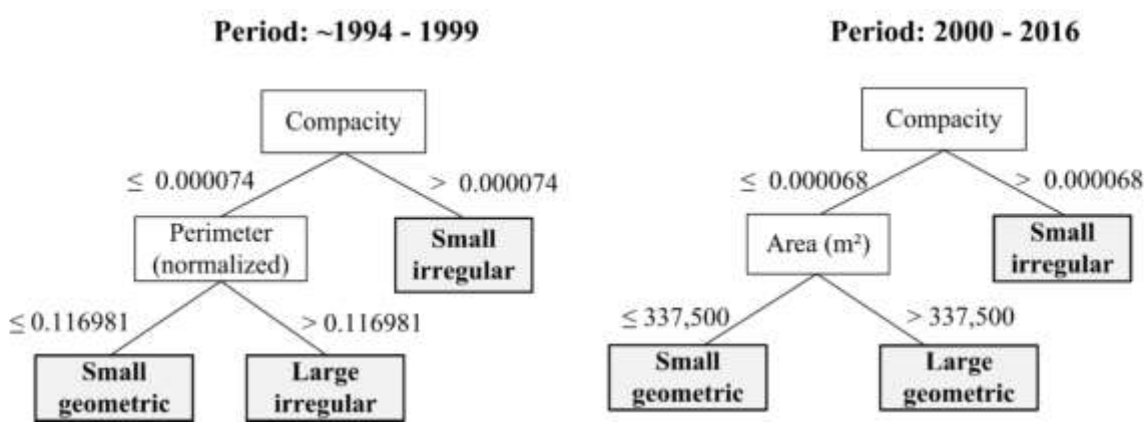


Fig. 4. Results of decision-tree classifications for the first (~1994-1999) and second (2000-2016) classification periods.

The confusion matrix in the first classification indicated that four polygons of the “small geometric” pattern was classified as “large irregular” (Supplementary Material, Table S1). The Kappa values were 0.97 (training sample versus classification) and 0.87 (validation sample versus classification).

The confusion matrix in the second classification indicated that only one sample of the “large geometric” pattern was classified as “small geometric.” This sample was a 27-ha polygon, and the threshold that separates “small geometric” from “large geometric” was 33.7 ha (Fig. 4). One sample of the “small geometric” pattern was classified as “small irregular” (Supplementary Material, Table S2). The Kappa values were 0.96 (training sample versus classification) and 1 (validation sample versus classification).

Deforestation-pattern classification through 2016 indicated that “small geometric” (44% or 9988 ha) and “small irregular” (31% or 7092 ha) were the most representative patterns in the Matupi settlement. The “large geometric” (18% or 4045 ha) and “large irregular” (8% or 1820 ha) patterns accounted for less area as of 2016 (Figs. 5 and 6).

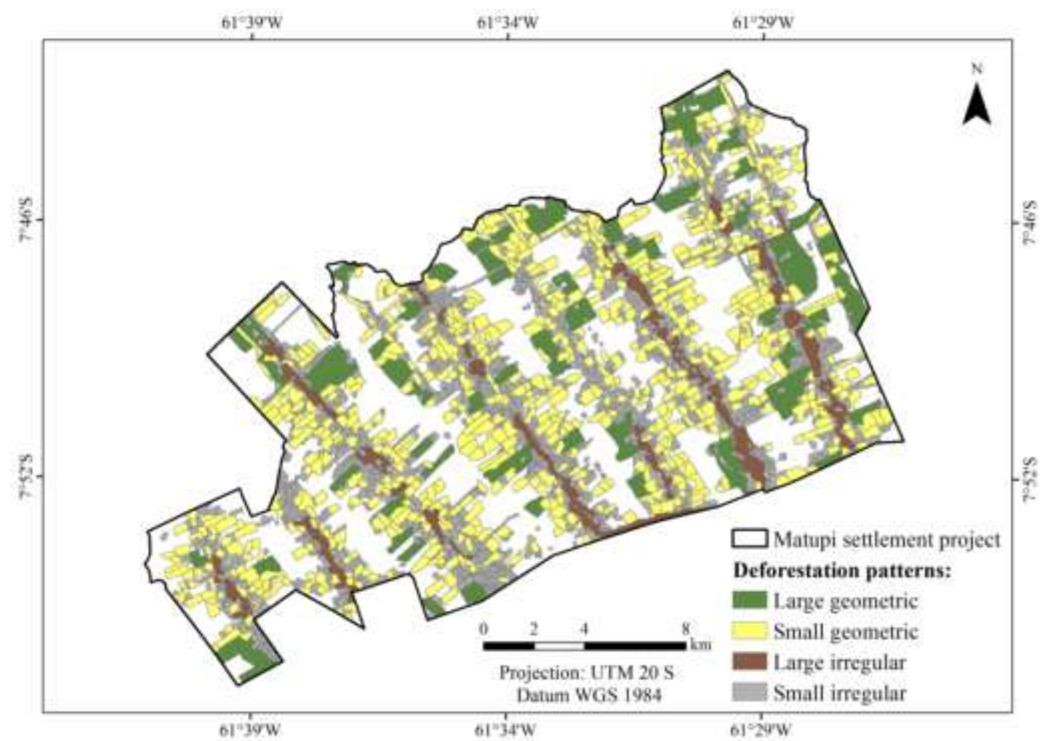


Fig. 5. Deforestation pattern classification in the Matupi settlement (2016).

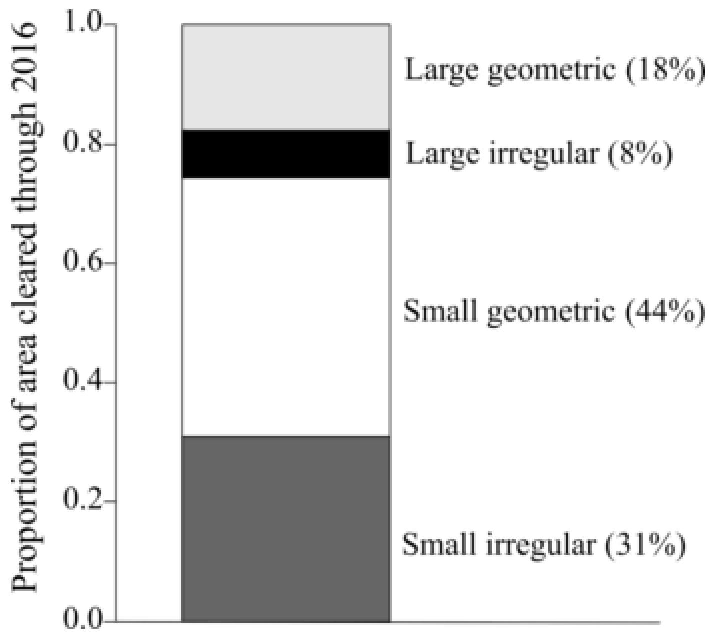


Fig. 6. Percentage of each deforestation pattern in relation to total deforestation.

"Small irregular" and "small geometric" were the patterns that encompassed the greatest numbers of patches (2428 polygons or 95% of the total). The mean size of "small irregular" polygons (4 ha) was smaller than that of the "small geometric" polygons (15 ha). However, both categories had some polygons with the same size (range = 1 – 20 ha for "small irregular" and 6 – 33.8 ha for "small geometric") (Fig. 7). The "large irregular" pattern (mean = 34 ha) had the least polygons (54) but had the widest size range (13 – 145 ha). "Large geometric" (mean = 59 ha) also encompassed a wide range of polygon sizes (34.1 – 167 ha), with some polygons larger than those in the "large irregular" category (Fig. 7).

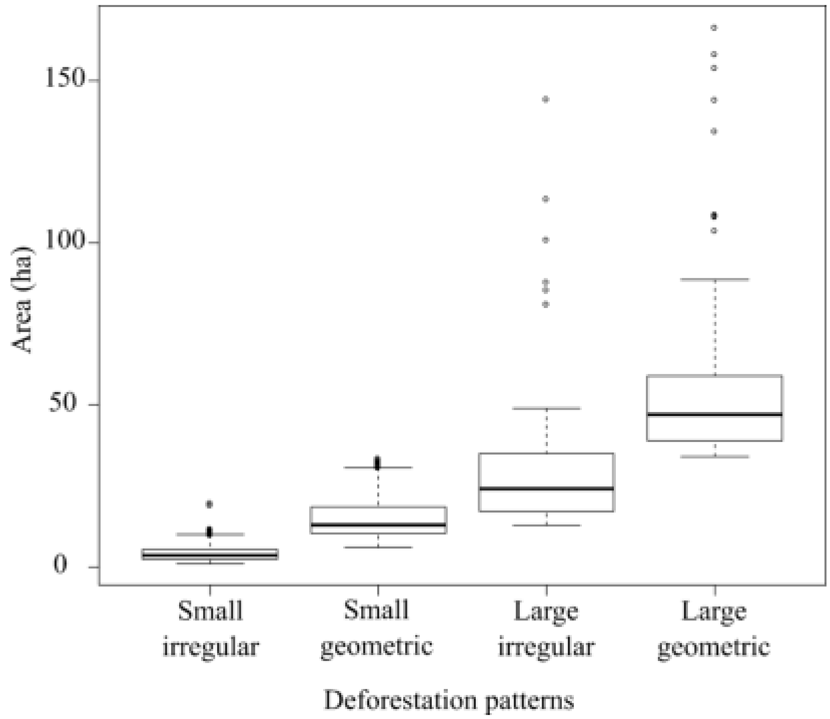


Fig. 7. Distribution of patch areas for each deforestation pattern.

3.3. Temporal dynamics of deforestation patterns

The mean contribution per year of each deforestation pattern to the total for the Matupi settlement over the period from 1995 to 2016 indicated that “large irregular” was the pattern with the largest area cleared per year (322 ha) from 1995 to 1999, followed by “small irregular” with a mean of 314 ha per year (Fig. 8).

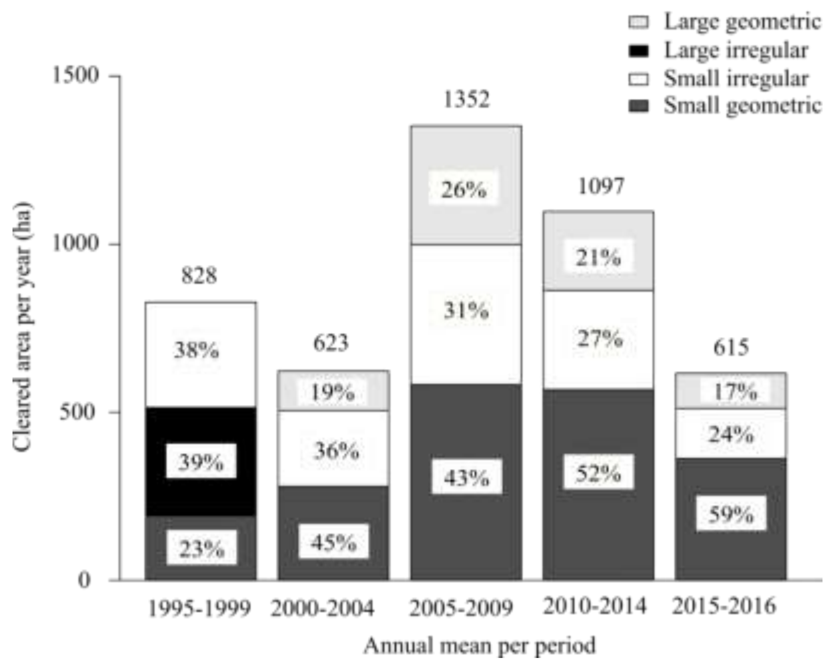


Fig. 8. Mean area cleared per year divided into time intervals and deforestation patterns.

Since 2000 the mean area of the "small geometric" type cleared per year was the largest in comparison with the other patterns. "Small geometric" started at a mean of 193 ha per year from 1995 to 1999 and increased in the years that followed to 279 ha (2000-2004), 582 ha (2005-2009) and 567 ha (2010-2014). A decrease was seen in recent years, with a rate of 362 ha per year in the 2015-2016 period. The "large geometric" pattern did not exist prior to 2000, so we only included this pattern from 2000 onwards (excluding it from the earlier period avoids confusion with the initial contiguous clearings along the access roads at the fronts of the lots). Since 2000 the "large geometric" pattern had an increase in the annual mean, rising from 118 ha per year (2000-2004) to 354 ha (2005-2009). In subsequent years, the rate for "large geometric" decreased from 234 ha (2010-2014) to 104 ha (2015-2016). "Small irregular" had mean areas cleared per year greater than those of "large geometric," with 226 ha (2000-2004), 416 ha (2005-2009), 296 ha (2010-2014) and 149 ha (2015-2016) (Fig. 8).

3.4. Actors associated with classified deforestation polygons

Association of actor-polygons with deforestation patterns indicated that the "small geometric" and "small irregular" types were the typical patterns of non-concentrating landholders. Only 2% (76.7 ha) of the area identified as occupied by non-concentrators was classified as "large geometric" because the areas of the two polygons of this type were larger than the threshold (33.7 ha) that separated "small geometric" from "large geometric" (Table 2). In relation to concentrators of non-neighboring lots, although the number of samples was small (n = 2), both polygons were classified as "small irregular," which is similar to the finding for non-concentrating landholders (Table 2).

Table 2. Actor-polygons found associated with classified deforestation patterns. Values in bold italics refer to polygon samples[1] used in the classification.

Actor category	Deforestation pattern Area in hectares (numbers of polygons)			Total area (polygons) found
	Small irregular	**Small geometric**	**Large geometric**	
Non-concentrators	***291.4 (85)*** + 1,508.3 (340)	***1,153.0 (68)*** + 1,582.7 (108)	76.7 (2)	4,612.1 (603)
Concentrators of non-neighboring lots	***4.7 (1)*** + 7.0 (1)	-	-	11.7 (2)
Concentrators of 2 lots	545.4 (122)	***27.3 (1)*** + 1,216.4 (81)	***589.5 (11)*** + 77.8 (2)	2,456.4 (217)
+Concentrators of ≥ 3 lots	104.3 (29)	394.6 (22)	***761.3 (10)*** + 34.5 (1)	1,294.7 (62)

[1] The large irregular pattern is not included (97 ha or 3 polygons).

Although the samples that were used for classification of concentrators of two or more lots were characterized by the "large geometric" pattern, "small" patterns (geometric and irregular) were also found in these landholder types. Thus, of the 2456-ha total area found to be held by concentrators of two lots, 22% (545 ha) was classified as "small irregular" and 51% (1216 ha + 27 ha used in classification) as "small geometric." However, "large geometric" is not a pattern that is excluded from this landholder category, since it encompassed an area of 667 ha (589.5 ha + 77.8 ha). For concentrators of ≥ 3 lots, "large geometric" was the predominant pattern in terms of area (61% or 796 ha), despite the fact that, in terms of the number of polygons, the most frequent types were "small irregular" (n = 29 polygons) and "small geometric" (n = 22) (Table 2).

3.5. Lot concentration (2011) and deforestation rates (1995-2011) by actor type

Lot concentration by individuals and families was found in 152 lots or 29% of the total analyzed (n = 516 lots). The area covered by landholders who concentrated lots represented 28% (9653 ha) of the settlement area (Fig. 9). Out of this total, 68% (6546 ha) represented concentration by families (n = 42 families and 105 lots concentrated) and 32% (3107 ha) by individuals (n = 18 individuals and 47 lots concentrated). The numbers of lots concentrated ranged from two to ten, with the most frequent number being two lots. Of the total area concentrated by actors with two lots (5905 ha), families represented 69% (4065 ha) and individuals 31% (1840 ha) (Fig. 9 and Table 3).

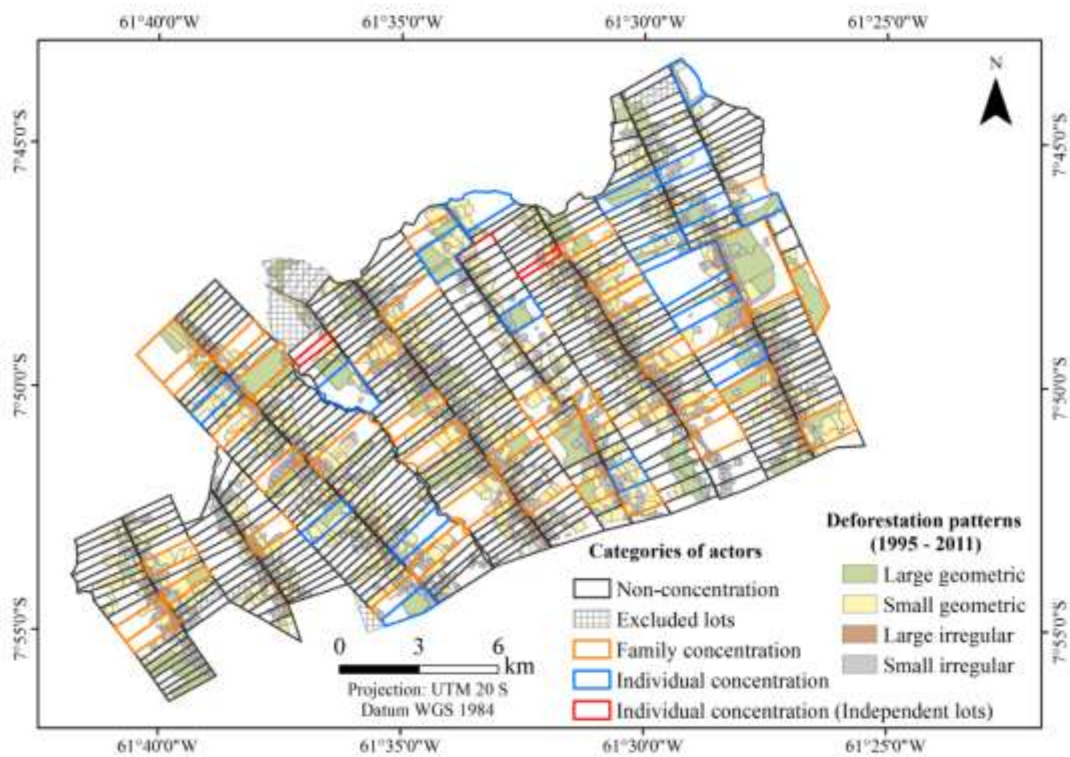


Fig. 9. Boundaries of landholdings updated to 2011 and deforestation patterns (1995 - 2011). The "Individual concentration (Independent lots)" is the same as "concentrators of non-neighboring lots" mentioned in the text.

Table 3. Types of concentration found in 2011 and numbers of lots concentrated in the Matupi settlement.

Concentration category	Numbers of landholders (concentrators)	Number of lots concentrated	Total numbers of lots concentrated for each actor type	Minimum and maximum landholding (ha)	Mean of landholding (ha)	Total area concentrated (ha)
Individual	14	2	28	118.5-163.3	131.4	1,840.2
	4	4	16	229.9-398.7	276.3	1,105.3
Individual and Family (non-neighboring lots)	3	3	3	49.5 - 60.2	53.9	161.8
Family	33	2	66	55.7-194.4	123.2	4,064.5
	4	3	12	181.8-246.3	213.0	852.0
	3	4	12	232.5-272.7	246.4	739.1
	1	5	5	-	-	291.3
	1	10	10	-	-	599.0
Total			152			**9,652.8**

Landholders with one lot were the largest category in terms of numbers (364 lots or 71%). The total area covered by this category was 23,517 ha or 68% of the Matupi settlement area in 2011 (34,796 ha, based on the vector map of lot boundaries) (Fig. 9). The sizes of the lots of non-concentrating actors ranged from 40.5 to 134.6 ha (mean = 64.6 ha).

Non-concentrators and concentrators of non-neighboring lots had similar mean annual clearing per landholding from 1995 to 2011, the annual rates being 1.7 ± 1.2 ha (mean ± SD) and 1.2 ± 1.5 ha, respectively. Concentrators of two lots had similar mean rates per year whether the concentration was by families (4.1 ± 2.8 ha) or individuals (5.1 ± 4.6 ha). Mean annual clearing per landholding in the case of families was similar for concentrators of three lots (9.0 ± 12.8 ha) and four lots (9.6 ± 11.3 ha), but individuals with four lots had a slightly lower mean rate (7.2 ± 8.8 ha) in comparison with families with the same numbers of lots (9.6 ± 11.3 ha). A family concentrating five lots had a lower mean (6.2 ± 12.2 ha) compared to those with three or four lots, and a family with ten lots had the highest mean (23.9 ± 38.7 ha).

The mean annual clearing from 1995 to 2011 per landholding indicated significant differences in all pairwise tests ($p < 0.001$) in comparing non-concentrators (n = 364 landholders or lots) with concentrators of two lots (n = 47 concentrators) and of three or more lots (n = 13 concentrators) (Fig. 10).

Similarly, the mean annual clearing per lot for the same period showed significant differences ($p < 0.001$) in comparing non-concentrators (1.7 ± 1.2 ha) with concentrators of two lots (2.2 ± 0.8 ha) and of three or more lots (2.2 ± 0.9 ha). No significant differences ($p = 0.54$) were found in the mean annual clearing per lot between concentrators of two and three or more lots (Table 4). However, when concentrators were analyzed separately in categories distinguishing families and individuals and the numbers of lots concentrated, we found that non-concentrators and three types of concentrators did not differ significantly ($p > 0.05$) in their mean annual clearing per lot. The categories were a family concentrator of 5 lots, individual concentrators of 4 lots and family and individual concentrators of non-neighboring lots (Supplementary Material, Tables S3 and S4).

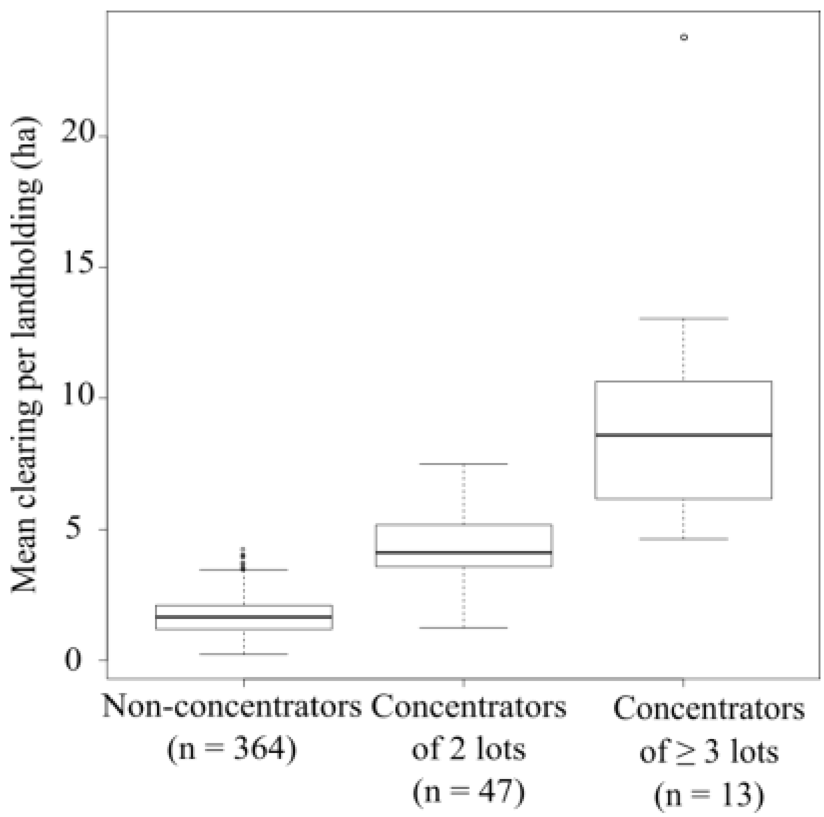


Fig. 10. Distribution of mean clearing per landholding from 1995 to 2011 separated into three groups: non-concentrators (n = 364 landholders), concentrators of 2 lots (n = 47 landholders) and concentrators of ≥ 3 lots (n = 13 landholders).

Table 4. Deforestation rate per lot from 1995 to 2011 in three groups of actors categories.

Actor category	Total no. of lots	Mean annual clearing per lot	SD	Mean total clearing per lot
Concentrators				
Concentrators of 2 lots	94	2.2	0.8	37.3
Concentrators of 3-10 lots	55	2.2	0.9	38.1
Non- concentrators	364	1.7	0.8	29.5

In general, non-concentrators and concentrators of non-neighboring lots had less clearing in comparison with concentrators of neighboring lots (Fig. 11). From 1995 to 2011 the total area cleared by non-concentrators (364 landholders or lots) was 10,750 ha and the mean clearing per landholding was 30 ha. For concentrators of non-neighboring lots (3 landholders) the total area cleared was 64 ha and the mean clearing per landholding was 21 ha. The total clearing from 1995-2011 in the lots of non-concentrators ranged from 4 to 73 ha per lot and for concentrators of non-neighboring lots the total clearing ranged from 8 to 30 ha per lot (Fig. 11).

For concentrators (families and individuals) of two adjacent lots, the total area cleared was 3504 ha and the mean clearing per landholding was 75 ha (n = 47 landholders: 14 individuals and 33 families). The total area cleared from 1995 to 2011 per landholder of this category ranged from 21 to 128 ha. The total clearing by concentrators of three lots was 609 ha, with the mean clearing per landholding being 152 ha (n = 4 landholders) and the total area cleared per landholding ranging from 134 to 181 ha. In the case of concentrators of four lots (n = 7 landholders), the total area cleared was 978 ha with mean clearing per landholding of 140 ha and the clearing per landholding ranging from 79 to 222 ha (Fig. 11).

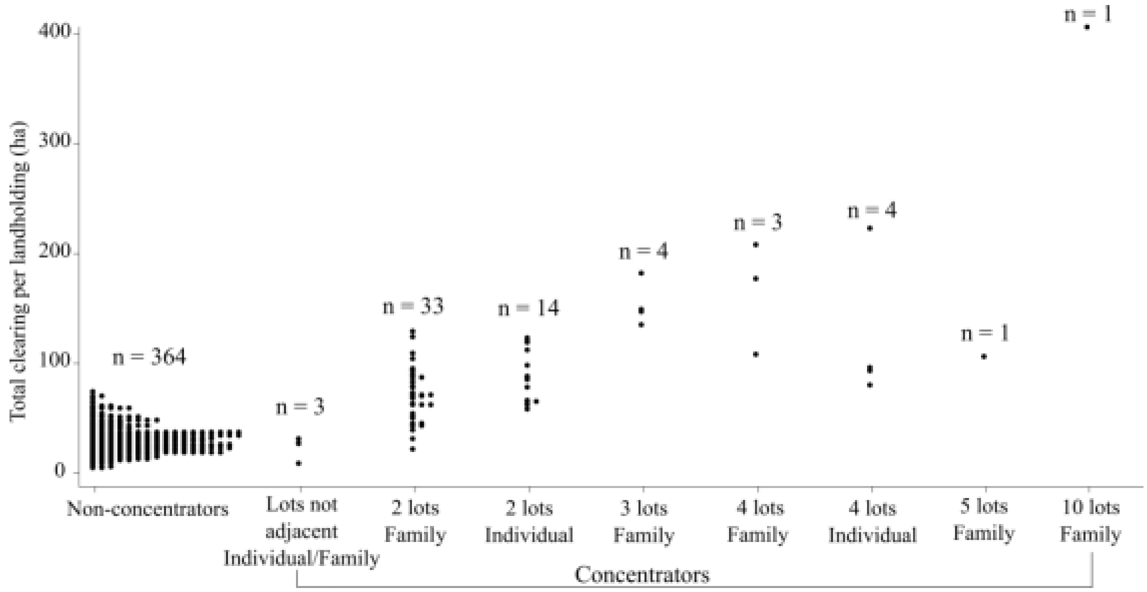


Fig. 11. Total area cleared per landholding from 1995 to 2011 (n = number of landholders per category).

Only 2% of non-concentrators (n = 8 landholders) had cumulative clearing less than 20% in their lots (i.e., in accordance with the Forest Code). All concentrators showed more than 20% of total clearing in the landholdings that they occupy (Fig. 12). Furthermore, 74% (n = 268) of non-concentrators cleared more than 50% of their lots. In the landholdings of concentrators, the percentage of landholdings with more than 50% cleared were: 87% (n = 41) for concentrators of 2 lots, 100% (n = 4) for concentrators of 3 lots and 86% (n = 6) for concentrators of 4 lots (Fig. 12).

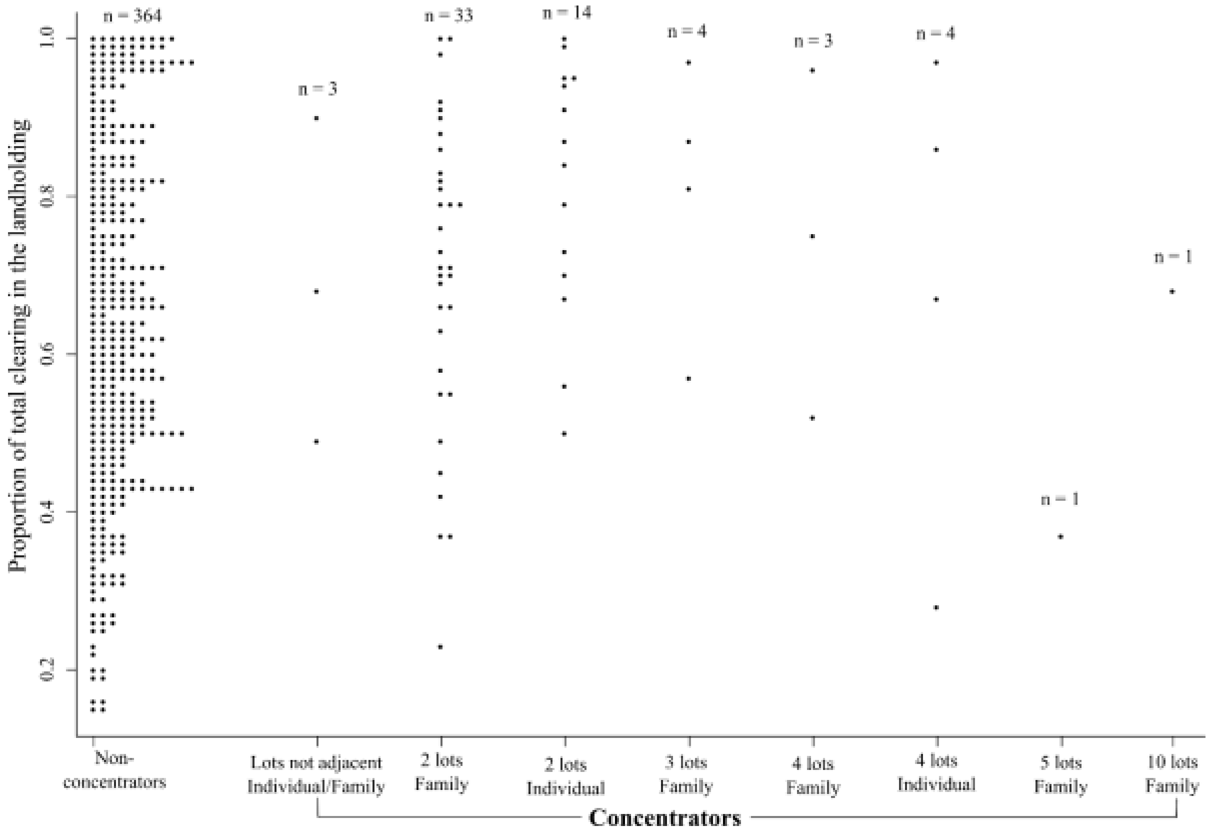


Fig. 12. Proportion of total clearing in each lot and landholding through 2016 (n = number of landholders per category).

However, because non-concentrating landholders were numerous, their contribution to total deforestation was greater (63% or 11,047 ha of the 17,426-ha total deforestation through 2011), as well as per year, as compared to the total for landholders who concentrate lots (Fig. 13).

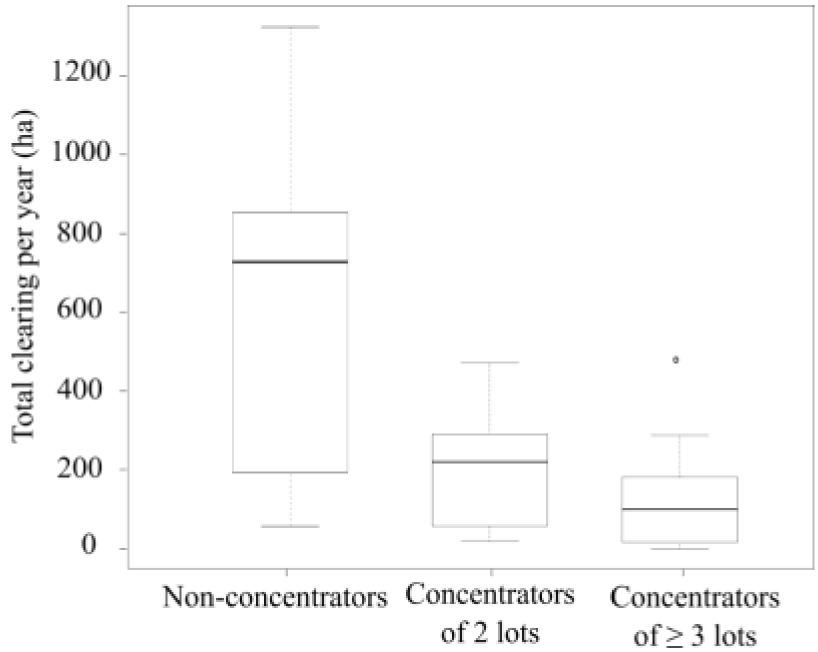


Fig. 13. Total area cleared in the period from 1995 to 2011 by type of actor (n = 17 years).

The proportion of area cleared through 2004 was similar for landholders with one and two lots (Fig. 14). After 2004, deforestation in areas of concentrators of two lots increased more, and in 2010 the clearing reached half of the total landholdings of this category. Through 2011, areas cleared by of non-concentrators still represented less than half of the landholding of this category. In areas cleared by of concentrators of ≥ 3 lots, the proportion deforested per landholding was lower through 2002 compared with other categories. However, since 2004 the proportion of clearing in this category increased and reached half of the landholding occupied by this category in 2008, which is earlier than the years for reaching this benchmark in the case of categories with fewer lots per landholder (Fig. 14).

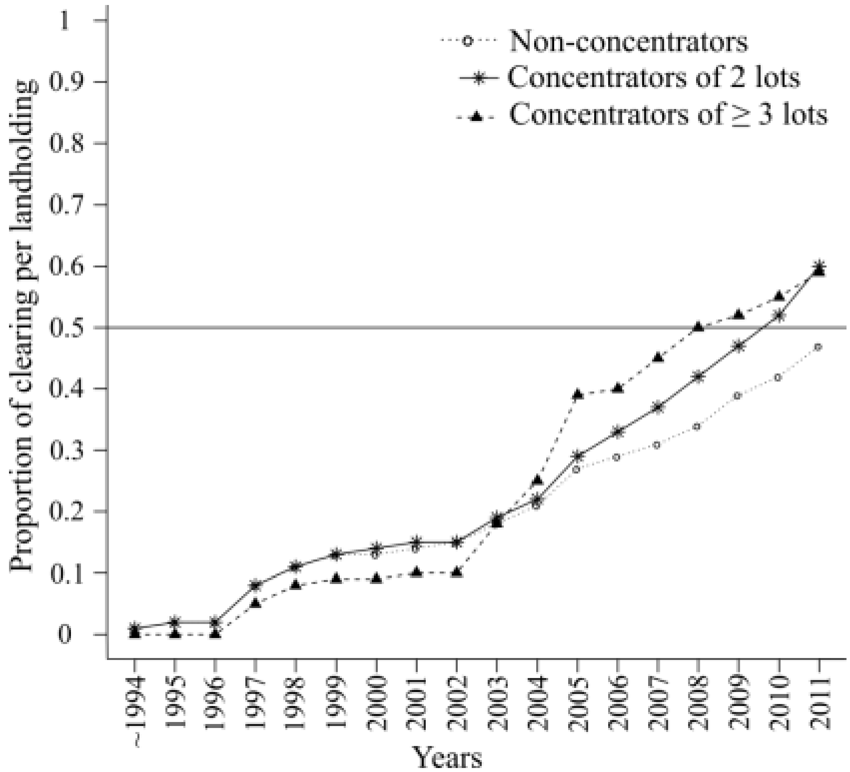


Fig. 14. Trajectory of deforestation through time per area occupied by each type of landholder. Proportion of clearing represents the proportion of clearing in relation to the total area occupied by the category.

The remaining forest in 2011 (17,370 ha) in areas of non-concentrators represented 72% (12,471 ha) of the total forest in 2011. For concentrators, remaining forest represented 23% (3938 ha) of the total forest in the Matupi settlement in 2011. The rest of the remaining forest (5% or 961 ha) was in lots that were excluded from our analyses.

Considering the percentage of forest per landholding for different actor categories, we found that non-concentrators and individual concentrators of four lots had similar results for the mean percentage of forest per landholding (52.5% ± 20.6% and 52.3% ± 31.8%) (Table 5). Family concentrators of three and four lots had the lowest mean percentage of forest per landholding (28.3% ± 21.0%), followed by a family concentrator of ten lots (32.4%) and individual concentrators of two lots (32.8% ± 21.0%). In contrast, the family concentrator of five lots had the greatest percentage of forest in the landholding (63.9%) (Table 5). This result suggests that landholding size is not related to the proportion of remaining forest in the landholding.

Table 5. Total deforestation (~2011) and remaining forest (2011) considering the categories of actors and the percentage of remaining forest (2011) per lot (non-concentrators and concentrators of non-neighboring lots) and per landholding for concentrators.

Actor type (n = number of landholders analyzed)	**Deforestation through 2011 (ha)**	**Forest in 2011 (ha)**	**Percentage of forest (2011) per landholding (mean ± SD)**
Non-concentrator (n = 364)	11,047 (47%)	12,471 (53%)	52.5 ± 20.6
Concentration by individuals:			
non-neighboring lots (n = 3)	64 (40%)	98 (60%)	61.0 ± 20.2
2 lots (n = 14)	1,213 (66%)	628 (34%)	32.8 ± 21.0
4 lots (n = 4)	488 (44%)	617 (56%)	52.3 ± 31.8
Concentration by families:			
2 lots (family) (n = 33)	2,332 (57%)	1,732 (43%)	41.4 ± 20.6
3 and 4 lots (family) (n = 7)	1,108 (70%)	483 (30%)	28.3 ± 21.0
5 lots (family) (n = 1)	105 (36%)	186 (64%)	63.9
10 lots (family) (n = 1)	405 (68%)	194 (32%)	32.4

4. Discussion

4.1. Concentrator and non-concentrator patterns and their deforestation rates

Our study focused on better understanding lot concentration in the Matupi settlement. The study shows how this process results in different actor types having distinct forest-clearing patterns. While mean annual clearing per landholding is an important indicator of the environmental impact of accommodating the different actor groups in the settlement, it is the deforestation rate per lot that best reflects the impact of lot concentration on the overall rate of deforestation, and thereby the environmental impact of this phenomenon. In general, concentrators clearly clear more per lot than non-concentrators, which speeds deforestation. The exceptions we found were a single family that concentrated 5 lots, four individual concentrators of 4 lots and the three cases of concentration of non-neighboring lots (See Supplementary Material, Tables S3 and S4). In 2011, non-concentrators and concentrators of two lots were the predominant actors in terms of area occupied in the settlement. Despite the mean annual clearing per landholding differing between them, deforestation patterns for both groups were similar (i.e., “small geometric” and “small irregular” patterns). However, the “large geometric” pattern (patches > 34 ha) can sometimes also be attributed to concentrators of two lots. In the case of non-concentrators, the “large geometric” pattern was very rare, only being found in two polygons out of a total of 603 polygons where the actor-polygon association could be identified (Table 2). This difference is not explained by the limited size of the landholding for non-concentrators (mean = 64.6 ha; min. = 40.5; max. = 134.6 ha), since there is sufficient area to allow clearing more than 34 ha. The size of the landholding is also not related to the percentage of remaining forest in landholdings of the different categories of actors. For example, for non-concentrators the mean size of lots (64.6 ha) was smaller than the landholding size of concentrators of two lots (individuals: 131.4 ha and families: 123.2 ha, see Table 3), but the non-concentrators had a higher percentage of remaining forest in 2011 in terms of area in hectares (see Table 5).

Our results in Matupi were similar to the findings of Godar et al. (2012b) in Pará, where these authors observed that actors who focused on cattle ranching with property sizes from 200 to 600 ha (and who were more capitalized) had less remaining forest in their properties in comparison with less-capitalized colonists with property sizes under 200 ha. In addition, a recent study in the Ouro Preto do Oeste settlement in Rondônia found that actors who deforested more for cropland or pasture (the main income activities) obtained larger incomes than those who deforested less. This is because clearing is linked to accumulation of household assets (Mullan et al., 2018). Thus, the income from pasture expansion is a motivation for asset accumulation that could be self-perpetuating for actors who concentrate land (Mullan et al., 2018).

We did not find major differences between annual clearing per landholding of family and individual concentrators. This suggests that the number of lots concentrated has more weight in the dynamics of clearing than does the type of concentration (family versus individual). In addition, the INCRA dataset reported (and we also found in the fieldwork) that cases (n= 10) of family concentration exist where a single member of the family is responsible for clearing in the landholding. The other family members either work in activities not directly related to production in the landholding or live outside of the settlement. Thus, in practice, decisions about clearing are made by one person. In our study, out of a total of 42 cases of family concentrators (105 lots: Table 3), where, in general, each member of the family occupies one lot, 44% (46 members of the concentrator families) lived in the settlement according to data in the INCRA occupation survey conducted in 2011. For individual landholders who concentrated neighboring lots, out of a total of 18 landholders (concentrating a total of 44 lots), 44% (8 landholders) lived in the settlement in one of the lots they occupied.

The small area cleared by concentrators of 2 and ≥ 3 lots was mostly cleared between 1995 and 2002. This suggests that the process of lot concentration started mainly in 2003, or eight years after the initial occupation of the settlement, and that the clearing before 2003 in the concentrated lots had been done by the previous landholders.

Similarly, da Silva (2012) found that 7.3 years is the average residence time of landholders in the Matupi settlement and only 3% of landholders interviewed were originally settled by INCRA. A similar trend was observed in a settlement located in Vale do Anari (in the state of Rondônia), where during the first six years of settlement occupation, cleared areas were concentrated near access roads, and patches had irregular linear patterns. After this early stage, medium and large landholders bought lots from previous settlers to establish cattle ranches. Large clearings started to appear and increased gradually through time as result of lot concentration. The patches associated with these landholders were > 50 ha in area (dos Santos Silva et al., 2008).

4.2. Small patches of deforestation

Our study found a total of 22,945 ha of clearing in the Matupi settlement, whereas PRODES estimated an area of 21,504 ha through 2016 (Brazil, INPE, 2018a). We mapped 1441 ha (6.7%) more clearing than PRODES. This could be due the larger minimum area detected by PRODES (6.25 ha) as compared to our study (1 ha), and because we considered roads as clearing (when visible in the Landsat images). The difference could also be at least partly a result of the different image dates used as the reference for the mapping (30 July 2016 by PRODES versus 12 August 2016 in our study). In addition, because we discriminated clearing considering the spectral response of land-cover change (i.e., clearcut, initial regeneration after clearcutting, and slash-and-burn), the numbers of small polygons increased by 19% (416 polygons), raising the total from 2135 (if interpretation was done without feature discrimination of clearing) to 2551 polygons. The small polygons were classified mainly as “small geometric” and “small irregular” patches. We decided to use the feature-discrimination approach because size and shape of patches are important metrics for differentiating the patterns and because this approach reduced the overestimation of area that occurs when we associate actors with polygons, in comparison to mapping without this discrimination. The result was therefore more detailed and achieved a better separation of deforestation that occurred in nearby areas in the same year but was done by different landholders.

A recent study has found a pervasive rise in small-scale deforestation in Brazilian Amazonia as a whole (Kalamandeen et al., 2018). Despite differences of scale between our study (local scale) and the study by Kalamandeen et al. (2018) (regional scale), we found a similar overall tendency, demonstrating that (i) as patch size increases the number of patches decreases and (ii) the contribution of small patches has increased through time.

In Brazil’s Legal Amazonia region, Escada et al. (2011) found that, of the 6646 km^2 deforested in 2009, 60% (4003 km^2) was in patches <25 ha in area while only 1.7% (113 km^2) was in patches >1000 ha in area. The same study found that the percentage of deforestation in patches < 25 ha in size increased from 22% (5897 km^2 out of 21,650 km^2 of deforestation) in

2002 to the 60% found in 2009. For annual clearing in Legal Amazonia in the same period, Rosa et al. (2012) found that patches 6.25-50 ha in area increased from 30% (6495 km^2) in 2002 to 73% (5449 km^2) in 2009. Rosa et al. (2012) suggested that the decline of large patches could be attributed to the historic trajectory of deforestation in some municipalities, lower deforestation rates being reflected in the smaller size of patches in recent deforestation. In addition, Rosa et al. (2012) suggested that some landholders changed their behavior to avoid detection by environmental monitoring, clearing small patches instead of large areas. Another factor that could contribute to the increase of small patches is fragmentation of some lots into smaller landholdings, despite the fact that the much more common pattern is one of consolidation of lots (i.e., incorporation of several lots in one landholding), as reported by D'Antona et al. (2011) in a rural settlement near Santarém (Pará). These authors found that, out of a total of 587 lots analyzed, 39 (7%) were fragmented into landholdings smaller than the original lot size, 4% were fragmented and partially merged with larger landholdings and 67% of the lots were merged in large landholdings without being fragmented. Although we lack information that would allow analysis of fragmentation of previously concentrated lots, we estimated by visual interpretation that there were 30 lots in the Matupi settlement that had been occupied by non-concentrators in 2011, which could be result of fragmentation of previous concentrated landholdings (Supplementary Material, Fig. S2). This could be a result of fragmentation of previously concentrated landholdings into individual lots, which is one of the processes reported near Santarém by D'Antona et al. (2011).

4.3. 'Peaks' and 'valleys' in observed deforestation

We observed three important phases in the deforestation trajectory in the Matupi settlement. The first phase refers to an initial occupation process (~1994 to 1996) with the arrival of the first settlers. In this phase, clearing started to appear mainly as small patches in the lots in the access roads nearest their connections to the Transamazon Highway, indicating that these lots were the first lots occupied. A study in Altamira (in Pará state) reported that landholders cleared 2 to 5 ha per year in the initial stages of settlement (McCracken et al., 1999).

The second phase started with the official increase of settlement area in 1997, resulting in an increase in the number of lots from 465 to 537. This represents occupation of lots by new landholders settled by INCRA. Clearing is done first at the lot front both to indicate land tenure and due the convenience of proximity to the access road. The "large irregular" pattern found in the early years of occupation along the access roads reflected the clearing done at the front of each lot. Clearing declined from 2000 to 2002, with values similar to the first phase. Only a few landholders lived in the settlement during this period, which could indicate an abandonment of lots occupied initially.

The last phase occurred since 2003 when clearing started to increase with peaks and lows through 2016, indicating that deforestation dynamics were more intense during this period in comparison with the first years of settlement. Since 2003, annual deforestation increased in the Matupi settlement, with a large area being cleared by concentrators, this being added to the continued contribution of non-concentrators. Part of the clearing is legal (up to 20% of each lot); however, most of the clearing is illegal. Between 2005 and 2006, command-and-control actions by the Brazilian Institute of Environment and Natural Resources (IBAMA) were intense in the settlement. Despite this, a major peak of deforestation occurred in 2005, followed by a decrease in 2006. Fines alone are not enough to stop all illegal deforestation in the settlement. Application of a fine, or the possibility of a fine, can result in some landholders forgoing clearing, as we observed during the fieldwork. We believe that command-and-control actions are more effective in the case of landholders who live in the settlement, which is a minority of landholders. For example, for non-concentrators, which is the group with the largest number of actors (364 landholders), only 28% (102 landholders) lived in the settlement in 2011. In the case of concentrators, 44% lived in the settlement.

A study by Schmitt (2015) reported that, although the effect of command-and-control is low and is not enough to stop all illegal deforestation in Legal Amazonia, some of the actors could be influenced by IBAMA's environmental inspection program. Thus, the decline of annual rates of deforestation observed between 2008 and 2013 in Brazil's Legal Amazonia region could be partially attributed to the inspection program (Schmitt, 2015). Note, however, that the bulk of the region-wide deforestation decline that occurred between 2004 and 2012 is explained by other factors (Fearnside, 2017).

The main activity in the Matupi settlement is cattle ranching, although a few families plant some agricultural crops in addition to their pasture. A dairy factory began operation in Matupi District in 2013, and it is currently the largest dairy factory in the state of Amazonas.

Landholders reported that beginning in 2010 a dairy-cattle “boom” occurred in the region. This could have contributed to increased deforestation in 2010-2011. During our fieldwork, we found many cooling platforms used to store milk at the front of the lots, indicating that dairy cattle were being raised. The milk is sold to the Matupi dairy factory. Landholders reported that dairy cattle are normally confined, in contrast to beef cattle. This means that dairy-cattle ranching requires less pasture area; for landholders who have only one lot it is therefore better to raise dairy cattle than beef cattle. However, both types of cattle need pasture, and clearing in the lots would tend to increase, even if at different speeds.

According to INPE’s TerraClass program for quantifying land cover in deforested areas, in 2014 pasture was the main land use in Matupi settlement, encompassing 82% (14,865 ha) of the total area cleared through 2013 (18,087 ha) (Brazil, INPE, 2018b). This agrees with the large-scale finding of Almeida et al. (2016), who found pasture to be the main land use in Legal Amazonia based on TerraClass data for 2008: out of a total of 707,274 km^2 that had been cleared through 2007, pasture encompassed 63% (447,160 km^2) in 2008 and only 5% (34,927 km^2) was in annual crop cultivation.

Despite the first landholders having received financing under an INCRA program to produce coffee and cacao, they did not have a structured chain to market the products, a means of transportation to distribute the products or technical assistance to better manage production. Lack of conditions to develop agricultural activities makes cattle ranching the best choice for Matupi landholders. This situation is similar to other settlements established along the Transamazon Highway, where settlements were designed without considering local limitations in terms of transportation of products, local markets, soil quality and other factors (Moran, 1981; Smith, 1982; Fearnside, 1986; Mahar, 1989; Caviglia-Harris and Harris, 2011). Amazon forest soils generally have high acidity and low natural fertility, making agriculture difficult. In addition, some areas also have steep topography, which contributes to most of the deforested area being used for pasture.

It is important to note that both increases and decreases in deforestation are influenced by economic factors such as commodity prices (Fearnside, 2017) and agricultural credit (Assunção et al., 2015). Deforestation rates are also influenced by political factors, such as election cycles (Rodrigues-Filho et al., 2015).

4.4. Environmental implications and future studies

Understanding the deforestation patterns of actors in a settlement project located in a region of cattle-ranching expansion can contribute to developing more refined spatial models of deforestation. Deforestation rates and the sizes of patches in the main deforestation patterns need to be associated with the actors in spatial models in order to simulate the contributions of these actors to future deforestation under different scenarios.

Our findings indicate a trend to increasing percentages of concentrators, especially concentrators of three and more lots, where “large geometric” is the predominant pattern (Fig. 8). This category of actor has a substantial impact in the settlement because the clearing per year by each of these actors is larger than that of other actors, since this type of actor is more capitalized in comparison to the other types. This type of concentrator has the potential to increase its contribution to deforestation in the future. The presence of lot concentrators is one of the indications that current agrarian-reform policies are weak. The purpose of the settlements is to alleviate the social problems associated with Brazil’s large population of landless farmers and, despite loopholes, the agrarian-reform program’s regulations are designed to prevent lot concentration.

Next steps are to compare deforestation rates and the patterns of actors in settlements with those located outside of settlements. A suggestion for future studies is to investigate other metrics that could distinguish patches oriented in the horizontal direction (i.e., lot width) in areas of concentration and in the vertical direction (i.e., from the front to back of the lot, which is typical in non-concentrator landholdings). This distinction could better differentiate landholders with one and two lots. The addition of other metrics not related to spatial patterns could be used to better differentiate non-concentrators from concentrators of non-neighboring lots. In addition, future studies could compare the deforestation patterns associated with the actors in different settlement types, such as those in the “conventional” category (e.g., the Matupi settlement) versus those in the “environmentally differentiated” category (e.g., Sustainable Development Projects and Agro-Extractivist Settlement Projects). In the “environmentally differentiated” category, the area is sometimes divided into lots in the same way as in the “conventional” category, but the actors have different profiles.

Brazil's official position is that deforestation is under control and will be slower in the future, as outlined in the country's commitments under the 2015 Paris Agreement (Brazil, 2015). However, a variety of trends in underlying forces suggests otherwise: ever greater population, investment and infrastructure development imply more rather than less deforestation (Fearnside, 2017). In addition, there are trends toward weakening environmental licensing and downgrading protected areas, among other reversals of previous achievements in this area (Fearnside, 2016, 2018a,b). Lot consolidation increases deforestation both by increasing the clearing rate in the lots that have been consolidated into larger landholdings and by the deforestation that occurs elsewhere in Amazonia by the former Matupi settlers who have sold their land to lot concentrators and moved on to more-distant frontiers. The land-tenure concentration effect documented in the present study adds one more reason suggesting that future deforestation in Brazil's Amazonian rural settlements will be faster than it was in the past.

5. Conclusions

The process of land concentration in settlement areas speeds deforestation.

Remote sensing and data-mining methods are capable of spatially identifying concentration of three or more lots, which is characterized by large geometric deforestation patterns.

The number of lots concentrated is more important in affecting the speed of clearing than is the question of whether the concentration is done by families or by individuals.

Despite the fact that lot concentrators can clear in patterns similar to non-concentrators, non-concentrators rarely clear in patterns similar to those of landholders with large numbers of lots (i.e., clearing patches > 34 ha per year).

Due the large number of lots occupied by non-concentrators, their contribution to total clearing was greater than that of concentrators. However, our study suggests that lot concentration is increasing through the time. This process threatens to increase deforestation by a few landholders. The social effect of lot concentration on the agrarian reform program is negative, since fewer families are benefitted and the social role of equity in land distribution is not achieved.

Because settlement projects are intended to address the social issues surrounding Brazil's large population of landless farmers, the agrarian-reform program responsible for settlements has regulations designed to limit lot concentration. The methods developed in the present study could help government authorities identify the actors who concentrate lots based on their deforestation patterns and monitor the land-tenure concentration in settlement projects in Brazilian Amazonia, especially in new frontier areas where the conversion of forest to pasture is intense.

Acknowledgments

We thank the National Institute for Research in Amazonia (INPA) (PRJ15.125), the National Institute of Science and Technology for the Environmental Services of Amazonia (INCT-SERVAMB), the National Council for Scientific and Technological Development (CNPq Proc. 573810/2008-7, 610042/2009-2), the Foundation for the Support of Research of the State of Amazonas (FAPEAM Proc. 708565) and the Brazilian Research Network on Climate Change (RedeClima) for financial and logistical support. The National Institute for Space Research (INPE) provided logistical support during the time that the first author spent at that institute processing and analyzing part of the data. Ana Paula Rezende of IDESAM (Institute for the Conservation and Sustainable Development of Amazonia), provided guidance for the fieldwork, and INCRA provided the 2011 Matupi settlement dataset. This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001.

References

Alencar, A., Pereira, C., Castro, I., Cardoso, A., Souza, L., Costa, R., Bentes, A. J., Stella, O., Azevedo, A., Gomes, J., Novaes, R., 2016. Desmatamento nos Assentamentos da Amazônia: Histórico, Tendências e Oportunidades. IPAM, Brasília, DF, Brazil. 93 pp. Available at http://ipam.org.br/wp-content/uploads/2016/02/Desmatamento-nos-Assentamentos-da-Amaz%C3%B4nia.pdf . (Last access 8 June 2018).

Almeida, C.A.D., Coutinho, A.C., Esquerdo, J.C.D.M., Adami, M., Venturieri, A., Diniz, C.G., Dessay, N., Durieux, L., Gomes, A.R., 2016. High spatial resolution land use and land cover mapping of the Brazilian Legal Amazon in 2008 using Landsat-5/TM and MODIS data. Acta Amazon. 46, 291-302. https://doi.org/10.1590/1809-4392201505504

Assunção, J., Gandour, C., Rocha, R., 2015. Deforestation slowdown in the Brazilian Amazon: prices or policies? Environ. Dev. Econ. 20, 697-722. https://doi.org/10.1017/S1355770X15000078

Branford, S., Torres, M., 2017. Temer signs law that could see millions of acres lost in the Amazon. Mongabay, 13 July 2017. https://news.mongabay.com/2017/07/temer-signs-law-that-could-see-millions-of-acres-lost-in-the-amazon (Last access 8 June 2018).

Brazil, 2015. Intended Nationally Determined Contribution towards Achieving the Objective of the United Nations Framework Convention on Climate Change. 10 pp. http://www4.unfccc.int/submissions/INDC/Published%20Documents/Brazil/1/BRAZIL%20iNDC%20english%20FINAL.pdf. (Last access 8 June 2018).

Brazil, INPE (Instituto Nacional de Pesquisas Espaciais), 2015. Nota Técnica – Correção da máscara do PRODES. http://www.obt.inpe.br/prodes/NT_deslocamentoMascara.pdf. (Last ccess7 July 2017).

Brazil, INPE (Instituto Nacional de Pesquisas Espaciais), 2018a. Projeto PRODES - Monitoramento da Floresta Amazônica Brasileira por Satélite. INPE, São José dos Campos, SP., Brazil. http://www.dpi.inpe.br/prodesdigital/ (Last access 8 June 2018).

Brazil, INPE (Instituto Nacional de Pesquisas Espaciais), 2018b. Projeto TerraClass2014. INPE, São José dos Campos, SP. http://www.inpe.br/cra/projetos_pesquisas/terraclass2014.php (Last access 8 June 2018).

Brazil, PR (Presidência da República), 2017. Lei No. 13.465, de 11 de julho de 2017. http://www.planalto.gov.br/ccivil_03/_ato2015-2018/2017/lei/l13465.htm . (Last access 8 June 2018).

Carrero G.C., Fearnside P.M., 2011. Forest clearing dynamics and the expansion of landholdings in Apuí, a deforestation hotspot on Brazil's Transamazon Highway. Ecol. Soc. 16(2), art. 26. http://www.ecologyandsociety.org/vol16/iss2/art26/ (Last access 8 June 2018).

Caviglia-Harris J.L., Harris D., 2011. The impact of settlement design on tropical deforestation rates and resulting land cover patterns. Agric. Resour. Econ. Rev. 40, 451-470. https://doi.org/10.1017/S1068280500002896

Caviglia-Harris, J.L., Sills, E.O., Mullan, K., 2013. Migration and mobility on the Amazon frontier. Popul. Environ. 34, 338-369. https://doi.org/10.1007/s11111-012-0169-1

D'Antona, A., VanWey, L., Ludewigs, T., 2011. Polarização da estrutura fundiária e mudanças no uso e na cobertura da terra na Amazônia. Acta Amazon. 41(2), 223-232. https://doi.org/10.1590/S0044-59672011000200006

da Silva, V.V., Vettorazzi, C.A., Padovani, C.R., 2011. Assentamento rural e a dinâmica da paisagem. In: XV Simpósio Brasileiro de Sensoriamento Remoto. Curitiba. Anais do XV Simpósio Brasileiro de Sensoriamento Remoto – SBSR 2011. Instituto Nacional de Pesquisas Espaciais (INPE), São José dos Campos, SP, Brazil. pp. 7000-7006. Available at http://marte.sid.inpe.br/col/dpi.inpe.br/marte/2011/07.28.19.56/doc/p0539.pdf (Last access 8 June 2018).

da Silva, V.V., 2012. Impacto das atividades produtivas na dinâmica da paisagem no assentamento Matupi, estado do Amazonas. Doctoral thesis. Universidade de São Paulo, Piracicaba, SP, Brazil. 117 pp. http://www.teses.usp.br/teses/disponiveis/91/91131/tde-26102012-172251/pt-br.php . (Last access 8 June 2018).

dos Santos Silva, M.P., Câmara, G., Escada, M.I.S., Souza, R.C.M., 2008. Remote-sensing image mining: Detecting agents of land-use change in tropical forest areas. Int. J. Remote Sens. 29, 4803-4822. https://doi.org/10.1080/01431160801950634

Escada, M.I.S., Maurano, L.S., Rennó, C.D., Amaral, S., Valeriano, D.M., 2011. Avaliação de dados dos sistemas de alerta da Amazônia: DETER e SAD. In: XV Simpósio Brasileiro de Sensoriamento Remoto. Curitiba. Anais do XV Simpósio Brasileiro de Sensoriamento Remoto – SBSR 2011. Instituto Nacional de Pesquisas Espaciais (INPE), São José dos Campos, SP, Brazil. pp. 2934-2943. http://marte.sid.inpe.br/col/dpi.inpe.br/marte/2011/06.27.16.55/doc/p1246.pdf . (Last access 8 June 2018).

Fearnside, P.M., 1986. Human Carrying Capacity of the Brazilian Rainforest. Columbia University Press, New York, NY. 293 pp.

Fearnside, P.M., 1987. Derrubada da floresta e roçagem de crescimento secundário em projetos de colonização na Amazônia brasileira e a sua relação à capacidade de suporte humano. Acta Amazon. 17(4) (suplemento), 123-141. https://doi.org/10.1590/1809-43921987175141

Fearnside. P.M., 1997. Environmental services as a strategy for sustainable development in rural Amazonia. Ecol. Econ. 20, 53-70. https://doi.org/10.1016/S0921-8009(96)00066-3

Fearnside, P.M., 2001. Land-tenure issues as factors in environmental destruction in Brazilian Amazonia: The case of southern Pará. World Dev. 29, 1361-1372. https://doi.org/10.1016/S0305-750X(01)00039-0

Fearnside, P.M., 2008a. Amazon forest maintenance as a source of environmental services. Anais da Academia Brasileira de Ciências 80, 101-114. https://doi.org/10.1590/S0001-37652008000100006

Fearnside P.M., 2008b. The roles and movements of actors in the deforestation of Brazilian Amazonia. Ecol. Soc. 13, art. 23. http://www.ecologyandsociety.org/vol13/iss1/art23/. (Last access 8 June 2018).

Fearnside, P.M., 2016. Brazilian politics threaten environmental policies. Science 353, 746-748. https://doi.org/10.1126/science.aag0254

Fearnside, P.M., 2017. Deforestation of the Brazilian Amazon. In: H. Shugart (ed.) Oxford Research Encyclopedia of Environmental Science. Oxford University Press, New York, NY. https://doi.org/10.1093/acrefore/9780199389414.013.102

Fearnside, P.M., 2018a. Challenges for sustainable development in Brazilian Amazonia. Sustain. Dev. 26, 141-149. https://doi.org/10.1002/sd.1725

Fearnside, P.M., 2018b. Why Brazil's new president poses an unprecedented threat to the Amazon**.** *Yale Environment 360*, 8 November 2018. https://e360.yale.edu/features/why-brazils-new-president-poses-an-unprecedented-threat-to-the-amazon

Fujisaka, S., Bell, W., Thomas, N., Hurtado, L., Crawford, E., 1996. Slash-and-burn agriculture, conversion to pasture, and deforestation in two Brazilian Amazon colonies. Agric. Ecosyst. Environ. 59, 115-130. https://doi.org/10.1016/0167-8809(96)01015-8

Geist, H.J., Lambin, E.F., 2001. What drives tropical deforestation? A meta-analysis of proximate and underlying causes of deforestation based on subnational case study evidence. LUCC Report Series, 4. pp. 66-72. http://www.pik-potsdam.de/~luedeke/lucc4.pdf . (Last access 8 June 2018).

Godar, J., Tizado, E.J., Pokorny, B., Johnson, J., 2012a. Who is responsible for deforestation in the Amazon? A spatially explicit analysis along the Transamazon Highway in Brazil. For. Ecol. Manage. 267, 58-73. https://doi.org/10.1016/j.foreco.2011.11.046

Godar, J., Tizado, E.J., Pokorny, B., Johnson, J., 2012b. Typology and characterization of Amazon colonists: A case study along the Transamazon highway. Hum. Ecol. 40, 251-267. https://doi.org/10.1007/s10745-012-9457-8

Kalamandeen, M., Gloor, E., Mitchard, E., Quincey, D., Ziv, G., Spracklen, D., Spracklen, B., Adami, M., Aragão, L.E.O.C., Galbraith, D., 2018. Pervasive rise of small-scale deforestation in Amazonia. Sci. Rep. 8(1), art. 1600. https://doi.org/10.1038/s41598-018-19358-2

Körting, T.S., 2012. GEODMA: A toolbox integrating data mining with object-based and multi-temporal analysis of satellite remotely sensed imagery. Brazil's National Institute for Space Research. Doctoral Thesis 123 pp. http://mtc-m16d.sid.inpe.br/col/sid.inpe.br/mtc-m19/2012/07.31.18.22/doc/publicacao.pdf. (Last access 8 June 2018).

Körting, T.S., Fonseca, L.M.G., Câmara, G., 2013. GeoDMA—Geographic data mining analyst. Comput. Geosci. 57, 133-145. https://doi.org/10.1016/j.cageo.2013.02.007

Lu, D., Li, G., Moran, E., Hetrick, S., 2013. Spatiotemporal analysis of land-use and land-cover change in the Brazilian Amazon. Int. J. Remote Sens. 34(16), 5953-5978. https://doi.org/10.1080/01431161.2013.802825

Mahar, D.J., 1989. Government Policies and Deforestation in Brazil's Amazon Region. The World Bank, Washington, DC. 66 pp. http://siteresources.worldbank.org/BRAZILINPOREXTN/Resources/3817166-1185895645304/4044168-1185895685298/020pub_br14.pdf (Last access 8 June 2018).

McCracken, S.D., Brondizio, E.S., Nelson, D., Moran, E.F., Siqueira, A.D., Rodriguez-Pedraza, C., 1999. Remote sensing and GIS at farm property level: Demography and deforestation in the Brazilian Amazon. Photogramm. Eng. Remote Sens. 65, 1311-1320. https://msu.edu/~moranef/documents/99-03_RemoteSensing_GISatFarm.pdf . (Last access 8 June 2018).

Michalski, F., Metzger, J.P., Peres, C.A., 2010. Rural property size drives patterns of upland and riparian forest retention in a tropical deforestation frontier. Glob Environ Change, 20(4), 705-712. https://doi.org/10.1016/j.gloenvcha.2010.04.010

Moran, E.F., 1981. Developing the Amazon: The Social and Ecological Consequences of Government-Directed Colonization along Brazil's Transamazon Highway. Indiana University Press, Bloomington, IN. 292 pp.

Mullan, K., Sills, E., Pattanayak, S. K., Caviglia-Harris, J., 2018. Converting forests to farms: the economic benefits of clearing forests in agricultural settlements in the Amazon. Environ and Resource Econ. 71(2), 427-455. https://doi.org/10.1007/s10640-017-0164-1

Nogueira, E.M., Yanai, A.M., Fonseca, F.O., Fearnside, P.M., 2015. Carbon stock loss from deforestation through 2013 in Brazilian Amazonia. Glob. Chang. Biol. 21, 1271-1292. https://doi.org/10.1111/gcb.12798

Rodrigues-Filho, S., Verburg, R., Bursztyn, M., Lindoso, D., Debortoli, N., Vilhena, A. M.G., 2015. Election-driven weakening of deforestation control in the Brazilian Amazon. Land Use Policy 43, 111–118. https://doi.org/10.1016/j.landusepol.2014.11.002

Rosa, I., Souza, C., Ewers, R.M., 2012. Changes in size of deforested patches in the Brazilian Amazon. Conserv. Biol. 26, 932-937. https://doi.org/10.1111/j.1523-1739.2012.01901.x

Schmitt, J., 2015. Crime sem castigo: a efetividade da fiscalização ambiental para o controle do desmatamento ilegal na Amazônia. Doctoral thesis. Universidade de Brasilia, Brasilia, DF, Brazil. 188 pp. http://repositorio.unb.br/bitstream/10482/19914/1/2015_JairSchmitt.pdf . (Last access 8 June 2018).

Smith, N.J.H., 1982. Rainforest Corridors: The Transamazon Colonization Scheme. University of California Press, Berkeley, CA. 248 pp.

Yanai, A.M., Nogueira, E.M., Graça, P.M.L.A., Fearnside, P.M., 2017. Deforestation and carbon stock loss in Brazil’s Amazonian settlements. Environ. Manage. 59, 393-409. https://doi.org/10.1007/s00267-016-0783-2

Zipperer, W.C., 1993. Deforestation patterns and their effects on forest patches. Landsc. Ecol. 8, 177-184. https://doi.org/10.1007/BF0012534

Chapter 2

Brazil's Amazonian deforestation actors: Clearing behavior on a cattle-ranching frontier

Aurora Miho Yanai[1], Paulo Maurício Lima de Alencastro Graça[1,4], Leonardo Guimarães Ziccardi[2], Maria Isabel Sobral Escada[3], Philip Martin Fearnside[1,4,5]

[1]Department of Environmental Dynamics, National Institute for Research in Amazonia (INPA), Av. André Araújo n° 2936, CEP 69067-375, Manaus, Amazonas, Brazil.

[2]Department of Forestry & Ecology, Evolutionary Biology and Behavior, Michigan State University, 480 Wilson Rd, East Lansing, MI 48824, USA

[3]Department of Image Processing, National Institute for Space Research (INPE), Av. Astronautas, n° 1758, CEP 12227-010, São José dos Campos, São Paulo, Brazil.

[4]Brazilian Research Network on Climate Change (RedeClima)

[5]Corresponding author

Email addresses: yanai@inpa.gov.br; pmlag@inpa.gov.br; isabel@dpi.inpe.br; leonardo.g.ziccardi@gmail.com; pmfearn@inpa.gov.br
Tel: +55(92) 3643-1822
Declaration of interest: none

Abstract

The spread of deforestation in terms of rate and size of clearing depends mainly on who the actors are on an Amazonian frontier. Land occupation and deforestation rates have increased substantially due to expansion of cattle ranching in recent years along the Transamazon Highway in the southern portion of Brazil's state of Amazonas. We estimated the contribution of different types of actors to land occupation and deforestation based on deforestation data (~1994 to 2018), the Rural Environmental Register or CAR (*Cadastro Ambiental Rural*), the road network and land categories, including public land without "destination" (assigned use), protected areas and agro-extractivist settlements. Actors are divided into "small" (< 100 ha), "semi-small" (100 - 400 ha), "medium" (> 400 - 1500 ha) and "large" (> 1500 ha). We focus on answering the following questions: (i) Who are the main actors and what are the predictors of deforestation? (ii) Is the patch size of clearing by different actors changing through the years? (iii) How is each actor type distributed spatially in relation to the Transamazon Highway and to access roads? (iv) How is deforestation in landholdings affected by distance to the Transamazon Highway? (v) How are the actors distributed in land categories (public land without destination, protected areas and agro-extractive settlement)? By 2018 most of the total area in landholdings had been cleared in the case of smallholders (72%) and semi-smallholders (49%), while medium landholders and largeholders usually still had large areas of forest, with only a small portion of the area occupied having been cleared (medium: 20%; large: 12%). Size of the landholding, year of first clearing and the distance between the landholding and the Transamazon Highway were the main predictors of deforestation, explaining 50.7% (adj $R^2 = 0.507$, $p < 0.001$) of the variance in the total area cleared in the landholdings and explaining 33.2% (adj $R^2 = 0.332$, $p < 0.001$) of the variance in the percentage of the landholding cleared in the. The patch size of annual clearings of small and semi-small actors showed an increase through time from 5.3 ± 4.9 ha (1995-2000) to 9.1 ± 10.0 (2013-2018) for smallholders and from 7.9 ± 10.1 ha to 16.1 ± 27.6 ha for semi-smallholder. Medium landholders maintained a pattern of patch size ranging from 20.7 ± 40.7 ha to 28.7 ± 43.7 ha. In contrast, largeholders showed a wide range from 4.0 ± 4.2 ha (1995-2000) to 65.5 ± 195.1 ha (2007-2012). The spatial distribution of actors in relation to roads showed that small (51.1%, n = 67) and semi-small (46.5%, n = 152) landholdings were located near (≤ 5 km) the Transamazon Highway as compared to medium (16.6%, n = 22) and large (5.4%, n = 2) landholdings. In general, most actors of all types were found in public land without destination. Some medium and large landholdings were found in an agro-extractivist settlement (medium: 7.8%; large: 28.0%) and in "conservation units" (protected areas for biodiversity) (medium: 21.1%; large: 20.7%). We suggest that, due their spatial distribution and the large percentage of forest cover in areas occupied by medium and large landholders, these actors will be the main contributors to future deforestation. Greater attention should be given to areas of public land without destination, and policies must be implemented to control the deforestation of these actors.

Keywords: CAR; landholding; deforestation; Amazon forest; actors; land-use change; rainforest, tropical forest

Highlights:

- Matupi is an Amazonian cattle-ranching frontier and deforestation hotspot.
- By 2018 clearing reached 72% for smallholders and 49% for semi-smallholders.
- In 2018 80% of remaining forest was in medium and large landholdings.
- Small and semi-small holdings are nearer the main road than medium and large ones.
- Future deforestation will be concentrated mainly in medium and large landholdings.

1. Introduction

Brazil's Amazon deforestation is one of the world's great environmental problems, and models capable of reliably simulating deforestation processes in this region are essential as sources of inputs to policy decisions to control these processes. "Actor-based" models are needed to represent these processes, and the present study provides information needed for such models for a cattle-ranching frontier where deforestation is taking place outside of official governmentorganized settlement projects. Cattle ranching is the main replacement for rainforest in Brazilian Amazonia.

Approximately 20% of the 4×10^6 km^2 originally forested portion of Brazil's 5×10^6 km^2 Legal Amazonia region had been cleared by 2018 (Brazil, INPE, 2019a). Annual deforestation rates in the region have been trending upwards since 2012, reaching 7536 km^2 in 2018 (Brazil, INPE, 2019b). Between August 2018 and June 2019, deforestation totaled 4575 km^2 (15%) higher than the deforestation from August 2017 to June 2018 (3975 km^2) (Brazil, INPE, 2019c). Environmental services provided by the forest, such as avoiding global warming, recycling water and maintaining biodiversity, are lost through deforestation (Foley et al., 2007; Fearnside, 2008a).

The rate, motivation and spatial distribution of deforestation in Brazilian Amazonia has varied at different locations and in different periods in the region's recent history. This is because deforestation results from the actions of different types of actors (Fearnside, 2008b, 2017; Strand et al., 2018). Previous studies of Legal Amazonia as a whole have provided an overview of clearing attributed to different actor types based on the sizes of the landholdings (Fearnside, 1993; Pacheco, 2009; Godar et al., 2014). Thus, the size of a landholding (i.e., the area occupied by an actor) is used to distinguish different actor types, since it reflects the level of an actor's wealth and the amount of clearing that the actor can do per year.

Studies at the local scale are more detailed and better suited to identifying specific types of actors and their deforestation patterns. However, most of the existing studies have been done in Mato Grosso and Pará States (Aldrich et al., 2006; Michalski et al., 2010; Godar et al., 2012a; Richards and VanWey, 2015; Assunção et al., 2017). Only a few studies have been done along the Transamazon Highway in the southern portion of Amazonas State, where deforestation rates have been increasing in recent years due expansion of a cattle-ranching frontier and migration of ranchers from Rondônia State and from southern and southeastern Brazil (Carrero and Fearnside, 2011). Because this is a new occupation frontier, there is a lack of studies to better understand the land occupation in this region by actors known as spontaneous squatters ("*posseiros*") (Fearnside, 2008b).

The aim of the present study is to estimate the contribution that different types of actors make to land occupation and deforestation through time (~1994 to 2018) on a cattle-ranching frontier. Specifically, we focus on answering the questions: (i) Who are the main actors and what are the predictors of their deforestation? (ii) Has the patch size of the annual clearing of each actor type changed through the years (1995 to 2018)? (iii) How is each actor type distributed spatially in relation to the main road (i.e., the Transamazon Highway) and in relation to access roads? (iv) How is deforestation in landholdings affected by distance to the Transamazon Highway?, and (v) How are the actors distributed among different land categories (public land without destination [i.e., federal or state land for which the government has not specified any particular use], protected areas and agro-extractive settlements)?

In order to provide an estimate of the deforestation of each actor type in terms of rate, patch size and spatial distribution, we used a landholding dataset from the Rural Environmental Registry (CAR = *Cadastro Ambiental Rural*) associated with cumulative deforestation through 1994 (the initial occupation process in our study area) and annual deforestation from 1995 to 2018. The CAR registers environmental information (e.g., area of landholding, legal reserve and area of permanent preservation) of rural landholdings. The information in the CAR is intended to be used for environmental monitoring and to control deforestation (Brazil, SFB, 2019). When complete, CAR data will provide a public dataset for all of Brazil's landholdings, including their boundaries, and this dataset has been used in recent studies to better understand the situation of landholdings in Legal Amazonia (Gollonow et al., 2018; Roitman, 2018).

Roads have an important role in land occupation and in driving deforestation to new forest areas. A recent study showed that 95% of all deforestation in the Amazonia biome is located within 5.5 km of highways and unofficial roads (Barber et al., 2014). We analyzed the importance of roads (the Transamazon Highway and access roads) for deforestation by each actor type. Identifying the deforestation actors and their spatial distribution in cleared areas and in the remaining forest can improve our comprehension of which actors cleared most in the past and which are likely to be responsible for future land-cover change. This is could contribute to policies for monitoring of deforestation and for command-and-control programs in new occupation frontiers in Amazonia.

2. Materials and Methods

2.1. Study area

The study was carried out in Matupi District, an administrative unit within a municipality (county), in this case the municipality of Manicoré, which is located in the southern portion of Brazil's state of Amazonas. Matupi District was formerly known as "km 180" (the distance between Humaitá and Matupi) and is located on the Transamazon Highway (BR-230). This main road provides a connection to Rondônia State via Highway BR-319 (Manaus-Porto Velho). The study area encompasses part of Manicoré, Humaitá and Novo Aripuanã municipalities covering a total of 20,767.3 km^2 (Fig. 1).

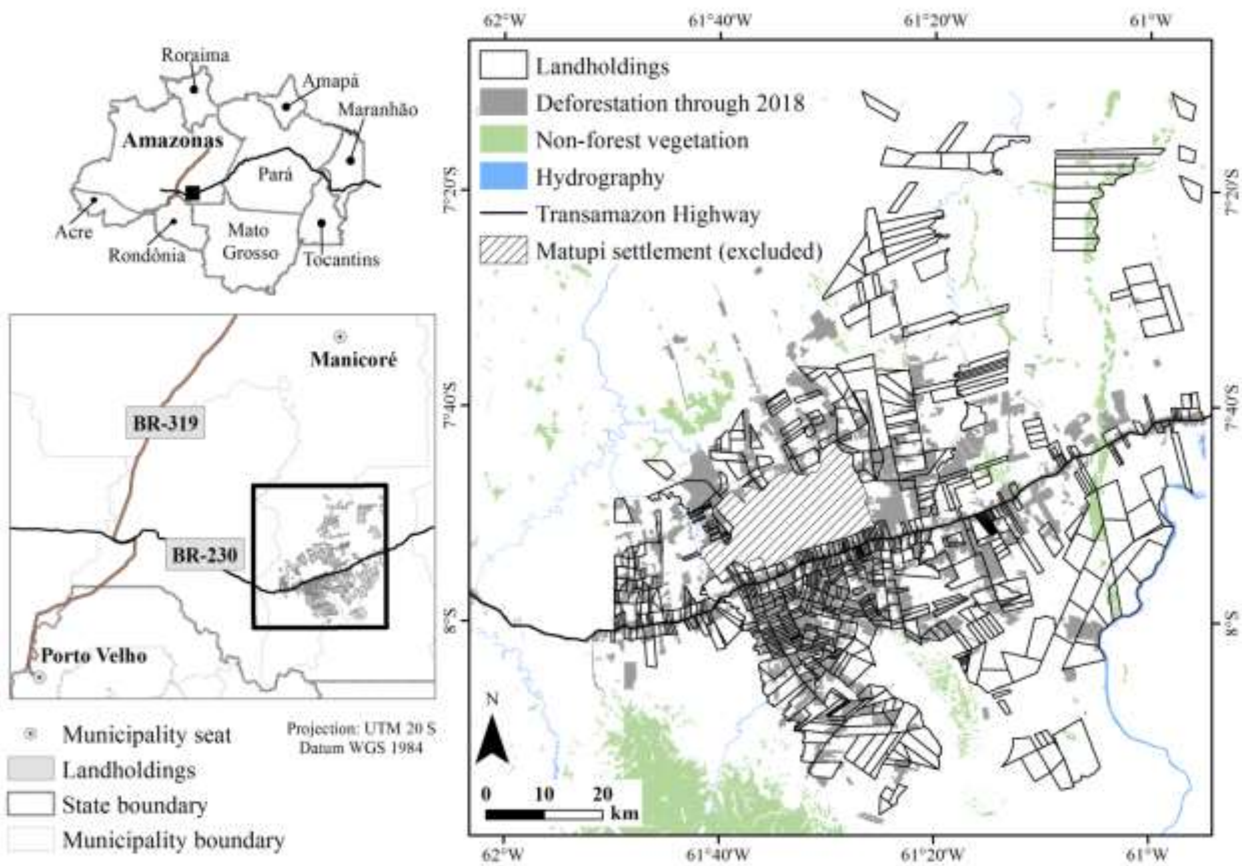


Fig. 1. Location of the study area.

The local actors have moved from Rondônia State or from the southern and southeastern parts of Brazil. Cattle ranching and logging are the main economic activities in Matupi and drive most of the forest degradation and clearing.

The study area is apportioned into the following land categories: public land without destination (23%), protected areas (conservation units: 27% and Indigenous Lands: 46%) and an agro-extractivist settlement (PAE: *Projeto de Assentamento Agroextrativista*) (3%).

The conservation units in the "sustainable use" category are national forests (n = 2) and an environmental protection area (*Área de Proteção Ambiental* = APA) (n = 1), while conservation units in the strictly protected category are a national park (n = 1) and a biological reserve (n = 1). The agro-extractivist settlement is a category that focuses on traditional populations to promote activities with low deforestation impact (e.g., agro-extractive activities and forest management). The specific spatial distribution of each land category with detailed boundaries of each conservation unit and Indigenous Land are shown in the Supplementary Material (Fig. S1).

The Matupi settlement area was excluded from the present study because we conducted a separate analysis of actors in this type of traditional settlement project (Yanai et al., in review).

2.2. Identification of actors based on the landholding size

To identify the types of actors in our study area, we associated the actor with the landholding size based on the fiscal modules defined by Brazil's National Institute for Colonization and Agrarian Reform (INCRA) for our study area (1 fiscal module is 100 ha in Matupi). We separated "smallholders" (1 to 4 fiscal modules) into two types due the large number of landholdings with sizes less than 400 ha and to allow comparisons with previous studies that defined "smallholders" as actors with landholdings < 100 ha. The actors with landholdings in the 100 to 400-ha range were named "semi-smallholders" based on L'Roe et al. (2016), who use this term to refer to a type of actor wealthier than a typical smallholder (< 100 ha). Although some previous studies defined actors occupying landholdings between 100 to 1000 as "medium landholders" (Pacheco, 2012; Fearnside, 1993), in the present study we assumed that "semi-smallholders" are actors between "small" and "medium," where their landholdings have a spatial distribution similar to "smallholders" but their clearing behavior is different because they have more financial resources to clear large areas (Table 1).

Table 1. Actor types and the landholding sizes based on the fiscal module (1 fiscal module in our study area = 100 ha).

Actor type	**Size of landholding (ha)**	**Fiscal Modules**
Smallholder	< 100	Landholding with area < 1 fiscal module
Semi-smallholder	100 - 400	Landholding with area between 1 to 4 fiscal modules
Medium landholder	> 400 - 1500	Landholding with area 4.1 to 15 fiscal modules
Largeholder	> 1500	Landholding with area > 15 fiscal modules

In our study area we identified 628 landholdings based on the vector map dataset of landholdings from the following sources: (1) the Rural Environmental Registry (CAR = *Cadastro Ambiental Rural*) updated to 1 November 2018 for Manicoré and Novo Aripuanã municipalities (Brazil, SFB, 2018) (n = 212); (2) INCRA's catalog of agrarian landholdings (*Acervo fundiário*) (n = 408) updated through 23 August 2018 (Brazil, INCRA, 2018a) and from (3) SIGEF (*Sistema de Gestão Fundiária*) (Brazil, INCRA, 2018b) (n = 8), which is INCRA's system that was developed to manage agrarian information in rural areas of Brazil.

To identify the landholdings in the SIGEF dataset we used the code of the boundary markers ("*marcos legais*") found at some of the boundaries of landholdings during our field work. The boundary markers are used to identify the legal limits (vertices) of the landholding. We only used SIGEF data for 8 landholdings because most of the boundary markers checked during our fieldwork were already recorded in the catalog of agrarian landholdings and in the CAR data.

We only maintained in our analysis landholdings with 100% of their area inside our study area. In cases of overlap between two or more landholdings we used the same approach as L'Roe et al. (2016), maintaining the most recent information based on the registry data or last rectification of the landholding information. However, when data from our fieldwork (i.e., the GPS point for a corner of a landholding obtained along the roads in 2016 and 2018) were more recent than the CAR data, we maintained the boundaries of the landholding in accordance with the data from our fieldwork. In addition, since the landholders' names were available in the catalog of agrarian landholdings and in the SIGEF data, we performed a merge between neighboring landholdings with the same landholder name.

More information about the CAR is available in the Supplementary Material.

2.3. Mapping deforestation through 2018 and estimation of clearing rates and patch sizes by actor type

We mapped deforestation from 1994 to 2018 in order to estimate the total area cleared, remaining forest in 2018, mean annual clearing and the sizes of patches of clearing (i.e., mapped annual polygons) by type of actor. We than performed an intersection between the vector map of landholding boundaries and the mapped deforestation.

Deforestation (i.e., clear-cut or areas in the initial process of regeneration) were mapped by visual interpretation on a computer screen at 1:50,000 scale, but to better delimit small polygons we increased the level of detail to 1:20,000 scale. We used images from Landsat-5 TM (1994 to 2011), ResourceSat-1 LISS-3 (2012) and Landsat-8 OLI (2013 to 2018) (path: 231; rows: 65 and 66) with spatial resolution of 30 m. The color composition used was the false color composition: shortwave infrared (Red), near infrared (Green), and red (Blue). We chose images with the least cloud cover from the U.S. Geological Survey (USGS) and from Brazil's National Institute for Space Research (INPE). An atmospheric correction using the FLAASH (Fast Line-of-sight Atmospheric Analysis of Hypercubes) tool in Envi software was applied to the images to help differentiate land-cover change and, when necessary, to compare clearing from a given year to the previous year. Cleared areas were mapped by visual interpretation starting in 1994, when land occupation in Matupi District was in its initial stages. Thus, the polygons mapped in 1994 represented cumulative deforestation, and the mapping of cleared areas from 1995 to 2018 represent annual deforestation. The area (ha) of each polygon was then calculated and, in order to reduce noise from small polygons, polygons < 1 ha in area were excluded, which means that the minimum area analyzed in our study was 1 ha. We only mapped clearing in forest vegetation; clearing in other types of vegetation, such as savanna and *campinarana*, was not included.

We mapped deforestation polygons rather than using data from PRODES (Project for Monitoring Amazonian Deforestation), a Brazilian government program for annual deforestation monitoring carried out by INPE. PRODES was not used because its vector map does not have digital annual deforestation mapping before 2000 for our study area and the minimum area mapped by PRODES is 6.25 ha. In addition, the PRODES deforestation dataset had a spatial adjustment of the vector mask (i.e., cumulative deforestation from 2013 and previous years) (Brazil, INPE, 2015), which impedes use of the vector map for our spatial-temporal analysis. However, we used the PRODES vector map to assist the mapping in specific areas or polygons in order to verify the agreement between our mapping and the PRODES dataset (Brazil, INPE, 2018).

To estimate the remaining forest, we subtracted from the total area of landholdings the areas of deforestation through 2018, water and non-forest vegetation. The areas of water and non-vegetation were obtained by supervised classification based on maximum likelihood. The areas of non-forest and water for each actor type are presented in Table S1 (Supplementary Material).

Mean annual clearing per actor was obtained from annual mapping data from 1995 to 2018 in each landholding, with the total area cleared in the period being divided by 24 years. To evaluate if the clearings were distinct between the actor types, we performed a non-parametric statistical test (Mann-Whitney U) because our dataset lacked normality.

To assess whether the size of annual polygons of deforestation changed through time from 1995 to 2018, we estimated the area of polygons in each landholding separately by actor type. To reduce noise caused by very small polygons (< 1 ha) within the boundaries of landholdings, which could affect our analysis, we excluded these small polygons. Thus, we analyzed the distribution of polygon sizes in four six-year periods: (i) 1995 to 2000; (ii) 2001 to 2006; (iii) 2007 to 2012; (iv) 2013 to 2018.

2.4. Mapping roads and evaluation of the distance of landholdings to roads

To evaluate the spatial distribution of landholdings in relation to the main road (the Transamazon Highway) and to the access road network (i.e., illegal or unofficial roads), we mapped roads by visual interpretation (scales between 1: 25,000 and 1: 50,000) using Landsat-8 images (2018) and GPS data from fieldwork from 22 August to 2 September 2016 and from 20 August to 1 September 2018. We then performed a proximity analysis between the vector map of the Transamazon Highway and access roads and the vector map of landholdings. Proximity analyses estimate distance as the shortest separation between the boundaries of two objects, in this case between landholdings and roads. Thus, the distance was equal to zero when a landholding boundary and a road shared at least one coordinate (x, y) or when one of the boundaries (e.g., a landholding polygon) contained or was within another boundary (e.g., a road line).

We used a 5.5-km buffer around all roads (Barber et al., 2014) to identify landholdings near roads. We then performed an intersection between the vector map of landholdings and the buffer.

2.5. Identifying the main predictors of deforestation in landholdings

We tested the following as predictor variables: actor type, landholding size, remaining forest area in 2018, distance to the Transamazon Highway, distance to secondary roads and year of first clearing in the landholding from 1995 to 2018. Distance to secondary roads was estimated in the same way as distance to the Transamazon Highway described above.

Landholdings either without clearing or with cumulative deforestation through 1994 were excluded from this analysis because we could not identify the first clearing in the landholdings of those with cumulative deforestation by 1994 and we could not evaluate the year of fist clearing for those landholding without clearing during our time analysis. Thus, a total of 267 landholdings were analyzed: small (n = 48), semi-small (n = 122), medium (n = 79) and large (n = 18). We assessed deforestation as the dependent variable in terms of absolute amount of deforestation from 1995 to 2018 (i.e., area in hectares), in the landholdings and in terms of the relative amount of deforestation (i.e., percentage of the landholding cleared). Analysis of the relative amount of deforestation is important because, although smallholders and largeholders may clear the same area in hectares, the impact of forest loss in relation to landholding size is different for these types of actors.

Correlation matrices were used to assess the level of correlation between the variables. Landholding size, distance to theTransamazon Highway, distance to secondary roads and year of first clearing were weakly correlated. Similarly, the dependent variables were weakly correlated. In contrast, actor type, landholding size and forest (2018) were strongly correlated (Fig. S2).

We assessed the power of the predictors by testing all variables together using the automated model selection feature available in the "glmulti" package in R software (Calcagno and de Mazancourt, 2010). The multiple regression models obtained were based on the Akaike Information Criterion (AIC) ranking calculated with the function in R for exhaustive screening of candidate models. Using the model results we selected the best predictors, which were: landholding size, distance to the Transamazon Highway and year of first clearing. We tested for interactions between landholding size and year of first clearing using an exploratory approach, and found that including these interactions resulted in better models as compared to the previous approach. The coefficients estimated for each variable in Equations 1 and 2 are available in Table S2.

Equation 1:

Deforestation (ha) = B_0 + (B_1×Landholding size) + (B_2×Year of first clearing) + (B_3×$Dist_{Highway}$) + (B_4 × Landholding size × Year of first clearing)

Equation 2:

Deforestation (%) = B_0 + (B_1×Landholding size) + (B_2×Year of first clearing) + (B_3×$Dist_{Highway)}$ + (B_4×Landholding size×Year of first clearing)

Deforestation (ha): Total area cleared in the landholding from 1995 to 2018
Deforestation (%): ($Clearing_{(1995\text{-}2018)}$ / Landholding size) × 100
B_0: intercept (equal of the value of the dependent variable when predictors are zero)
B_1 to B_4: Estimated coeficients (Table S2)
$Dist_{Highway}$: Distance between the landholding and the Transamazon Highway

The best-fitted models with interactions were used to predict deforestation using Breiman's random forest algorithm (Breiman, 2011). This is an effective statistical approach used for ecological modeling, yielding superior predictive capability (Prasad et al., 2006). Of all landholdings (n = 267), 70% were randomly selected to be used in training the model and the remaining 30% were used in the valdation step. In the validation step the deforestation predicted by the model explained 56.6% (adj $R^2 = 0.566$, $p < 0.001$) of the variance in observed deforestation in terms of area. In relation to the percentage of deforestation, the model explained 39.7% (adj $R^2 = 0.397$, $p < 0.001$). We then applied the Random Forests algorithim to predict deforestation values using the whole dataset. All analyses were performed in the R environment (R Core Team, 2019, version 3.6.0).

2.6. Distribution of landholdings by land category

To evaluate the spatial distribution of landholdings among the different land categories (protected areas [conservation units and Indigenous Lands], agro-extractivist settlements and public land without destination), we made a single vector map with conservation units merged, Indigenous Lands merged and the agro-extractivist settlement and public land without destination. "Public land without destination" was defined as the area where the government has not assigned any specific destination, such as a protected area, an Indigenous Land or a settlement.

The vector map of landholding boundaries was intersected with the vector map of land categories to determine where each actor type was spatially distributed. Information on the tolerance thresholds for overlap between landholdings and land categories is available in the Supplementary Material.

3. Results

3.1. Actor types, landholdings, deforestation and remaining forest

We analyzed a total of 628 landholdings (289,994 ha) with sizes ranging from 6 to 4838 ha. In terms of numbers of landholdings per actor type, smallholders and semi-smallholders were the majority (72.9%, n=458) in relation to medium landholders and largeholders (27.1%, n=170). However, in terms of area of landholdings per actor type, medium landholders and largeholders occupied 70.8% (205,349 ha) of the total area analyzed, while smallholders and semi-smallholders occupied only 29.2% (84,645 ha). The mean size of large landholdings was 28.8 times greater than that of small landholdings, 9.7 greater than the semi-small landholdings and 2.4 times greater than the medium landholdings. Medium landholdings were, on average, 12 times larger than small landholdings and 4.1 times larger than semi-small landholdings (Table 2).

Table 2. Characteristics of landholdings by actor type.

Actor type	Number of landholdings	Total area (ha)	Landholding size Mean ± SD (ha)	Min. - Max of landholding size (ha)
Smallholder (<100 ha)	131 (20.9%)	10,109 (3.5%)	77 ± 22	6 - 99.87
Semi-smallholder (100-400 ha)	327 (52.1%)	74,536 (25.7%)	228 ± 99	100 - 400
Medium landholder (>400-1,500 ha)	133 (21.2%)	123,237 (42.5%)	927 ± 355	404 – 1,492
Largeholder (>1,500 ha)	37 (5.9%)	82,112 (28.3%)	2,219 ± 590	1,515 – 4,838
Total	**628 (100%)**	**289,994 (100%)**		

Small and semi-small landholdings represented most of the deforestation through 2018 (56.4% or 44,079 ha) in comparison with medium and large landholdings (43.6% or 34,063 ha) (Table 3). Most of the remaining forest was in medium and large landholdings (80.5% or 165,319 ha). Small and semi-small landholdings represented only a small portion of the remaining forest in 2018 (19.6% or 40,182 ha) (Table 3 and Fig. 2).

Table 3. Estimates of deforestation through 2018 and of remaining forest in hectares per actor type. *Estimated from 1995 to 2018 (24 years), only including landholdings with total clearing ≥ 1 ha.

Actor type	Deforestation through 2018 in hectares			Annual mean clearing per landholding Mean ± SD (ha)*	Forest in 2018 in hectares	
	Total	Total per landholding Mean ± SD	Min. - Max. per landholding		Total	Min. - Max. per landholding
Smallholder < 100 ha (n=131)	7,298 (9.3%)	56 ± 26	0 - 99	1.8 ± 1.1 (n=128)	2,806 (1.4%)	1 – 89
Semi-smallholder 100-400 ha (n= 327)	36,781 (47.1%)	112 ± 83	0 - 394	4.3 ± 3.3 (n=296)	37,376 (18.2%)	1 – 394
Medium landholder > 400-1,500 ha (n= 133)	24,511 (31.4%)	184 ± 236	0 – 1,324	9.2 ± 10.1 (n=106)	97,311 (47.4%)	8 – 1,486
Largeholder >1,500 (n=37)	9,552 (12.2%)	258 ± 509	0 – 1,877	16.7 ± 24.7 (n=22)	68,008 (33.1%)	249 – 4,646
Total	**78,143 (100%)**	**124 ± 182**		**5.2 ± 7.8 (n=552)**	**205,501 (100%)**	

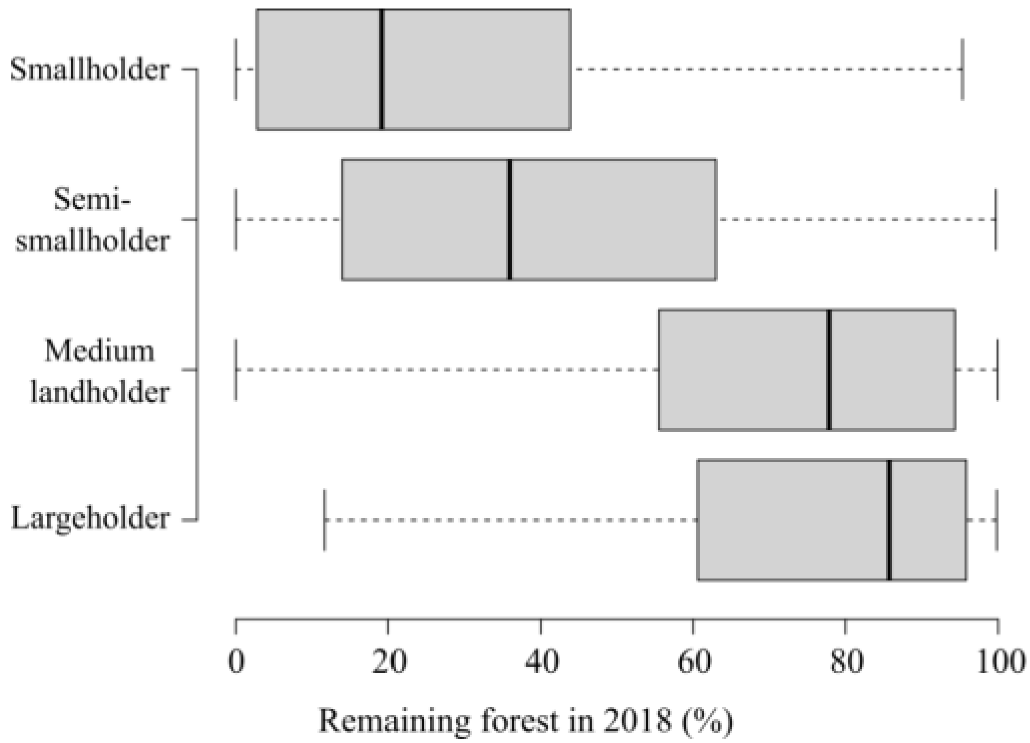


Fig. 2. Percentage of forest remaining per landholding in 2018 by actor type. The black line dividing each gray box is the median of the data (middle quartile); gray box: interquartile range (IQR) = Q1 (first quartile or 25th percentile) – Q3 (third quartile or 75th percentile); dashed lines (whiskers) represent the range of data outside the middle 50%.

Medium landholders and largeholders both started with cumulative deforestation through 1994 of only 0.9% in relation to total area occupied by each category (medium: 1080 ha and large: 713 ha). Cumulative deforestation increased 19.9% (24,511 ha) from 1995 to 2018 for medium landholders and 11.6% (9552 ha) for largeholders. Over this 24-year period the area cleared in medium landholdings increased by 22.7 times, and in large landholdings the cleared area increased by 13.4 times (Fig. 3).

Smallholders and semi-smallholders started with larger percentages of cumulative deforestation through 1994 as compared to medium landholders and largeholders (small: 16.4% or 1659 ha and semi-small: 8.1% or 6087 ha). Through 2018 cumulative deforestation of smallholders increased by 4.4 times, reaching 7298 ha or 72.2% of the total area occupied. In contrast, clearing by semi-smallholders increased 6.0 times in relation to the initial year (1994), reaching 36,781 ha or 49.3% of the total area occupied (Fig. 3).

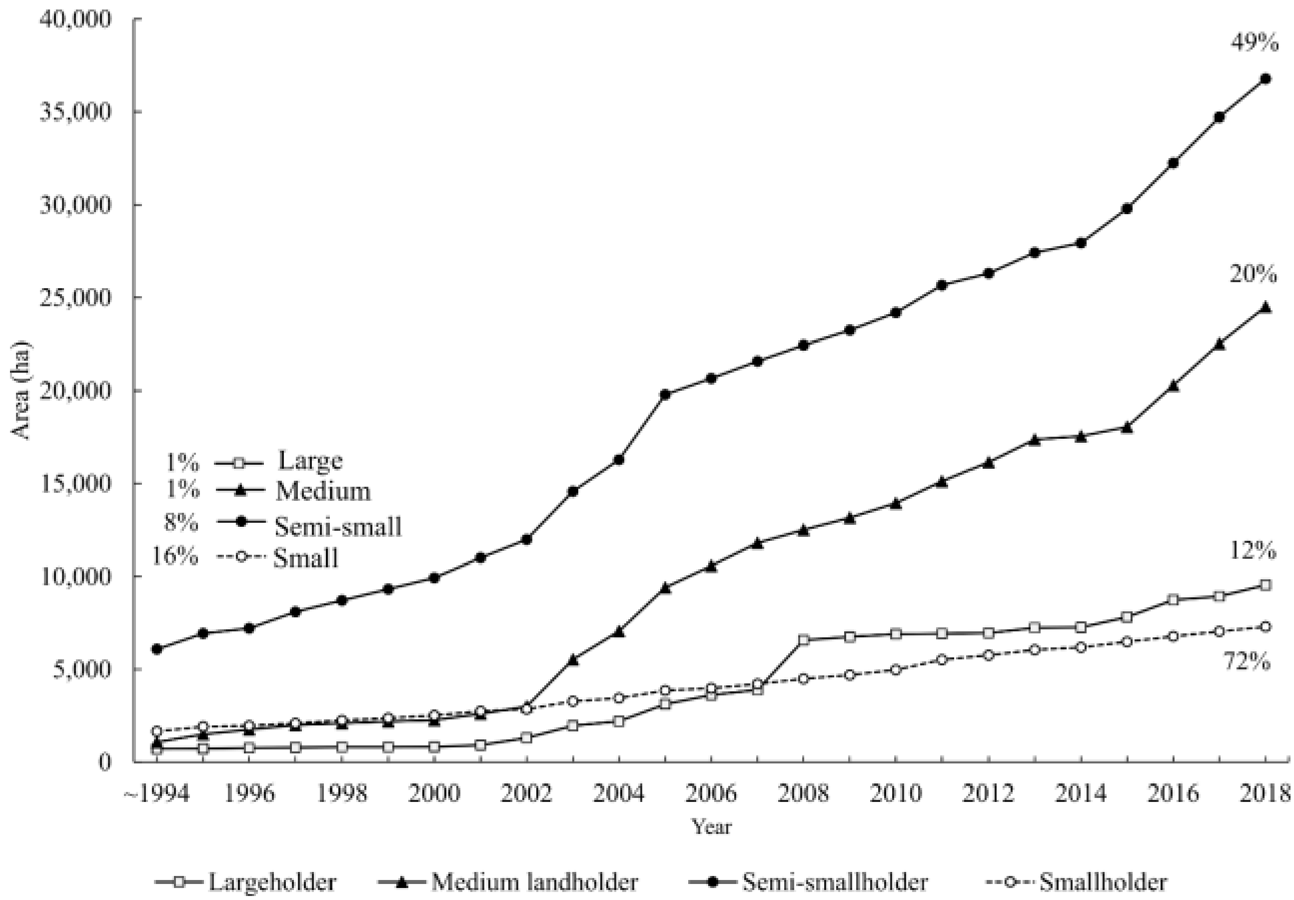


Fig. 3. Cumulative deforestation from ~1994 to 2018 for each actor type. The percentages shown for the initial (~1994) and final (2018) years analyzed indicate the total area cleared in relation to the area occupied by the actors.

Despite the high mean annual clearing of largeholders (16.7 ± 24.7 ha), no significant difference was found comparing mean annual clearing of largeholders and other actors (small, $p = 0.25$; semi-small, $p = 0.96$ and medium, $p = 0.69$) (Table 3). The small number of largeholders (n=22) in the sample and the value of the median (3.0 ha) being close to those of the semi-smallholders (3.6 ha) and the smallholders (1.9 ha) probably contributed to this result. Only medium landholders showed a high value of the median (7.1 ha) in comparison to other actor types (Fig. 4). Significant differences by the pairwise Mann-Whitney U non-parametric test ($p < 0.001$) were found in comparing medium landholders, semi-smallholders and smallholders and between small and semi-smallholders.

The distribution of mean annual clearing over 24 years (1995-2018) in the landholdings indicated that clearings in medium and large landholdings had low means (0.1 to 0.9 ha) and a wide range of area cleared (1.2 to 22.7 ha, n = 9 landholdings), similar to the annual clearing in small and semi-small landholdings, but also with high values of clearing per landholding (27.7 to 78. 2 ha, range: 664.1 to 1877.2 ha, n = 7) (Fig. 4).

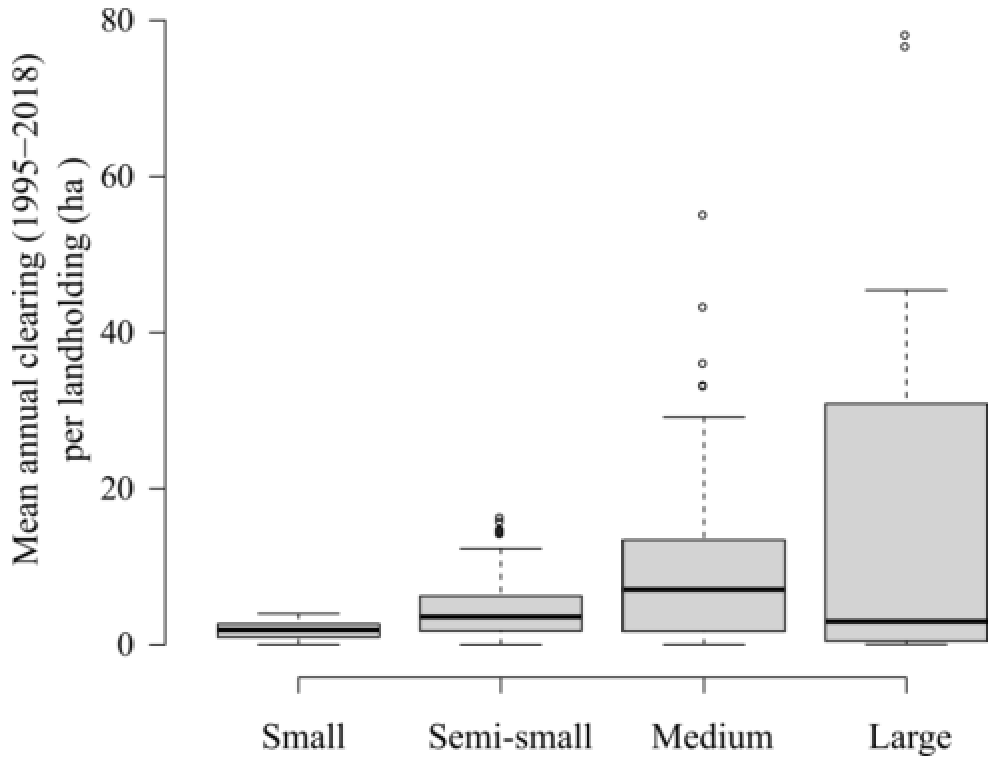


Fig. 4. Distribution of mean annual clearing from 1995 to 2018 per landholding of the different actor types. The black line dividing each box is the median of the data (middle quartile); gray box: interquartile range (IQR) = Q1 (first quartile or 25th percentile) = Q3 (third quartile or 75th percentile); dashed lines (whiskers) represent the range of data outside the middle 50%; circles represent outliers.

3.2. Patch size of deforestation by actor type

The sizes of patches (i.e., polygons of clearing) for each actor type were analyzed in six-year intervals to evaluate the temporal dynamics of the actors' clearing. In general, comparing the initial interval of land occupation (1995-2000) to recent years (2013-2018), the patch size (mean ± SD) for all actors showed a pattern of increase from 8.2 ± 14.8 ha (1995-2000) to 19.2 ± 38.9 ha (2013-2018). The second interval (2001-2006) had values similar to those of the most recent years with 18.3 ± 36.2 ha, and in the third interval (2007-2012) we observed a decrease in the values (15.9 ± 52.3 ha). This decrease was also found in areas of semi-smallholders and medium landholders. The largest patch size was found in this period (1142 ha) in the area of the largeholders (Table 4).

Smallholders and semi-smallholders had a tendency of increased patch size through the years (initial and last interval) from 5.3 ± 4.9 ha to 9.1 ± 10.0 for smallholders and from 7.9 ± 10.1 to 16.1 ± 27.6 for semi-smallholders. The sizes of patches of semi-smallholders were greater than those found in smallholders, as expected due the larger sizes of the semi-small landholdings.

The patches of medium landholders showed a similar size pattern through the intervals analyzed, with similar values between the first interval (1995-2000: 20.7 ± 40.7 ha) and the third interval (2007-2012: 20.7 ± 48.0 ha), and between the second interval (2001-2006: 28.7 ± 43.7 ha) and last interval (2013-2018: 27.0 ± 53.8 ha). In addition, since 2007 this type of actor cleared large patches (> 500 ha) in comparison to the initial years of land occupation.

Largeholders showed a substantial increase in the mean size of patches from the first to the third interval: 4.0 ± 4.2 ha (1995-2000); 43.6 ± 85.7 ha (2001-2006); 65.5 ± 195.1 ha (2007-2012). The high values in the third interval were affected by large patches (500 ha, 700 ha and 1142 ha) cleared in the 2008. In addition, in contrast with the pattern observed in medium landholders (who had an increase in mean patch size in the last year), we found a decrease in the sizes of patches (36.4 ± 70.0 ha) in largeholder areas (Table 4). A more detailed distribution of patches by actor type in the intervals analyzed can be found in Fig. S3 (Supplementary Material).

Table 4. Patch size estimated in six-year intervals from 1995 to 2018 for each actor type.

Actor type	**Patch size in hectares (mean ± SD and range: minimum-maximum ha)**			
	1995-2000	**2001-2006**	**2007-2012**	**2013-2018**
All landholders	8.2 ± 14.8 (1-243)	18.3 ± 36.2 (1-433)	15.9 ± 52.3 (1-1,142)	19.2 ± 38.9 (1-536)
Smallholders	5.3 ± 4.9 (1- 28)	8.0 ± 7.8 (1- 50)	8.5 ± 8.9 (1- 51)	9.1 ± 10.0 (1- 62)
Semi-smallholders	7.9 ± 10.1 (1- 94)	14.5 ± 27.1 (1- 371)	11.2 ± 15.1 (1- 156)	16.1 ± 27.6 (1- 225)
Medium landholders	20.7 ± 40.7 (1- 243)	28.7 ± 43.7 (1- 364)	20.7 ± 48.0 (1- 530)	27.0 ± 53.8 (1- 536)
Largeholders	4.0 ± 4.2 (1- 22)	43.6 ± 85.7 (1- 433)	65.5 ± 195.1 (1-1,142)	36.4 ± 70.0 (1- 357)

3.3. Distribution of actors in relation to distance to the main road

Although, all actor types were found on the edges of the Transamazon Highway, smallholders and semi-smallholders were closer to the Transamazon Highway as compared to medium landholders and largeholders. The maximum distance that smallholders and semi-smallholders were found in relation to Transamazon Highway was 23.7 km (small) and 41.4 km (semi-small). In contrast, medium landholders and largeholders were found at distances up to 65.2 km (medium) and 47.6 km (large) (Fig. 5).

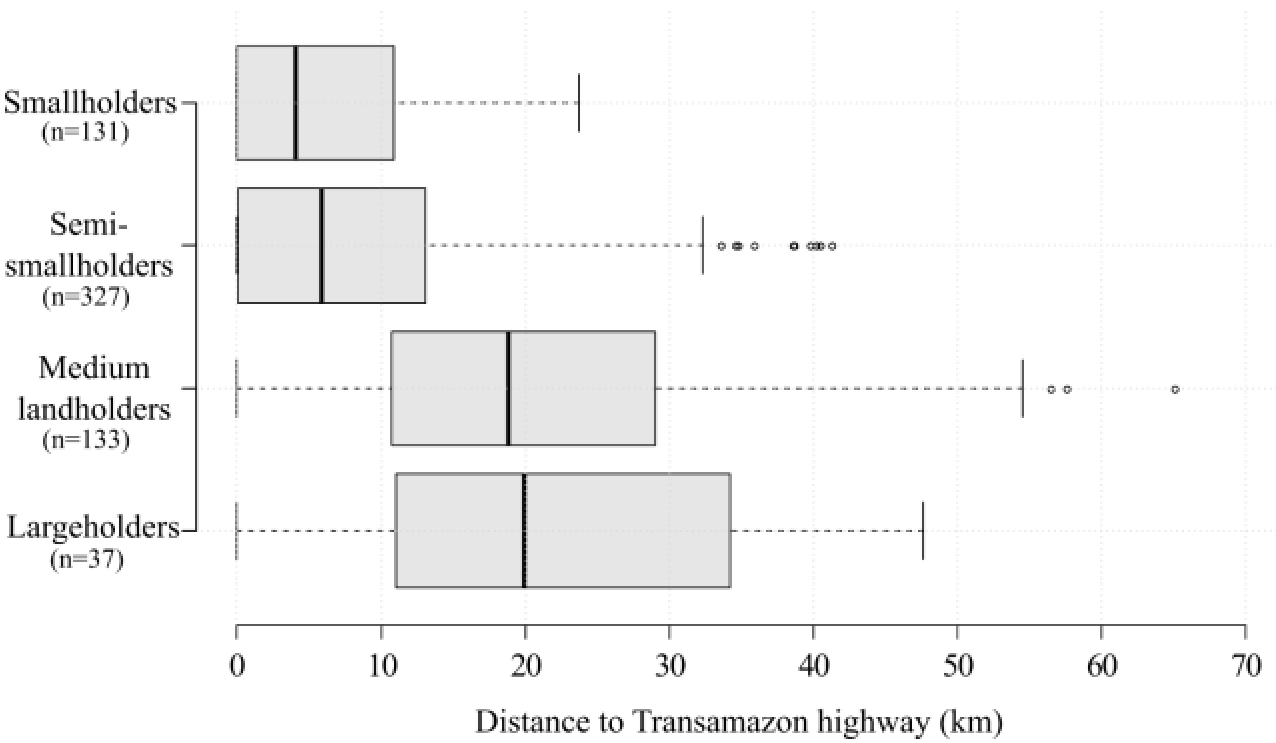


Fig. 5. Distribution of actors in relation to the Transamazon Highway (BR-230). The black line dividing each box is the median of the data (middle quartile); gray box: interquartile range (IQR) = Q1 (first quartile or 25th percentile) – Q3 (third quartile or 75th percentile); dashed lines (whiskers) represent the range of data outside the middle 50%; circles represent outliers.

The mean distances of actors of each type to the Transamazon Highway were 6.3 ± 6.5 km (smallholders) and 8.6 ± 9.5 km (semi-smallholders), 21.2 ± 15.4 km (medium landholders) and 22.3 ± 13.8 km (largeholders). No significant difference was found between the distance of small and semi-smallholders ($p = 0.08$) in relation to the Transamazon Highway, and a similar result was found between large and medium landholdings ($p = 0.62$). However, significant differences were found between large and small ($p < 0.001$), large and semi-small ($p < 0.001$) and between medium and small ($p < 0.001$) and medium and semi-small landholdings ($p < 0.001$).

In terms of numbers of actors with landholdings located ≤ 5 km from the Transamazon Highway, we found that most of the small landholdings (51.1%, n = 67) were near this main road, followed by semi-small (46.5%, n = 152), medium (16.6%, n = 22) and large (5.4%, n = 2) landholders. In addition, the buffer (5.5 km) around all roads (main road and access roads) mapped through 2018 showed that 80.0% or 231,900 ha of the total area occupied by actors was within the buffer area. All small landholdings were located near roads and 323 (98.8%) of semi-small landholdings had 50-100% of the landholding area within the 5.5-km buffer. In the case of medium and large landholdings, the numbers decreased to 112 (84.2%) and 24 (64.9%).

3.4. Drivers of deforestation in the landholdings

Size of landholding, year of first clearing and the distance from the landholding to the Transamazon Highway were important predictors of total deforestation from 1995 to 2018. The model (Equations 1 and 2) showed that all these predictors together explain 50.8% (adj $R^2 = 0.5076$, $p < 0.001$) of the variance in the total area cleared in the landholdings and 33.2% (adj $R^2 = 0.3325$, $p < 0.001$) in terms of percentage of clearing in relation to landholding size. Thus, larger landholdings that started their land occupation in recent years have less clearing than smaller landholdings with old occupation (Fig. 6).

There is a tendency for large landholdings with little clearing to be located far from the Transamazon Highway as compared to small landholdings with high amounts of clearing, which tend to be located near the main road (Figs. 5 and 8).

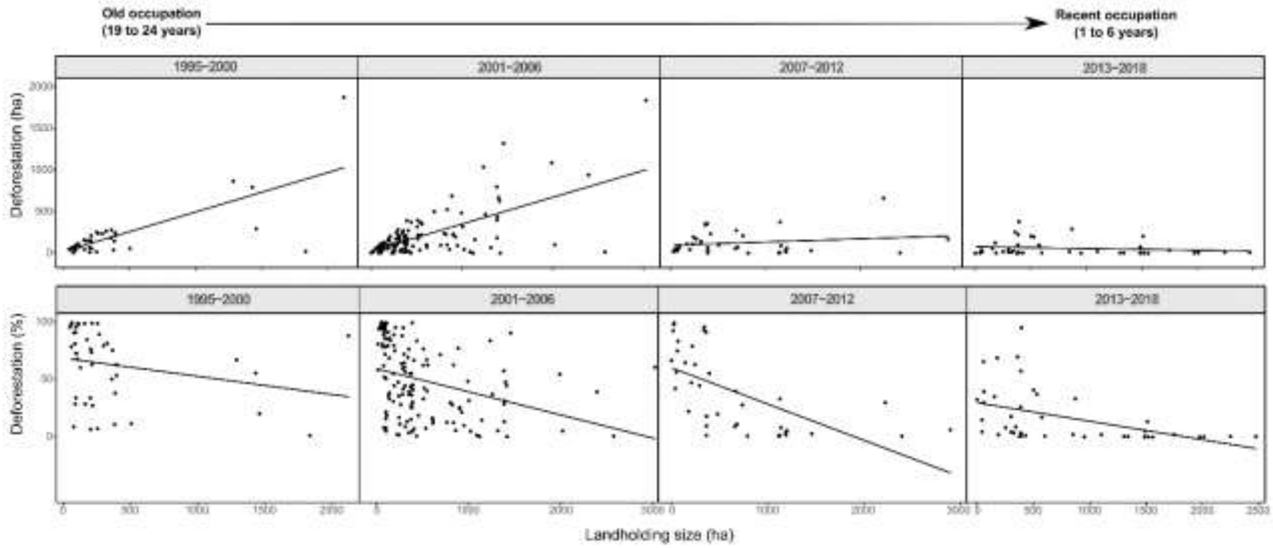


Fig. 6. Relation of landholding size to deforestation in terms of area (above) and percentage (below) according to the time of occupation.

Only 13% of both small (n = 6) and semi-small (n = 16) landholdings are classed as recent occupation (1 to 6 years: 2013-2018), medium landholdings have a similar result with 18% (n = 14). In contrast, 44% (n = 8) of large landholdings were occupied recently (1 to 6 years).

The area of deforestation predicted by our model using the random forests framework explains 77.3% (adj $R^2 = 0.7731$, $p < 0.001$) of the variance in the observed (real) deforestation from 1995 to 2018. When the percentage of deforestation was predicted, deforestation predicted by the model explained 67.1% (adj $R^2 = 0.6712$, $p < 0.001$) of the variance in the observed percentage of deforestation. The results indicated that our model and the predictors used were well suited to predicting deforestation in the landholdings in our study area. The residuals are shown in the Supplementary Material (Fig. S4). Thus, large landholdings with recent occupation cleared less than large landholdings with older occupation (Fig. 7).

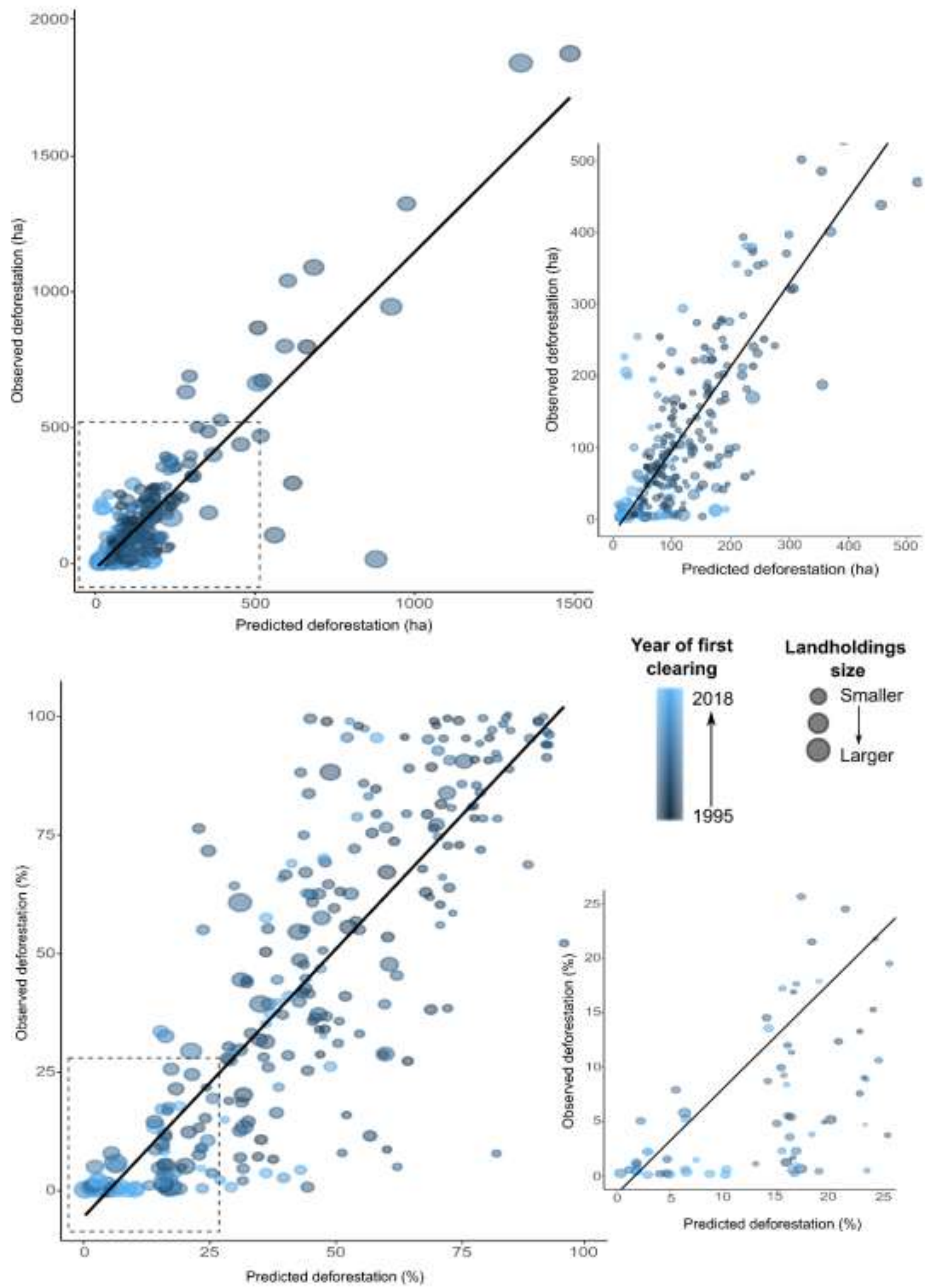


Fig. 7. Relation between real and predicted deforestation in terms of area (left) and in terms of percentage (right). Symbols indicate landholding size (values are continuous: larger sizes have larger circles), and the time of first clearing is shown by the color scale from gray (old) to blue (recent). A square frame outlined with dotted line is a zoomed view.

3.5. Landholdings by land category

In the "public land without destination" in our study area (total area without destination = 485,842 ha), 43.3% (210,264 ha) was occupied by landholdings analyzed in the study. We found that most of actors were located in "public land without destination": smallholders (99.9%), semi-smallholders (95.9%), medium landholders (70.3%) and largeholders (51.3%). Medium landholders and largeholders were also found in the agro-extractivist settlement and in conservation units, indicating occupation or the intention to occupy the land by these actors. In addition, one medium landholder, whose landholding was registered in the CAR, was found in an Indigenous land; we also found some overlap of small and semi-small landholdings with Indigenous land due their being located on the boundaries between public land without destination and Indigenous land (Table 5 and Fig. 8).

Table 5. Distribution of actor types in different land categories.

Land category	Smallholders (ha)	Semi-smallholders (ha)	Medium landholders (ha)	Largeholders (ha)	Total
Public land without destination	10,081 (99.9%)	71,408 (95.9%)	86,659 (70.3%)	42,115 (51.3%)	210,264 (72.5%)
Agro-extractivist settlement	0	2,469 (3.3%)	9,607 (7.8%)	23,026 (28.0%)	35,102 (12.1%)
Conservation units	0	442 (0.6%)	26,011 (21.1%)	16,968 (20.7%)	43,422 (15.0%)
Indigenous land	13 (0.1%)	156 (0.2%)	960 (0.8%)	-	1,130 (0.4%)

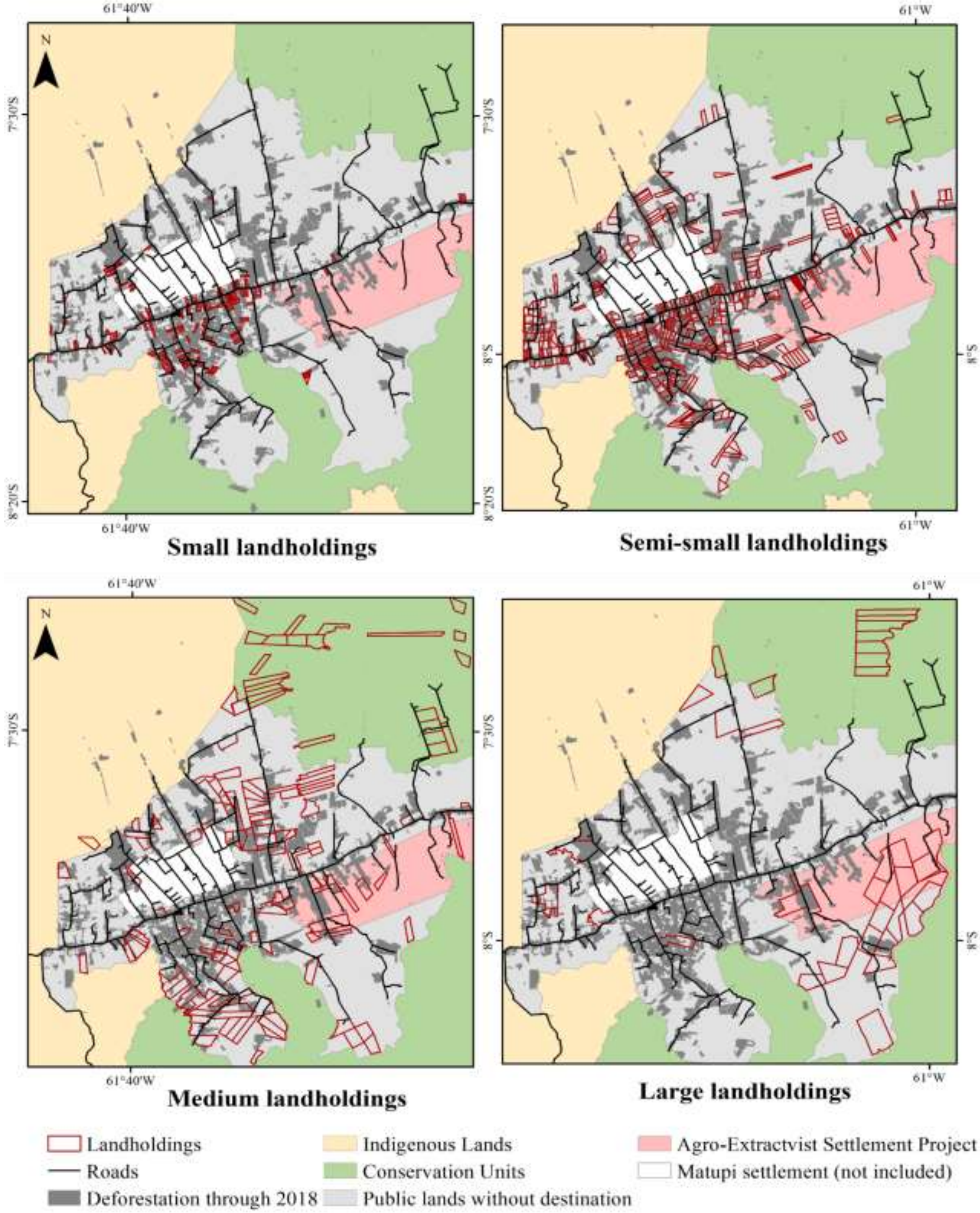


Fig. 8. Distribution of landholdings, roads in 2018 and land categories.

4. Discussion

We found that medium landholders and largeholders accounted for the majority of the total area occupied (70.8% or 205,349 ha). Despite the mean annual clearing of these larger actors being greater than that of smaller actors, they encompassed a major portion of the remaining forest.

The sizes of patches of clearing in medium and large landholdings were larger than those of other actors. The medium and large landholdings were more spread out and were located at the ends of the access roads, far from the Transamazon Highway. Medium and large landholdings were found in protected areas and in the agro-extractivist settlement, which are land categories where these types of actors are not legally allowed.

4.1. Landholding size, deforestation dynamics and distance to roads

Our findings indicated that the clearing process (i.e., year of first clearing) occurred earlier in areas occupied by smallholders than in areas occupied by large landholdings. The proximity of smallholders to the Transamazon Highway and to previous deforestation located close to this main road also had an important role and contributed to consolidate the deforestation in most of the area occupied by small landholdings (Figs. 5 and 8).

In contrast, the medium and large landholders arrived later, and their holdings are therefore located further from the main road. These actors are therefore more spread out in the remaining forest in public land without destination, protected areas and in the agro-extractivist settlement (Figs. 9A, 9B and 9C). Most of these landholdings are not connected directly to the Transamazon Highway, but rather are located on the boundaries between land categories and at the ends of access roads in more isolated areas (Fig. 9D). This pattern for large landholdings has also been observed in the Xingu-Iriri region in Pará State (dos Santos Silva et al., 2008)

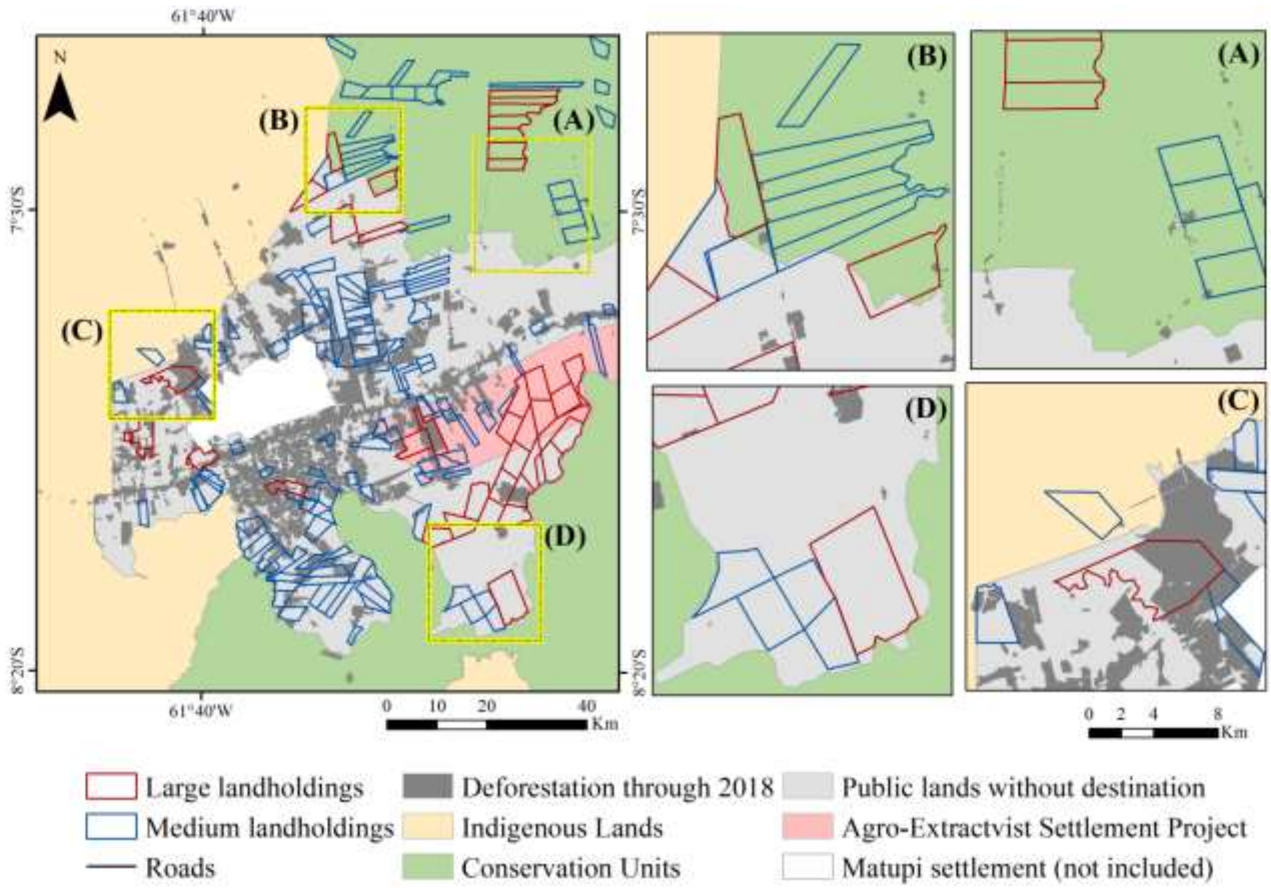


Fig. 9. Distribution of large and medium landholdings. Medium and large landholdings with clearing and unofficial roads can be observed inside conservation units (A and B). A medium landholding is located in an Indigenous land (C). Large landholdings are often found at the ends of access roads (D).

In this regard, an important concern in our findings is that 80% of remaining forest in 2018 in the landholdings analyzed was in medium and large landholdings. We therefore suggest that medium landholders and largeholders will be the main potential contributors to future deforestation. Large cattle ranchers tend to use the entire area of their landholdings for pasture, and they open new areas whenever they have the opportunity (D'Antona et al., 2006; Godar et al., 2012a,b). However, in our study area most of the large cattle ranchers had not yet converted the whole area of their landholdings to pasture either because they started their land occupation recently (~ 6 years) or because they appear to be land speculators who are planning to sell the landholding after an expected future increase in the value of the land. A previous study in Amazonia estimated that 9 to 13% of the land is vulnerable to speculation, and land speculation is a driver that contributes to the profitability of extensive ranching (Bowman et al., 2012). In addition, the strategic location far from the main road reduces the probability that they will be monitored *in loco* by command-and-control actions.

Our finding that smallholders (< 100 ha) contributed less to total deforestation through 2018 than other actor types (Table 3) is in line with results from studies for Brazil's Legal Amazon region as a whole. Such studies have estimated deforestation by smallholders in different periods: annual deforestation in 1991 (Fearnside, 1993), cumulative deforestation through 2003 (Pacheco, 2009) and cumulative deforestation through 2011 (Godar et al., 2014). A similar pattern was also found in a local-scale study along the Transamazon Highway, where both the contribution of smallholders to total deforestation through 2007 and the mean clearing per landholding were smaller than for medium and largeholders (Godar et al., 2012a). Our results are also in line with findings indicating that larger and younger landholdings hold more forest than do smaller and older landholdings (Michalski et al., 2010).

Largeholders are the main actors responsible for the expansion of unofficial roads and for deforestation resulting in frontier expansion (Godar et al., 2012a,b). Loggers are also important participants in opening access to the forest by building roads (i.e., "*ramais"*) (Arima et al., 2016). Logging activity can be identified through satellite images in Matupi District (Lima et al., 2019). We also identified logging in Landsat images (2016-2018) and during our fieldwork and, since logging and cattle ranching are the main economic activities in Matupi, it is likely that areas with logging activity could later be converted to pasture.

4.2. Dynamics of patch size by actor type

Our results indicate that smallholders and semi-smallholders have a tendency of increase the size of patches of clearing through the years. Medium landholders did not show any substantial change in the size of patches of clearing, the largeholders' patches showed a fluctuation in size through the intervals analyzed (Table 4). Despite medium landholders and largeholders being able to clear large areas in a single year in comparison to other actors, we observed that, in general, these actors cleared small patches. A few patches larger than 500 ha could be found in medium and large landholdings. A previous study suggested that small increments in clearing (< 25 ha) in medium and large landholdings result in a more fragmented pattern of clearing and could reflect the intention of these actors to avoid the monitoring system

(Assunção et al., 2017). Therefore, if no effective policies to control deforestation exist in these areas, there is a high chance of deforestation spreading in these landholdings.

We suggest that medium and largeholders located far from the consolidated area of deforestation are clearing in small patches either in order to indicate land tenure or because they are in the initial process of land occupation. In addition, logging could be occurring before the forest is clearcut for cattle ranching.

4.3. Land categories

Most landholdings were distributed in areas of public land without destination as we expected. However, we also found semi-small, medium and large landholdings with either all or a portion of the landholding located either in protected areas or in an agro-extractivist settlement, despite the restriction on land occupation in these land categories (Table 5 and Fig. 8). In the state of Mato Grosso, the CAR has registered 50 landholdings (370,366 ha) inside conservation units and Indigenous Lands (Roitman et al., 2018). This shows that the CAR has the potential to improve the current policies for monitoring deforestation in the Amazon region and to help identify the intention of occupying land illegally in protected areas with the expectation of receiving land tenure in the future.

Local actors do not know about the existence of the agro-extractivist settlement. Since this area has low governance, semi-smallholders, medium landholders and largeholders have been raising cattle in an area meant only for extractivist activities and where only smallholders should be living.

In the future most of the remaining forest will be restricted to protected areas if the expansion of deforestation in public land without destination proceeds. Another study has shown that municipalities near an area with high deforestation pressure (i.e., the “arc of deforestation”) had more than 55% of their remaining forest restricted to conservation units and that clearing was occurring inside these areas because forest outside of conservation units had almost all been cleared (Rosa et al., 2017).

4.4. Environmental implications and future studies

The speed of clearing is distinct among the actors and, as we found that most of the forest cover in small and semi-small landholdings has already been cleared, our main concern is about the remaining forest in areas of medium and largeholders. Since they are wealthier than small and semi-small landholders, a high rate of deforestation is expected when these actors decide to expand their pasture areas. The size of a landholding is a key to indicating the deforestation pattern in terms of rate and the size of the area cleared per year. How the actors use the land has a substantial effect on the amount of forest available for clearing through time (D'Antona et al., 2006; Michalski et al., 2010).

It is important to consider that a large actor can divide the landholding into small areas and sell them to smallholders, or, alternatively, a largeholder can buy multiple small landholdings and transform them into a single large landholding (Aldrich et al., 2006). The area occupied by an average largeholder (landholding > 1500 ha, mean: 2219 ha) in our study area represents the occupation of 28 smallholders (landholding <100 ha, mean: 77 ha) or 9 semi-smallholders (landholding 100-400 ha, mean: 228 ha). Similarly, in Pará State an average landholding occupied by a large-scale cattle rancher (1850 ha, properties > 600 ha) is equivalent to the space occupied by 25 smallholder families (< 100 ha) (Godar et al., 2012a).

Deforestation actors can change their clearing behavior if the incentives for clearing are removed. Measures that can discourage deforestation include cutting subsidized credit given to pasture, stopping the "regularization" of land claims, and punishing actors who clear illegally (Fearnside, 2008b, 2017).

Converting the forest to pasture is not an indication of "development" because the portion of actors benefited per unit area cleared is very low and this deforestation does little or nothing to increase the wellbeing of local populations (Fearnside, 2017). Alternatives for the local population include mechanisms to reward the forest's environmental services in order to maintain the large carbon stock in landholdings in the state of Amazonas, which is the state with the largest carbon stock in Legal Amazonia (Nogueira et al., 2015).

One challenge is to identify the potential locations where the main deforestation actors will be spatially distributed in areas of frontier expansion. This is needed if strategic policies to halt the spread of deforestation are to be developed for new frontier areas. Future studies are needed to assess deforestation specifically in the "legal reserves" (*reservas legais*) and "areas of permanent preservation" (*áreas de preservação permanente*) of the various types of landholdings. The “legal reserve” is an area that Brazil’s Forest Code (Law 12,651 of 2012, replacing Law 4771 of 1965) requires to be maintained in forest in each rural property, and the “area of permanent preservation” is an area where the Forest Code requires forest to be maintained along watercourses and on steep hillsides. Enforcement of the Forest Code is a central part of Brazil’s efforts to contain deforestation (West et al., 2019).

5. Conclusions

By identifying who the actors are and how these actors’ landholdings are distributed spatially in relation to roads and to previous clearings helps to identify the actor types that have contributed most to deforestation in the past and those that are likely to be the major deforestation actors in the coming years.

In our study area the landholdings occupied by smallholders and semi-smallholders showed high percentages of clearing. The proximity of their landholdings to the main road and the increase of clearing patch size through the years contribute to consolidating the deforested areas in most of the small and semi-small landholdings.

In contrast, medium and large landholders are more spread out in the landscape and, in general, are located far from previously cleared areas. Thus, the landholdings occupied by these actors still have large percentages of forest cover. Medium and large landholders who are located close to the main road had greater deforestation rates and larger total clearing than did those at greater distance from the main road.

The rate of deforestation and the size of clearing patches depend on the types of the actors who move into the remaining forest. In our case, medium and large landholders will likely be the major potential actors in future deforestation if policies to control deforestation are not properly implemented.

Acknowledgments

We thank the National Institute for Research in Amazonia (INPA) (PRJ15.125), the National Institute of Science and Technology for the Environmental Services of Amazonia (INCT-SERVAMB), the National Council for Scientific and Technological Development (CNPq Proc. 573810/2008-7, 610042/2009-2), the Foundation for the Support of Research of the state of Amazonas (FAPEAM Proc. 708565) and the Brazilian Research Network on Climate Change

(RedeClima) for financial and logistical support. The National Institute for Space Research (INPE) provided logistical support during the time that the first author spent at that institute processing and analyzing part of the data. Ana Paula Rezende of IDESAM (Institute for the Conservation and Sustainable Development of Amazonia) provided guidance for the fieldwork, and INCRA provided the 2011 Matupi settlement dataset. This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) (Finance Code 001).

References

Aldrich, S.P., Walker, R.T., Arima, E.Y., Caldas, M.M., Browder, J.O., Perz, S. 2006. Land-cover and land-use change in the Brazilian Amazon: Smallholders, ranchers, and frontier stratification. Economic Geography 82(3), 265-288. https://doi.org/10.1111/j.1944-8287.2006.tb00311.x

Arima, E.Y., Walker, R.T., Perz, S., Souza Jr, C. 2016. Explaining the fragmentation in the Brazilian Amazonian forest. Journal of Land Use Science 11(3), 257-277. https://doi.org/10.1080/1747423X.2015.1027797

Assunção, J., Gandour, C., Pessoa, P., Rocha, R. 2017. Property-level assessment of change in forest clearing patterns: The need for tailoring policy in the Amazon. Land Use Policy 66, 18-27. https://doi.org/10.1016/j.landusepol.2017.04.022

Barber, C.P., Cochrane, M.A., Souza Jr, C.M., Laurance, W.F. 2014. Roads, deforestation, and the mitigating effect of protected areas in the Amazon. Biological Conservation 177, 203-209. https://doi.org/10.1016/j.biocon.2014.07.004

Bowman, M.S., Soares-Filho, B.S., Merry, F. D., Nepstad, D.C., Rodrigues, H., Almeida, O.T. 2012. Persistence of cattle ranching in the Brazilian Amazon: A spatial analysis of the rationale for beef production. Land Use Policy 29(3), 558-568. https://doi.org/10.1016/j.landusepol.2011.09.009

Brazil, INCRA (Instituto Nacional de Colonização e Reforma Agrária). 2018a. Acervo fundiário do INCRA. http://acervofundiario.incra.gov.br/i3geo/geodados/AMAZONAS/ (Last access 23 August 2018).

Brazil, INCRA (Instituto Nacional de Colonização e Reforma Agrária). 2018b. SIGEF (Sistema de Gestão Fundiária). https://sigef.incra.gov.br/ (Last access 30 October 2018).

Brazil, INPE (Instituto Nacional de Pesquisas Espaciais). 2015. Nota Técnica – Correção da máscara do PRODES. http://www.obt.inpe.br/prodes/NT_deslocamentoMascara.pdf. (Last access 19 August 2019).

Brazil, INPE (Instituto Nacional de Pesquisas Espaciais), 2018. Projeto PRODES - Monitoramento da Floresta Amazônica Brasileira por Satélite. INPE, São José dos Campos, SP., Brazil. http://www.dpi.inpe.br/prodesdigital/ (Last access 8 June 2018).

Brazil, INPE (Instituto Nacional de Pesquisas Espaciais). 2019a. Projeto PRODES Digital. INPE, São José dos Campos, SP, Brazil. http://www.dpi.inpe.br/prodesdigital/prodesmunicipal.php (Last Access 19 July 2019).

Brazil, INPE (Instituto Nacional de Pesquisas Espaciais). 2019b. Projeto PRODES – Monitoramento da Floresta Amazônica Brasileira por Satélite. INPE, São José dos Campos, SP, Brazil. http://www.obt.inpe.br/prodes/dashboard/prodes-rates.html (Last Access 19 July 2019).

Brazil, INPE (Instituto Nacional de Pesquisas Espaciais). 2019c. Alertas do DETER na Amazônia em junho somam 2.072,03 km². INPE, São José dos Campos, SP, Brazil. http://www.inpe.br/noticias/noticia.php?Cod_Noticia=5147 (Last Access 19 July 2019).

Brazil, SFB (Serviço Florestal Brasileiro). 2018. Cadastro Ambiental Rural (CAR). SFB, Brasília, DF, Brazil. http://www.car.gov.br/publico/imoveis/index (Last access 1 November 2018).

Brazil, SBF (Serviço Florestal Brasileiro). 2019. Cadastro Ambiental Rural – CAR (Cartilha Orientações Básicas). SFB, Brasília, DF, Brazil. http://www.florestal.gov.br/publicacoes/504-cadastro-ambiental-rural-car-orientacoes-basicas (Last Access 18 August 2019).

Breiman, L. 2001. Random forests. Machine Learning 45(1), 5-32. https://doi.org/10.1023/A:1010933404324

Brown, D.S., Brown, J.C., Brown, C. 2016. Land occupations and deforestation in the Brazilian Amazon. Land Use Policy 54, 331-338. https://doi.org/10.1016/j.landusepol.2016.02.003

Calcagno, V., de Mazancourt, C. 2010. glmulti: An R package for easy automated model selection with (generalized) linear models. Journal of Statistical Software 34(12), 1-29. https://doi.org/10.18637/jss.v034.i12.

Carrero G.C., Fearnside P.M. 2011. Forest clearing dynamics and the expansion of landholdings in Apuí, a deforestation hotspot on Brazil's Transamazon Highway. Ecol. Soc. 16(2), art. 26. http://www.ecologyandsociety.org/vol16/iss2/art26/ (Last access 8 June 2018).

D'Antona, Á.O., VanWey, L.K., Hayashi, C.M. 2006. Property size and land cover change in the Brazilian Amazon. Population and Environment 27(5-6), 373-396. https://doi.org/10.1007/s11111-006-0031-4

dos Santos Silva, M.P., Câmara, G., Escada, M.I.S., Souza, R.C.M. 2008. Remote-sensing image mining: Detecting agents of land-use change in tropical forest areas. Int. J. Remote Sens. 29, 4803-4822. https://doi.org/10.1080/01431160801950634

Fearnside, P.M. 1993. Deforestation in Brazilian Amazonia: The effect of population and land tenure. Ambio 22(8), 537-545.

Fearnside, P.M. 2008a. Amazon forest maintenance as a source of environmental services. Anais da Academia Brasileira de Ciências 80, 101-114. https://doi.org/10.1590/S0001-37652008000100006

Fearnside, P.M. 2008b. The roles and movements of actors in the deforestation of Brazilian Amazonia. Ecology and Society 13, art. 23. http://www.ecologyandsociety.org/vol13/iss1/art23/. (Last access 8 June 2018).

Fearnside, P.M. 2017. Deforestation of the Brazilian Amazon. In: H. Shugart (Ed.) Oxford Research Encyclopedia of Environmental Science. Oxford University Press, New York, USA. https://doi.org/10.1093/acrefore/9780199389414.013.102

Foley, J.A., Asner, G.P., Costa, M.H., Coe, M.T., DeFries, R., Gibbs, H.K., Howard, E.A., Olson, S., Patz, J., Ramankutty, N. Snyder, P. 2007. Amazonia revealed: Forest degradation and loss of ecosystem goods and services in the Amazon Basin. Frontiers in Ecology and the Environment 5, 25-32. https://doi.org/10.1890/1540-9295(2007)5[25:ARFDAL]2.0.CO;2

Godar, J., Tizado, E.J., Pokorny, B., Johnson, J. 2012a. Who is responsible for deforestation in the Amazon? A spatially explicit analysis along the Transamazon Highway in Brazil. For. Ecol. Manage. 267, 58-73. https://doi.org/10.1016/j.foreco.2011.11.046

Godar, J., Tizado, E.J., Pokorny, B., Johnson, J. 2012b. Typology and characterization of Amazon colonists: A case study along the Transamazon Highway. Human Ecology 40, 251-267. https://doi.org/10.1007/s10745-012-9457-8

Godar, J., Gardner, T.A., Tizado, E.J., Pacheco, P. 2014. Actor-specific contributions to the deforestation slowdown in the Brazilian Amazon. Proceedings of the National Academy of Sciences 111(43), 15591-15596. https://doi.org/10.1073/pnas.1322825111

Gollnow, F., Hissa, L.D.B.V., Rufin, P., Lakes, T. 2018. Property-level direct and indirect deforestation for soybean production in the Amazon region of Mato Grosso, Brazil. Land Use Policy 78, 377-385. https://doi.org/10.1016/j.landusepol.2018.07.010

Lima, T.A., Beuchle, R., Langner, A., Grecchi, R.C., Griess, V.C. Achard, F. 2019. Comparing Sentinel-2 MSI and Landsat 8 OLI imagery for monitoring selective logging in the Brazilian Amazon. Remote Sensing 11(8), art. 961. https://doi.org/10.3390/rs11080961

L'Roe, J., Rausch, L., Munger, J., Gibbs, H.K. 2016. Mapping properties to monitor forests: Landholder response to a large environmental registration program in the Brazilian Amazon. Land Use Policy *57*, 193-203. https://doi.org/10.1016/j.landusepol.2016.05.029

Michalski, F., Metzger, J. P., Peres, C.A. 2010. Rural property size drives patterns of upland and riparian forest retention in a tropical deforestation frontier. Glob Environ Change 20(4), 705-712. https://doi.org/10.1016/j.gloenvcha.2010.04.010

Nogueira, E.M., Yanai, A.M., Fonseca, F.O., Fearnside, P.M. 2015. Carbon stock loss from deforestation through 2013 in Brazilian Amazonia. Global Change Biology 21, 1271-1292. https://doi.org/10.1111/gcb.12798

Pacheco, P. 2009. Agrarian reform in the Brazilian Amazon: Its implications for land distribution and deforestation. World Development 37(8), 1337-1347. https://doi.org/10.1016/j.worlddev.2008.08.019

Pacheco, P. 2012. Actor and frontier types in the Brazilian Amazon: Assessing interactions and outcomes associated with frontier expansion. Geoforum 43(4), 864-874. 10.1016/j.geoforum.2012.02.003

Prasad, A.M., Iverson, L.R., Liaw, A. 2006. Newer classification and regression tree techniques: Bagging and random forests for ecological prediction. Ecosystems 9(2), 181–199. https://doi.org/10.1007/s10021-005-0054-1.

Roitman, I., Vieira, L.C.G., Jacobson, T.K.B., da Cunha Bustamante, M.M., Marcondes, N.J.S., Cury, K., Estevam LS., Costa Ribeiro, R.J., Ribeiro, V., Stabile, M.C.C., Miranda Filho, R.J., Avila M.L. 2018. Rural Environmental Registry: An innovative model for land-use and environmental policies. Land Use Policy 76, 95-102. https://doi.org/10.1016/j.landusepol.2018.04.037

Rosa, I.M., Gabriel, C., Carreiras, J.M. 2017. Spatial and temporal dimensions of landscape fragmentation across the Brazilian Amazon. Regional Environmental Change 17(6), 1687-1699. https://doi.org/10.1007/s10113-017-1120-x

Strand, J., Soares-Filho, B., Costa, M.H., Oliveira, U., Ribeiro, S.C., Pires, G.F., Oliveira, A., Rajão, R., May, P., van der Hoff, R., Siikamäki, J., Motta, R.S., Toman, M. 2018. Spatially explicit valuation of the Brazilian Amazon forest's ecosystem services. Nature Sustainability 1(11), 657-664. https://doi.org/10.1038/s41893-018-0175-0

West, T.A.P., Börner, J., Fearnside, P.M. 2019. Climatic benefits from the 2006–2017 avoided deforestation in Amazonian Brazil. Frontiers in Forests and Global Change 2, art. 52. https://doi.org/10.3389/ffgc.2019.00052

Chapter 3

Simulating the deforestation patterns of actors on a cattle-ranching frontier

Aurora Miho Yanai[1], Paulo Maurício Lima de Alencastro Graça[1,3], Maria Isabel Sobral Escada[2], Philip Martin Fearnside[1,3,4]

[1]Department of Environmental Dynamics, National Institute for Research in Amazonia (INPA), Av. André Araújo n° 2936, CEP 69067-375, Manaus, Amazonas, Brazil.

[2]Department of Image Processing, National Institute for Space Research (INPE), Av. Astronautas, n° 1758, CEP 12227-010, São José dos Campos, São Paulo, Brazil

[3]Brazilian Research Network on Climate Change (RedeClima)

[4]Corresponding author

Email addresses: yanai@inpa.gov.br; pmlag@inpa.gov.br; isabel@dpi.inpe.br; pmfearn@inpa.gov.br

Abstract

To better understand the present and future contribution of specific actors on the cattle-ranching frontier along the Transamazon Highway in the southern portion of Brazil's Amazonas State, we simulated the deforestation patterns of actors located inside a settlement project, outside the settlement, in "public land without destination" (*terras devolutas*) and in protected areas. In our model, dynamic feedback occurs independently for each actor type and land category. This represents a more-refined approach as compared to previous studies where the study area was regionalized based on a broader context. Actors were classified based on the area of their landholdings, with those in the settlement project being divided into "non-concentrators" (those with only one lot, or ~100 ha) and "concentrators" of different numbers of lots managed together as a larger landholding. The recent tendency of high deforestation rates (2013-2018) in our study area was considered through two business-as-usual (BAU) scenarios. In the first BAU scenario, we used the deforestation rates in terms of area (BAU Scenario with Absolute Rates, or BAU-SAR) and the second BAU scenario we applied rates in terms of percentage in relation to the area of remaining forest in the landholdings and in the land categories (BAU Scenario with Relative Rates, or BAU-SRR). The results showed that in both scenarios deforestation increased substantially through 2050. In the BAU-SRR deforestation increased more gradually in than in the BAU-SAR. Most of the remaining forest of non-concentrators, concentrators of 2 lots and concentrators of 3 and 4 lots in the Matupi settlement showed a substantial reduction by 2050. Outside of the settlement, similar reduction occurred for smallholders (landholdings < 100 ha) and semi-smallholders (landholdings of 100 – 400 ha) and in areas of public land without destination in the BAU-SAR scenario. In contrast, a concentrator of 10 lots in the Matupi settlement, medium landholders and largeholders and landholdings in protected areas had more than 50% forest cover remaining by 2050. In landholdings in public land without destination 43% of the forest cover remained by 2050 in the BAU-SRR simulation, in contrast to only 10% in the BAU-SAR simulation. By simulating the deforestation patterns of actors who contributed to land-cover change we can have a

more detailed understanding of the deforestation dynamics in the landholdings of the different actors and in different land categories.

1. Introduction

After a decline in annual deforestation rates in Brazil's Legal Amazonia region after 2004 until a low point of 4571 km^2 was reached in 2012, the rates have trended upward, reaching 9762 km^2 in 2019, the highest rate registered in one decade (Brazil, INPE, 2019). The continuing increase in the last years has caused widespread concern over the future of the Amazon forest, mainly in areas with high deforestation pressure, where land occupation by different actors has an important role into advancing the cattle-ranching frontier (Aldrich et al., 2006). It has been estimated that the privatization of public lands in Brazilian Amazonia could promote illegal occupation in over the 70 million hectares in areas of public forest without destination (Azevedo-Ramos and Moutinho, 2018).

The dynamics of deforestation are complex because they represent the actions of different actors. The history of deforestation in Brazilian Amazonia has shown that the behavior of actors is influenced by government policies, which can either control deforestation (e.g., enforcement of laws, restriction of credit access for cattle ranching and expansion of protected areas) (Nepstad et al., 2009, 2014) or encourage deforestation by weakening environmental governance (e.g., reducing or halting command-and-control actions and freezing the creation of new protected areas), as occurred in 2019 (Ferrante and Fearnside, 2019).

Spatially explicit modeling tools allow us to better understand the future deforestation trajectory both in space and through time under different scenarios. Modeling the behavior of actors is needed where the dynamics of deforestation are attributed to different actors who interact with the environment in distinct ways. Despite the importance of models that include actors who contribute to deforestation, only a few studies have considered the actions of actors in the Brazilian Amazon (Deadman et al., 2004; Bell, 2011; West et al., 2018). This is because is a challenge to include human decision-making in models of land-cover change.

We simulated the deforestation patterns of different actors using a systems-dynamics approach that deals with actor categories. The systems-dynamics approach is appropriate for situations where the behavior of a large number of agents is similar (Gilbert, 2008). Thus, in our modeling, the landscape was regionalized where each portion of the landscape area represents an autonomous land unit. The land unit hosting a land cover (e.g., deforestation and forest) and can change due the decision of a human agent (e.g., pasture expansion) (Le et al., 2012).

In the present study we simulate the deforestation patterns of different actor types through two approach to deforestation rates with the aim of answering the question of: how the landscape will change in the landholdings of different actor types on the cattle-ranching frontier if the recent deforestation trend continues.

By modeling the deforestation of different actor types we can gain new insights into the deforestation dynamics in the landholdings and develop specific policies for each type of actor. This information can help in efforts to protect the remaining forest both inside and outside of landholdings, thus avoiding the loss of the environmental services that the forest provides to humans (West et al., 2019).

2. Materials and Methods

2.1. Study area

The study was conducted in the Matupi District, which is an administrative unit of the municipality (county) of Manicoré located in the southern part of Brazil's Amazonas State. Matupi District is located on the Transamazon Highway (BR-230) and is also known as "km 180," which refers to the distance between Matupi and Humaitá. The Transamazon Highway provides a connection to Rondônia State (the major source of population migration) via Highway BR-319 (Manaus - Porto Velho). The study area encompasses a total area of 20,767 km^2 covering portions of Manicoré, Humaitá and Novo Aripuanã municipalities (Fig. 1).

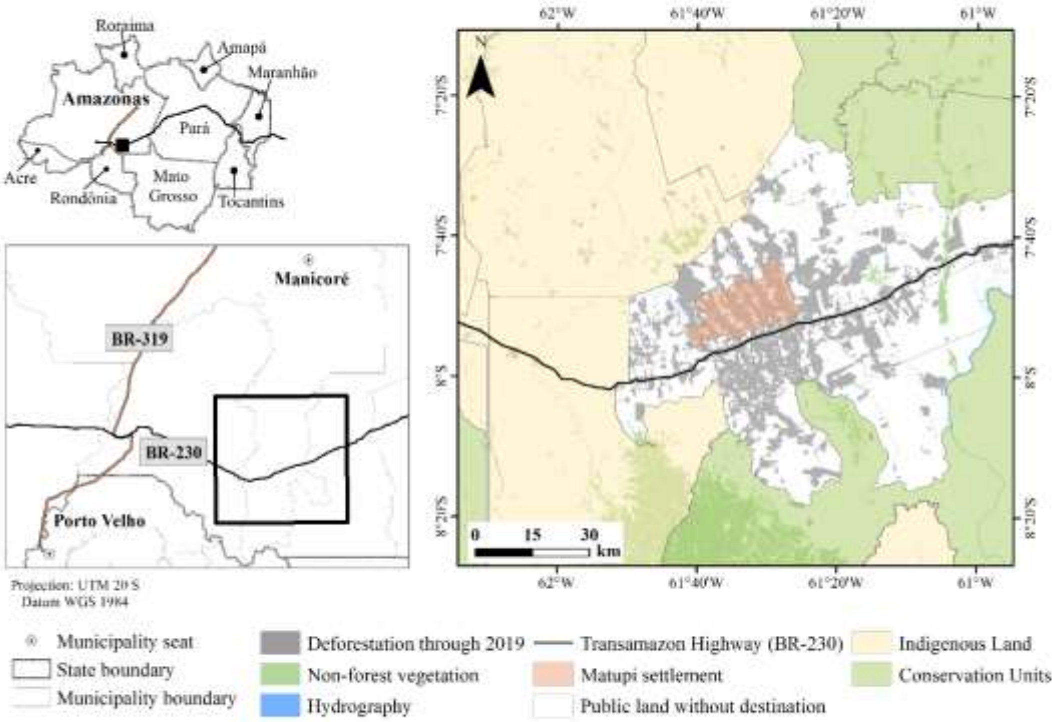


Fig. 1. Study area.

Cattle ranching and logging are the main drivers of deforestation and degradation in the region. The expansion of these economic activities contributed to the local dynamics of deforestation (Fig. S1). Local actors, who come mainly from Rondônia State and from the southern and southeastern regions of Brazil, buy or otherwise occupy land to establish cattle ranches.

The initial occupation process in Matupi District was due the creation of the Matupi settlement project along the Transamazon Highway in 1992, although the occupation only started in 1995 (da Silva et al., 2011). Along with the occupation of the Matupi settlement, areas of public land without destination surrounding the Transamazon Highway also began to be occupied during this time, and deforestation began expanding both inside and outside of the settlement.

To reduce the pressure of deforestation on the remaining forest, protected areas were created in the surrounding area of Matupi District. Indigenous Lands were created between 1997 and 2012 and conservation units between 1998 and 2016. Specifically, conservation units in the strict-protection category were created in 2006 (a national park) and in 2016 (a biological reserve). Conservation units in the sustainable-use category were created in 1998 and 2016 (national forests) and in 2016 (an environmental protection area). A part of an agro-extractivist settlement (9% or 934 km^2) is encompassed in the study area. This type of settlement focused on the traditional population to promote activities related to agro-extractivism and forest management. However, the same types of actors found in public land without destination can also be found in the agro-extractivist settlement.

2.2. Modeling framework and input dataset

The steps in simulating the deforestation patterns of each actor type and in each land category are described in Figure 2.

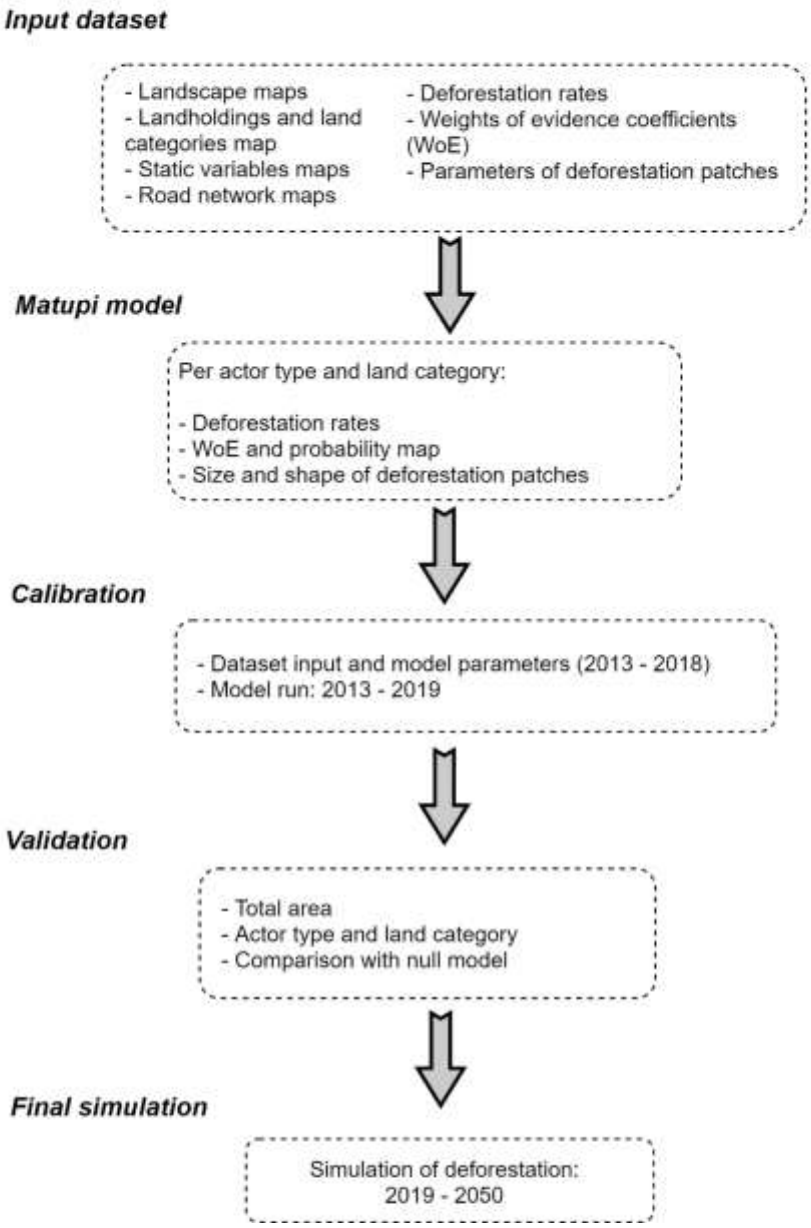


Fig. 2. Framework describing steps of the modeling for each actor type and land category.

We simulated deforestation of actors located in the (i) Matupi settlement based on the identification of actors who concentrated lots, (ii) outside of the settlement based on the landholding size and (iii) land categories for deforestation patterns of unknown actors, which refers to a mix of actors similar to those located outside of the settlement. However, since we could not identify the specific location and landholding boundaries of these actors, we simulate the general deforestation patterns in each land category (Fig. 3).

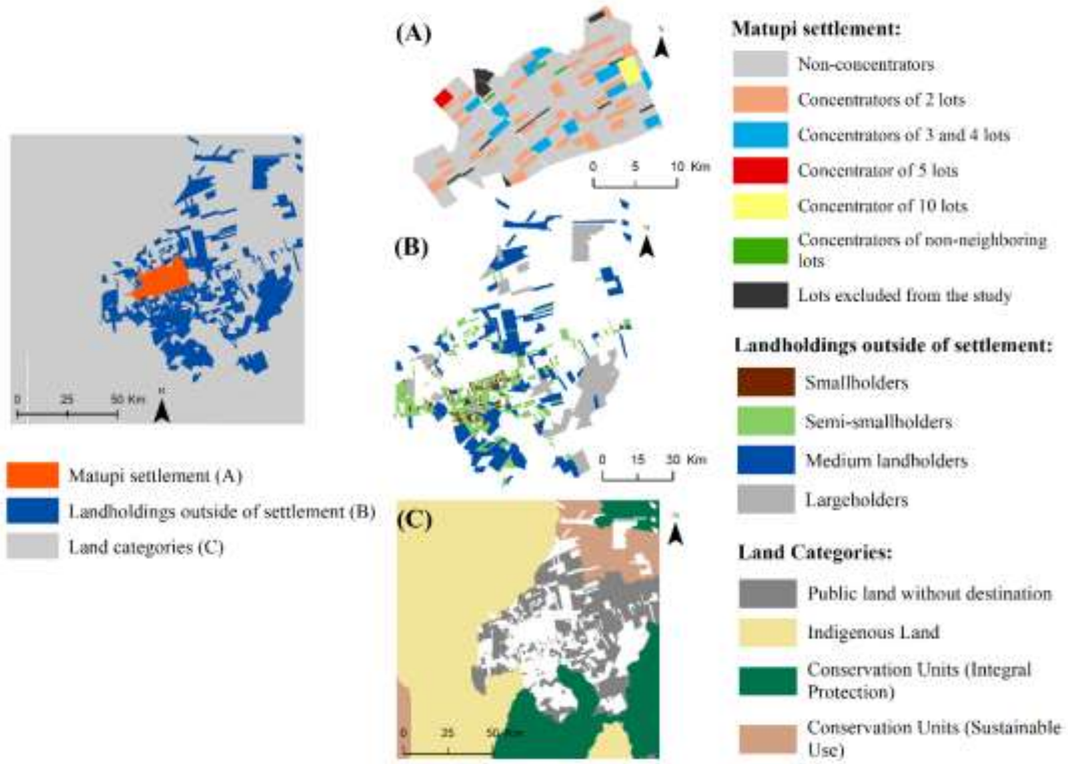


Fig. 3. Spatial distribution of actors landholdings and of land categories: (A) actors in the Matupi settlement based on the lots concentration. We excluded lots for which we have no information. (B) actors located outside of the settlement and (C) unknown actors located in the different land category types.

The input dataset used in the model consisted of biophysical variables, deforestation drivers (e.g., roads and distance to an urban area) and variables that discourage the advance in deforestation to specific areas, such as conservation units and Indigenous Lands. In addition, we have variables to assist the road constructor module in Dinamica-EGO software, where new roads are simulated in each iteration (i.e., in each model time step). Deforestation and the road network are thus updated in each time step of the simulation. The spatial resolution of the maps was 30 m (Table 1).

Table 1. Variables used in the model.

Input maps	Description	Year	Source
Landscape	Land cover map. Classes: forest and deforestation	2013*, 2018* and 2019**	Visual interpretation on the computer screen using Landsat and Resource-Sat images (1994-2019)
Roads	Main road: Transamazon Highway; Secondary roads: settlement access roads (*vicinais*) and logging roads	2013* and 2019**	
Landholdings and land categories	Regionalization of the study area based on the actor's spatial distribution and land categories	2011: Matupi settlement; 2018: landholdings and land categories	- Lots updated based on the field occupation survey collected in 2011; - Landholdings based on the CAR dataset (Brazil, SFB, 2018); - Conservation Units (Brazil, ICMBIO, 2016) Indigenous Lands (Brazil, FUNAI, 2015). Available at: http://www.funai.gov.br/index.php/shape
Elevation	SRTM (Shuttle Radar Topography Mission, NASA)	Obtained in 2016	USGS (https://earthexplorer.usgs.gov/)
Slope	Derived by elevation (SRTM)		
Protected areas	• Conservation Units of sustainable use and integral protection • Indigenous Lands	Obtained in 2015 and 2016	- Conservation Units (Brazil, ICMBIO, 2016) - Indigenous Lands (Brazil, FUNAI, 2015).
Soils	Types of soils in the study area	2015	Brazil, IBGE (2019)
Vegetation	Types of vegetation in the study area	2015	RADAMBRASIL (Brazil, IBGE, 2019)
Distance to Matupi district urban area	Polygon of urban area of Matupi District	2018	INCRA (Brazil, SFB, 2018)
Distance to rivers	Calculated in the Dinamica-EGO based on the river class of landscape map	2018	Maxver classification based on OLI/Landsat-8 images
Distance to timber companies	Timber companies (buffer of 500 m)	2016	GPS points obtained during the field work
Inputs for the road constructor module			
Attractivity	High values in Public lands and low values in protected areas and in the Matupi settlement (ranged between 0 and 100).	-	Based on the land-category classes
Friction	High values in protected areas and low values in public lands and in the Matupi settlement (ranged between 0 and 200).	-	Based on the land category classes

* Calibration and validation phases;
** Final simulation phase.

The maps of landholdings and land categories were produce based on the previous studies in the Matupi settlement (Chapter 1) and outside of the settlement (Chapter 2). In the Matupi settlement, we found actors who do not concentrate lots and actors who concentrate between 2 and 10 lots (Fig. 3a). The concentration was done by individuals or by members of the same family that live together or in neighboring lots and the clearing is done together; each type of actor in Matupi settlement has a distinct deforestation dynamic (Fig. S2).

Actors located outside of the settlement were identified spatially based on the dataset of landholdings in the Rural Environmental Registry (CAR = *Cadastro Ambiental Rural*) (Brazil, SFB, 2018), INCRA's catalog of agrarian landholdings (*Acervo fundiário*) and the SIGEF (*Sistema de Gestão Fundiária*) (Brazil, INCRA, 2018a), which is the system with which INCRA manages agrarian information (Brazil, INCRA, 2018b). The identification on actors was based on the sizes of landholding based on the number of fiscal modules (in our study area is 100 ha per fiscal module). Smallholders represent actors with landholdings <100 ha; Semi-smallholders (100 - 400 ha); Medium landholders (>400 - 1500 ha) and largeholders (>1500 ha) (Fig. 3b). The deforestation dynamic of each actor type is shown in Fig. S3.

The remainder of the study area was regionalized according to the land category. These categories were public land without destination and protected areas (Indigenous Land and Conservation Units) (Fig. 3c).

A part of an agro-extractivist settlement is included in our study area, but we merged this area with the area of public land without destination since we observed during the field work (2016 and 2018) and in a previous analysis (Yanai et al., in review, see Chapter 2) that deforestation patterns and actors in the agro-extractivist settlement were similar to those in public land without destination. This procedure also contributed to reducing the time for model processing.

2.3. Matupi model

The Matupi model was developed in the Dinamica-EGO platform, which uses the cellular automata approach and the Bayesian probability method. The premise of models based on cellular automata is that it is possible to represent a complex pattern by modeling the following components: (i) cell space; (ii) cell state; (iii) neighborhood and (iv) transition rule (Deadman et al., 1993). In our study the transition is forest to deforestation. Thus, the spatial configuration of deforestation is defined by a set of transition rules that determine the attribute of a given cell, which also influences its neighboring cells. The Bayesian approach assists in determining the allocation of transition probabilities similar to a predictor pattern, which is based on the weights-of-evidence (WoE) coefficient (Deng et al., 2010). The spatial probability maps show the area of forest that is most favorable to being cleared, and it is updated in each iteration in the model in accord with the simulated expansion of deforestation.

The Matupi model uses the concept of "region," which means that the study area was divided into different areas to run independently, and at the end of each time step all regions are merged. The regions of our study area represent the area occupied by different types of actors (Fig. 3). Thus, in the model the dynamic feedback occurs independently for each actor type and land category. This represents a more-refined approach as compared to previous studies where the study area was regionalized based on a broader context, for example, based on road density, land categories and areas with influence of roads (Ramos et al., 2018; Roriz et al., 2017). In the present study, deforestation rates, probability maps and the sizes and shapes of deforestation patches were specified for each actor type and land category (Fig. 4).

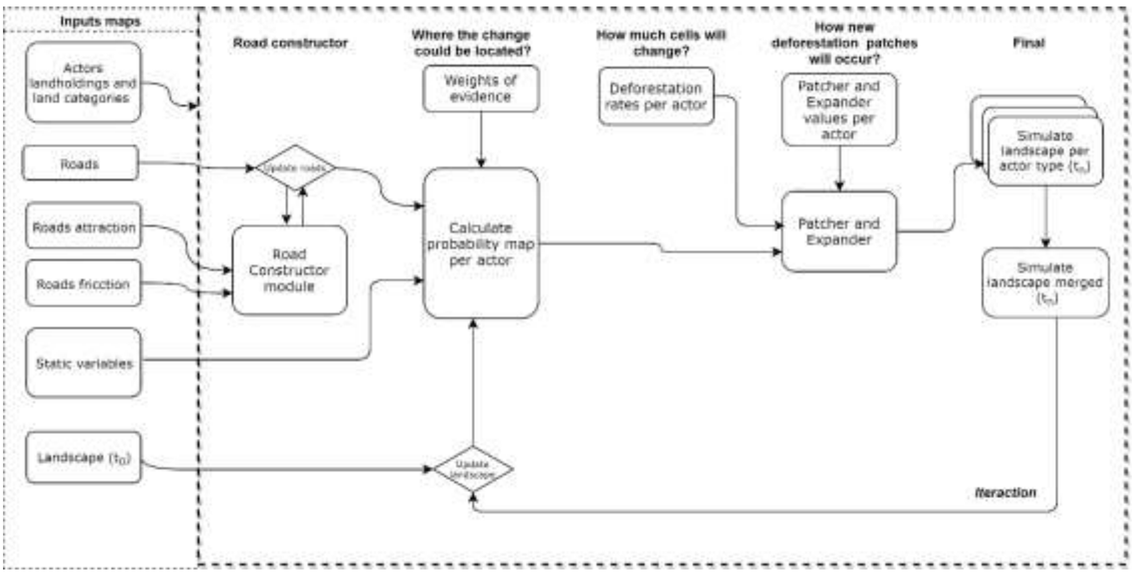


Fig. 4. Modeling framework based on the deforestation actors in Dinamica-EGO.

2.3.1. Matupi scenarios

To test model performance, we ran two scenarios considering the deforestation pattern from 2013 to 2018, which refers to the calibration and validation phases. Thus, both scenarios encompass the recent trend of increasing deforestation rates in the Matupi region (Fig. S1, S2, S3 and S4). The major difference between the scenarios is that the first scenario used deforestation rates in terms of absolute area cleared (ha^{-1} $year^{-1}$), which means that in each year the model tried to convert the same amount of forest area to deforestation. This approach represents actors as not slowing their annual deforestation rates in terms of area as long as there is enough remaining forest to be cleared.

The second scenario used a percentage of clearing (i.e., relative rates) in relation to the remaining forest area (forest area × %cleared/100). Thus, in each year a relative amount of forest was converted to deforestation. In this scenario there is a reduction in the area cleared per year over the course of the simulation as a result of the decreasing area of remaining forest. It represents actors as slowing their clearing with the decrease of the remaining forest available to be clear. This is the default pattern that models in Dinamica-EGO use to calculate the land-use and cover change rates and is applied in the simulation scenarios.

We named the first scenario “Business-as-usual scenario with absolute rates” (BAU-SAR) and the second scenario “Business-as-usual scenario with relative rates” (BAU-SRR). Both scenarios follow the premises: (i) deforestation follows the recent trend of high deforestation rates; (ii) the deforestation pattern (i.e., size and shape of patches) of each actor type and land category follows the recent pattern observed in the landholdings and land categories; (iii) the weakening of environmental enforcement (e.g., command-and-control actions), freezing the creation of new protected areas and the absence of compliance with the Forest Code by 2050. The weakening of the environmental governance in the current political context in the Brazil has been reported by previous studies (Brito et al., 2019; Ferrante and Fearnside, 2019).

2.3.1. Rates of deforestation

We estimated deforestation rates in terms absolute amount (i.e., number of cells of forest cleared every year) based on the mean of cells cleared from 2013 to 2018. The rates were estimated for each actor type and land category and were used in the BAU scenario with absolute rates (BAU-SAR). For the BAU scenario with relative rates (BAU-SRR) we ran the transition matrix model provided by Dinamica-EGO to obtain the mean percentage of forest loss per year between 2013 and 2018 (Table 2).

Table 2. Deforestation rates for each category in the model.

Actor types and land categories	BAU-SAR: absolute rates 2013-2018 (area in ha)	BAU-SRR: relative rates 2013-2018 (%)*
Non-concentrators	761.6	9.66%
Concentrators of 2 lots	125.6	7.86%
Concentrators of 3 and 4 lots	48.2	6.17%
Concentrator of 5 lots	2.3	1.58%
Concentrator of 10 lots	0.3	0.12%
Concentrators of non-neighboring lots	2.0	5.41%
Smallholders	215.1	7.62%
Semi-smallholders	1,772.1	4.45%
Medium landholders	1,430.9	1.48%
Largeholders	450.5	0.69%
Public Land	6,599.6	2.67%
Indigenous Land	57.6	0.01%
Conservation Unit of Strict Protection	104.2	0.06%
Conservation Unit of Sustainable Use	34.2	0.01%

*This rate represents the percentage of remaining forest class that will be converted in deforestation

In the BAU-SAR simulation, the deforestation rates were constant, which means that if there is enough remaining forest area available to clear by 2050, the same area of forest will be cleared in every model time step. However, if the threshold is reached (i.e., there is not enough forest area to clear as specified), then, the model uses a percentage of deforestation in relation to the remaining forest area. The "percentage of deforestation" refers to deforestation rates estimated by the transition matrix model from landscape maps between 2013 and 2018 for each modeled area, which is the same as is used for BAU-SRR simulation.

In the simulation of the BAU scenario with relative rates (BAU-SRR), we applied the rates obtained from the transition matrix with the aim of comparing these with the absolute rates from the BAU-SAR simulation. Thus, in every model time step a percentage of forest area is cleared based on the values for deforestation rates estimated from the transition rates (Table 2).

2.3.2. Identification of areas favorable to deforestation: Weights-of-Evidence (WoE)

Weights-of-evidence (WoE) are used to produce the probability map for each actor and land category, indicating the forest areas most likely to be cleared each year based on the variables that either attract deforestation (e.g., proximity of roads and areas previously cleared) or inhibit deforestation (e.g., protected areas). WoE values were obtained based on the landscape maps from 2013 to 2018.

One important assumption of WoE is that the variables used to calculate the deforestation probability map should be conditionally independent (Bonham-Carter et al., 1989). We therefore performed a correlation test, which refers to the pairwise tests for all categories using Cramer's coefficient and the Joint Information Uncertainty (Almeida et al., 2003). Thus, the values ranged from 0 (variables are independent) to 1 (total dependence between the variables). If the value is ≥ 0.5, one of the variables should be excluded. Table 3 shows the variables used in the model for each actor type and land category after evaluation of the correlation.

Table 3. Variables for which weights-of-evidence coefficients were used in the model for each actor type and land category. The blank boxes indicate that the variable was excluded because it showed a correlation with another variable.

			Actor types and land categories													
			Non-concentrators	Conc. 2 lots	Conc. 3 and 4 lots	Conc. 5 lots	Conc. 10 lots	Individual conc.	Smallholders	Semi-smallholders	Medium landholders	Largeholders	Public land	Indigenous Lands	Conservation Units Sustainable Use	Conservation Units Strict Protection
Variables	**Distance to**	Secondary roads	●	●	●	●	●	●	●	●	●	●	●	●	●	●
		Deforestation	●	●	●	●	●	●	●	●	●	●	●	●	●	●
		Transamazon Highway	●	●	●	●	●	●	●	●		●	●	●		●
		River		●	●		●	●	●	●	●	●	●	●	●	●
		Timber companies	●	●		●			●	●		●	●		●	
		Urban areas	●	●	●	●	●	●	●	●			●	●	●	●
	Elevation		●	●	●		●		●	●	●	●	●	●	●	●
	Protected areas		×	×	×	×	×	×	×		●		×	×	●	●
	Slope		●	●	●	●	●	●	●	●	●	●	●	●	●	●
	Vegetation		●			●	●		●	●		●	●	●	●	●
	Soil					●	●	●				●				

×: Does not apply in this actor type or land category.

The protected area variable was included in the categories of conservation units because we estimated WoE for all types of "sustainable-use" conservation units (national forest and environmental protection area) and "strict protection" conservation units (national park and biological reserve).

Small landholdings were not found in protected areas and only one semi-small landholding was found in the national forest, but since the protected area variable showed high correlation (>0.5) with many other variables we decided to exclude it. Despite also having largeholders in the protected area, we decided to exclude this variable because test runs of the model to 2050 with and without the protected area WoE indicated no difference in the results for large landholdings located in the protected area.

2.3.3. Sizes and shapes of deforestation patches

Two allocation algorithms (expander and patcher) are responsible for distributing the simulated deforestation patches based on the probability map. The "expander" function is responsible for increasing the boundaries of previously cleared areas. The "patcher" function is initiates new clearing through a seeding mechanism in areas of forest with high probability of being cleared.

Since the majority of the clearing is in the form of expansion of previous patches of deforestation, we established 70% as the percent of change to be allocated through the expansion of deforestation patches, and the rest to be allocated through the formation of new patches of deforestation.

The patcher and expander parameters in the Matupi settlement were estimated based on the previous analyses of deforestation patterns (see Chapter 1) between 2013 and 2016. For non-concentrators the means of the values for the small-irregular and small-geometric patterns were applied. For concentrators of 2 lots we used the small geometric pattern, while concentrators of non-neighboring lots followed the small irregular pattern and concentrators of between 3 and 10 lots followed the large geometric pattern.

For actors outside of the settlement and in the different land categories, the means and variances of patches were estimated based on the period between 2013 and 2018. The variance values used were based on the largest patch size found for each actor and landholding category.

Isometry values range from 0 to 2, where values close to 2 indicate patches that are more compact, and values close to 0 indicate patches that are more elongated (stretched). The isometry values were adjusted by running the model and testing different values until the shapes of the patches approximated those observed on the satellite imagery (Table 4).

Table 4. Parameters of deforestation patches used the model.

Actor type	Transition function parameters: Patcher and Expander		
	Mean (ha)	**Variance (ha)**	**Isometry**
Matupi settlement (2013-2016):			
Non-concentrators	8.6	32.7	1.5
Concentrators of non-neighboring lots	4.2	19.3	1.5
Concentrators of 2 lots	16.6	32.7	1.5
Concentrators of 3 and 4 lots	49.7	104.0	1.5
Concentrator of 5 lots	49.7	104.0	1.05
Concentrator of 10 lots	49.7	104.0	1.5
Landholdings outside the settlement (2013-2018):			
Smallholders	7.4	56.1	1.5
Semi-smallholders	15.3	212.5	1.5
Medium landholders	25.2	505.2	1.05
Largeholders	35.5	360.5	1.05
Land categories (2013-2018):			
Public land	38.5	1,031.3	1.05
Indigenous Land	11.5	93.4	1.5
Conservation Units - Sustainable Use	7.1	43.1	1.2
Conservation Units - Strict Protection	18.2	95.4	1.5

2.4. Model validation

Spatial validation was done using the fuzzy similarity approach, which compares the real increment of deforestation in the landscape (2013-2018) with the simulated deforestation patches for the same period. This comparison is based not only on a cell-by-cell comparison, but also on the cell's neighborhood considering the window size in accord with the cell size used in the landscape map (i.e., the spatial resolution of the map). The validation performed two pairwise comparisons: (i) initial landscape map (2013) × simulated landscape map (2019) and (ii) initial landscape map (2013) × real landscape map (2019) (Hagen, 2003; Almeida et al., 2008). The parameter used to evaluate similarity was set to constant decay, where a value equal to 1 refers to the similarity value if the corresponding cells are found in the search window, and zero if not. We also ran the null model, which refers to a model where all WoE coefficients were set to zero, resulting in random deforestation (Negret et al., 2019). The null model serves as benchmark for judging the strengths and weaknesses of simulation model (Hagen-Sanker and Lajoie, 2008).

The null model was compared to our model with the WoE values fit during the calibration phase. Our model obtained similarity values >51% with a 11 × 11-cell window size (330 m × 330 m) in validations with both absolute and relative rates. This window size represents an area of 10.9 ha based on the spatial resolution of our study (30 m). In contrast, the null model showed an inferior performance, with 51% similarity with absolute rates and 50% with relative rates, both only being achieved with a 27 × 27-cell window size (Fig. 5).

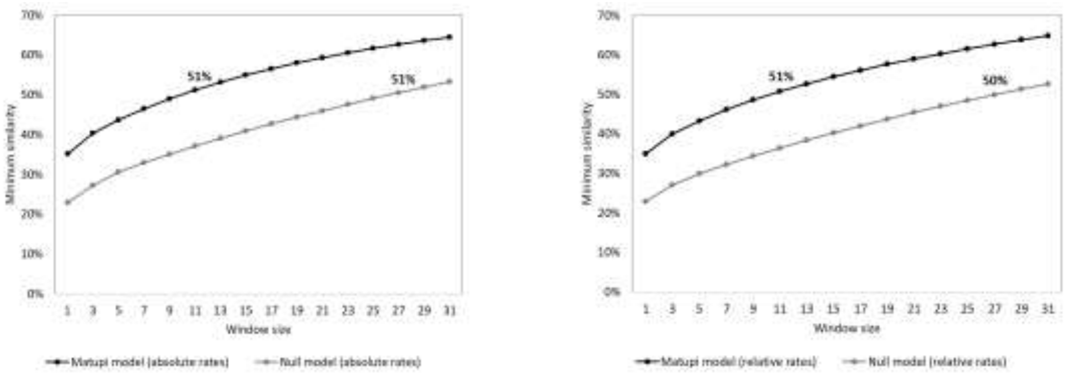


Fig. 5. Minimum similarity in the Matupi model and the null model using absolute rates and relative rates.

We also ran the validation model for each actor type and land category. In general, our model performed better than a null model for each actor type and land category. Only the concentrators of 5 lots in the Matupi settlement showed a better performance in the null model in comparison with our model. For Indigenous Lands and strict-protection conservation units neither of the models reached a minimum similarity ≥50%, but values for our model were better than those of the null model (Tables S1 and S2).

Validation in terms of quantity (i.e., area cleared) between the real and the simulated 2019 landscapes showed that our model overestimated deforestation mainly for largeholders (absolute rates: by 2.4% or 237 ha; relative rates: by 3.4% or 332 ha), and for non-concentrators (absolute rates: by 1.5% or 223 ha) and semi-smallholders (absolute rates: by 0.9% or 311 ha). In contrast, our model underestimated deforestation mainly for medium landholders (absolute rates: by 4.5% or 1201 ha; relative rates: by 4.4% or 1166 ha) and in public land without destination (absolute rates: 6.0% or 5016 ha; relative rates: 4.6% or 3817 ha) (Table S2).

3. Results

The cumulative deforestation through 2019 encompassed 10% (197,211 ha) of the forest area in the entire study area. The simulation showed an increase in deforestation between 2019 and 2050 in the study area of 310,673 ha in the business-as-usual scenario with absolute rates (BAU-SAR) and of 215,604 ha in the business-as-usual scenario with relative rates (BAU-SRR). These values indicate a reduction by 2050 of 18% (BAU-SAR) and 12% (BAU-SRR) in forest cover in the study area as a whole in relation to the remaining forest that was present in the 2019.

Figures 6 and 7 show the distribution of deforestation by 2050 for the study area as a whole, for the Matupi settlement, for public land without destination, and for small, semi-small, medium and large landholdings.

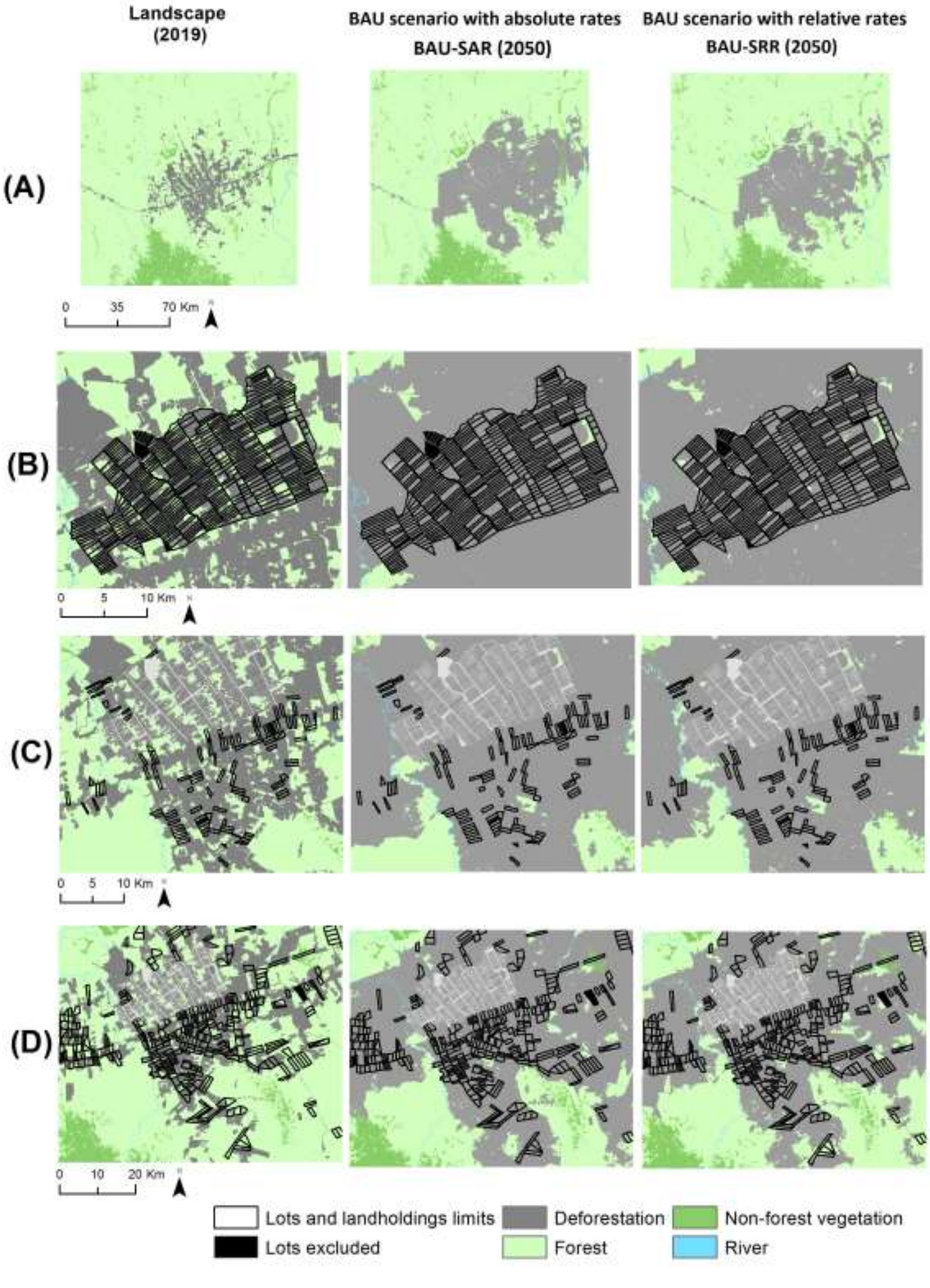


Fig. 6. Deforestation in 2019 (real) and 2050 in simulated scenarios for (A) the study area as a whole, (B) the Matupi settlement, (C) smallholders and (D) semi-smallholders.

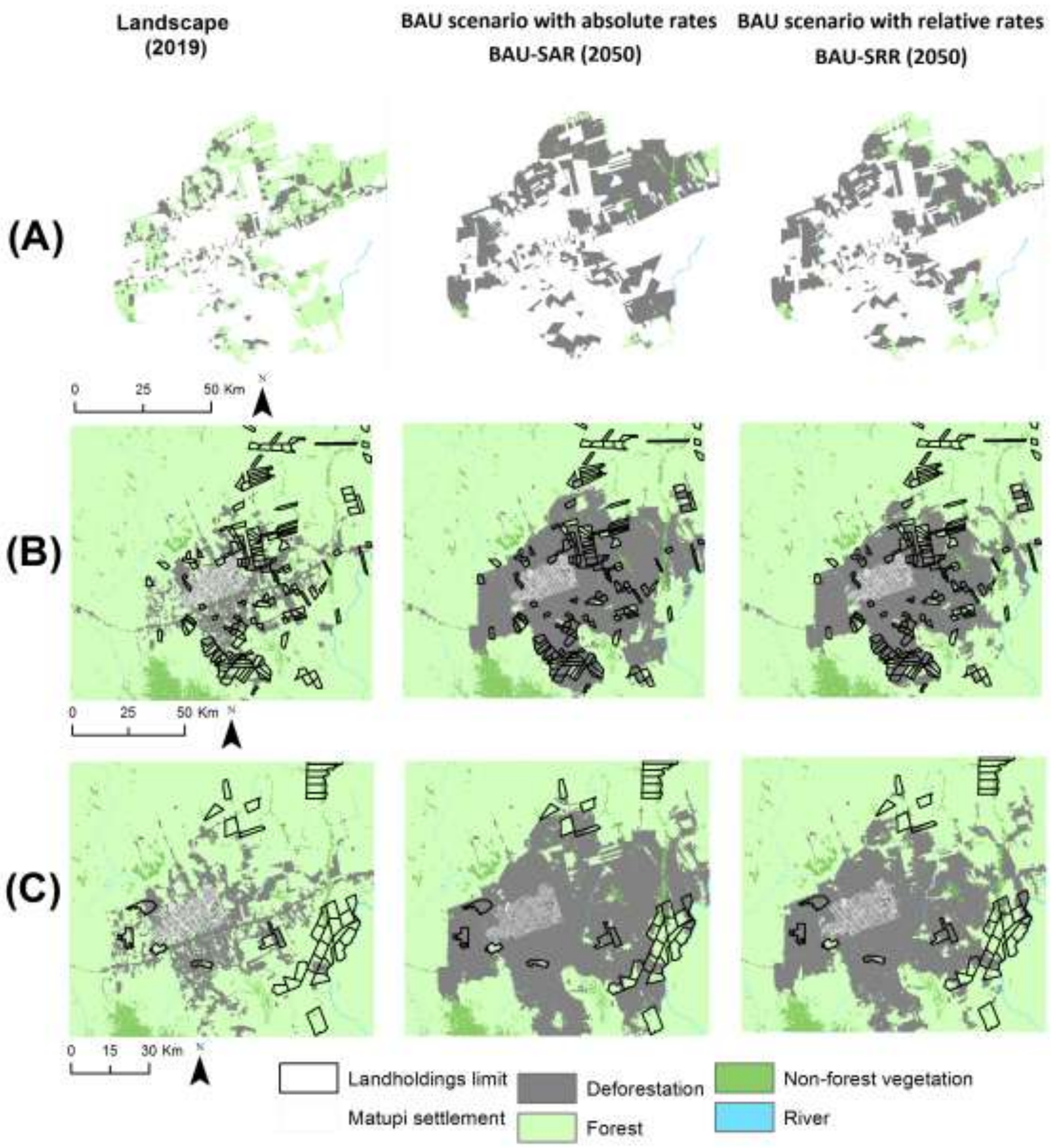


Fig. 7. Deforestation in 2019 (real) and 2050 in simulated scenarios for (A) public land without destination, (B) medium landholders and (C) largeholders.

3.1. Matupi settlement project

Cumulative deforestation through 2019 for actors in the Matupi settlement ranged from 79% or 4636 ha (concentrators of 2 lots) to 65% or 189 ha (the concentrator of 5 lots) in relation to the total forest area in the areas they occupied. Non-concentrators and concentrators of 3 and 4 lots both had 74% (17,509 ha and 2007 ha, respectively) of forest cleared by 2019. The concentrator of 10 lots and concentrators of non-neighboring lots both had 68% (409 ha and 110 ha, respectively) of total forest cleared by 2019.

The simulation showed that the percentage of remaining forest in 2050 in the landholdings of non-concentrators and concentrators of 2, 3 and 4 lots ranged from 1% to 3% in the BAU-SAR and from 4% to 14% in the BAU-SRR. The concentrator of 5 lots and concentrators of non-neighboring lots showed different percentages of remaining forest between the simulations, with a greater portion of forest-cover loss in the BAU-SAR than in the BAU-SRR. In contrast to other actors in the Matupi settlement, the concentrator of 10 lots maintained a very large part of the forest (97%) during the simulation due the deforestation rates used being very low (0.3 ha for the BAU-SAR and 0.12% for the BAU-SRR) (Tables 5 and 6).

Table 5. BAU scenario with absolute rates (BAU-SAR): remaining forest in hectares and in percentages in relation to 2019 for actors in the Matupi settlement.

Actors	Remaining forest (ha)				
	2019	**2020**	**2030**	**2040**	**2050**
Non-concentrators	5,163	4,402 (85%)	359 (7%)	132 (3%)	49 (1%)
Concentrators of 2 lots	1,198	1,072 (90%)	58 (5%)	26 (2%)	12 (1%)
Concentrators of 3 and 4 lots	624	576 (92%)	95 (15%)	28 (4%)	16 (3%)
Concentrator of 5 lots	94	91 (98%)	70 (75%)	48 (52%)	27 (28%)
Concentrator of 10 lots	188	188 (100%)	186 (99%)	185 (98%)	183 (97%)
Concentrators of non-neighboring lots	46	44 (96%)	25 (55%)	6 (14%)	1 (2%)

Table 6. BAU scenario with relative rates (BAU-SRR): remaining forest in hectares and in percentages in relation to 2019 for actors in the Matupi settlement.

Actors	Remaining forest (ha)				
	2019	**2020**	**2030**	**2040**	**2050**
Non-concentrators	5,163	4,665 (90%)	1,690 (33%)	613 (12%)	223 (4%)
Concentrators of 2 lots	1,198	1,104 (92%)	488 (41%)	216 (18%)	96 (8%)
Concentrators of 3 and 4 lots	624	586 (94%)	311 (50%)	165 (26%)	88 (14%)
Concentrator of 5 lots	94	92 (99%)	79 (85%)	69 (73%)	59 (63%)
Concentrator of 10 lots	188	188 (100%)	186 (99%)	185 (98%)	183 (97%)
Concentrators of non-neighboring lots	46	44 (95%)	26 (56%)	15 (34%)	10 (21%)

The deforestation trajectory for non-concentrators in the BAU scenario with absolute rates (BAU-SAR) increased to a peak (in 2025), and in the following years the area cleared remained stable because only a small portion of the forest remained uncleared (< 761 ha), and the model started to use the relative rates from 2013 to 2018 for these actors. For concentrators of 2 lots the peak was reached in 2027, and for concentrators of 3 and 4 lots the peak was reached in the 2031. Concentrators of 5 and 10 lots used the absolute rates (2.3 ha and 0.3 ha per year) throughout the BAU-SAR simulation since there was enough area of remaining forest for the rates be applied up to the end of simulation (Fig. 8).

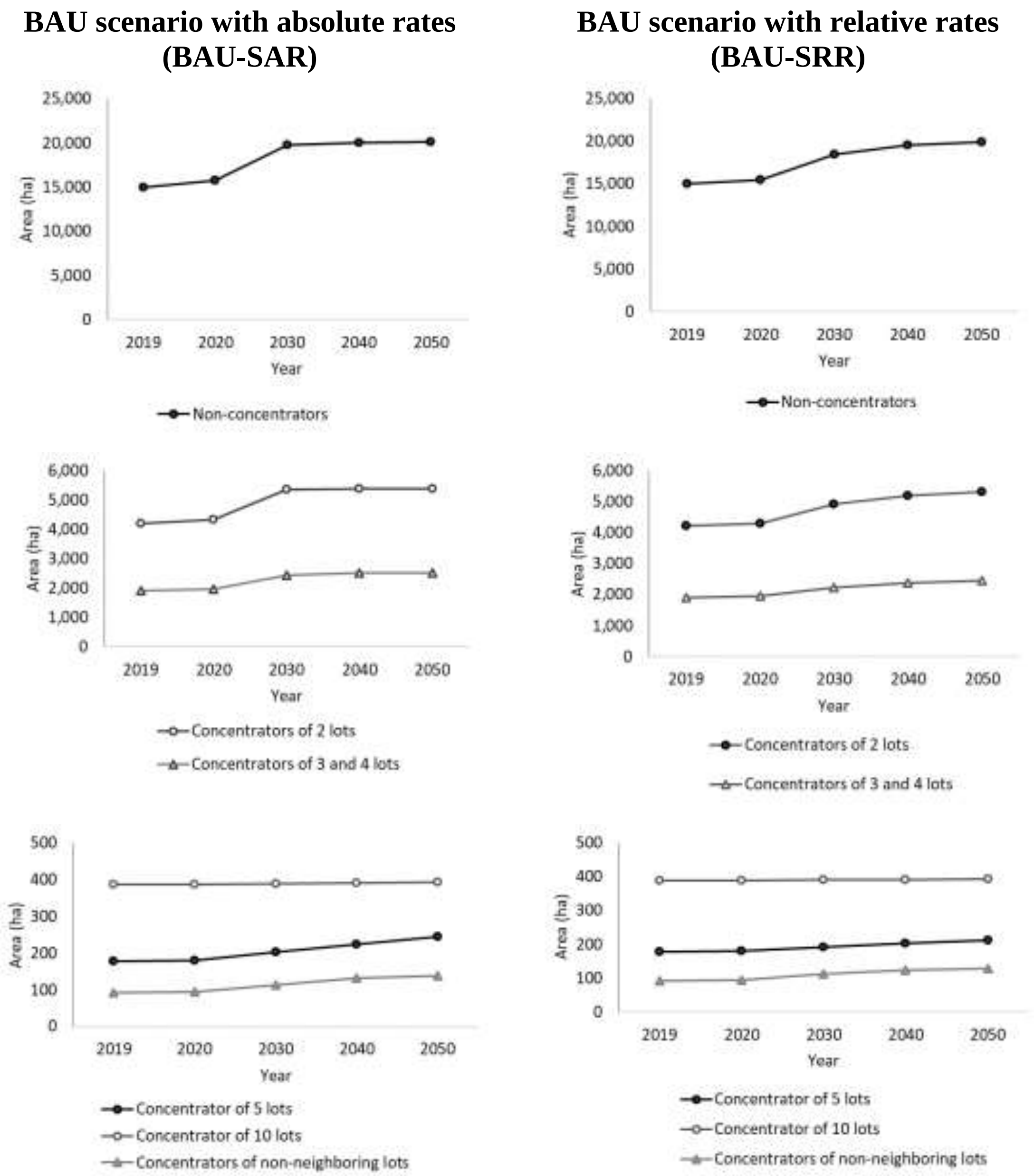


Fig. 8. Cumulative deforestation from 2019 to 2050 in simulated scenarios for each actor type in the Matupi settlement.

3.2. Landholdings outside the Matupi settlement

In the landholdings of smallholders and semi-smallholders the cumulative deforestation by 2019 encompassed more than 50% of the total forest cover in areas occupied by these actors: smallholders (74% or 7488 ha) and semi-smallholders (52% or 38,643 ha). The percentage are lower in medium and large landholdings: medium landholders (23% or 27,728 ha) and largeholders (13% or 9943 ha).

Landholdings occupied by smallholders and semi-smallholders showed more reduction in the percentage of remaining forest through 2050 than in landholdings of medium landholders and largeholders. In the BAU scenario with absolute rates (BAU-SAR) most of the remaining forest in small landholdings had already been cleared by 2030 (97%). In the BAU scenario with relative rates (BAU-SRR) smallholders showed a gradual decrease in forest cover, and by 2050 only 9% (193 ha) of forest remained in the area occupied by this actor type.

Semi-smallholders showed a difference in forest loss between the simulation, where by 2050 only 2% of the forest remained in the BAU-SAR simulation and 24% in the BAU-SRR simulation (Tables 7 and 8). In the BAU-SAR simulation 1772 ha of forest was cleared per year in the semi-small landholdings (Table 2), which contributed to the substantial forest reduction after 2030.

In areas occupied by medium landholders and largeholders, despite the decrease of remaining forest through the years, more than 50% of the forest was still present by 2050 in these actor's landholdings in both scenarios (Tables 7 and 8). Although in every model iteration an area of 1431 ha in the medium landholdings was cleared in the BAU-SAR simulation, this was not enough to result in a substantial reduction of the forest area in the landholdings occupied by these actors (Tables 2 and 8).

Table 7. BAU scenario with absolute rates (BAU-SAR): remaining forest in hectares and in percentages relative to 2019 for actors outside the Matupi settlement.

Actors	Remaining forest (ha)				
	2019	**2020**	**2030**	**2040**	**2050**
Smallholders	2,232	2,017 (90%)	76 (3%)	35 (2%)	17 (1%)
Semi-smallholders	33,161	31,388 (95%)	13,668 (41%)	1,103 (3%)	701 (2%)
Medium landholders	90,991	89,561 (98%)	75,252 (83%)	60,944 (67%)	46,636 (51%)
Largeholders	66,012	65,562 (99%)	61,059 (92%)	56,555 (86%)	52,051 (79%)

Table 8. BAU scenario with relative rates (BAU-SRR): remaining forest in hectares and in percentages relative to 2019 for actors outside the Matupi settlement.

Actors	Remaining forest (ha)				
	2019	2020	2030	2040	2050
Smallholders	2,232	2,062 (92%)	935 (42%)	424 (19%)	193 (9%)
Semi-smallholders	33,161	31,684 (96%)	20,095 (61%)	12,745 (38%)	8,084 (24%)
Medium landholders	90,991	89,646 (99%)	77,235 (85%)	66,542 (73%)	57,330 (63%)
Largeholders	66,012	65,555 (99%)	61,153 (93%)	57,046 (86%)	53,216 (81%)

Semi-smallholders and medium landholders followed similar deforestation patterns, with a substantial deforestation increase after 2020 in both scenarios. Although in the BAU-SAR, deforestation slowed after 2037 because it reached a threshold where the area of forest available for clearing was less than the absolute annual rate (1772 ha year^{-1}). Since in the other scenario (BAU-SRR) deforestation increased gradually in relation to the percentage of remaining forest, we did not see this slowdown, but we observed that cumulative deforestation in 2050 was similar for semi-smallholders and medium landholders: 61,083 ha for semi-small landholdings and 60,191 ha for medium landholdings (Fig. 9).

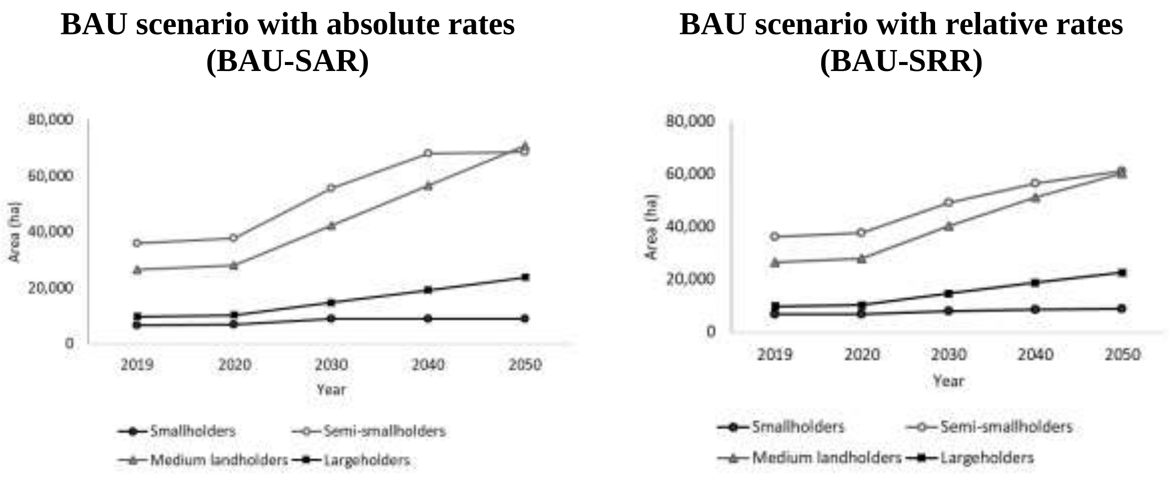


Fig. 9. Cumulative deforestation from 2019 to 2050 in the scenarios simulated in the landholdings outside of the Matupi settlement.

3.3. Land categories

The cumulative deforestation by 2019 in public land without destination represented 26% (78,425 ha) of the total forest area. In protected areas, the total deforestation by 2019 encompassed only 1% of the forest cover for all types of protected areas (Indigenous Lands, sustainable-use conservation units and strict-protection conservation units).

Public land without destination showed a substantial decrease of remaining forest by 2050 in both scenarios, where in SAR simulation only 10% (23,220 ha) of the forest remained by 2050 (Table 9). In contrast, protected areas, did not show a great difference between the scenarios in terms of percentage of remaining forest in 2050 relative to 2019 (Tables 9 and 10).

Table 9. BAU scenario with absolute rates (BAU-SAR): remaining forest in hectares and in percentages relative to 2019 in the different land categories.

Actors	Remaining forest (ha)				
	2019	2020	2030	2040	2050
Public land without destination	227,805	221,205 (97%)	155,210 (68%)	89,215 (39%)	23,220 (10%)
Indigenous Lands	846,582	846,525 (100%)	845,950 (100%)	845,374 (100%)	844,799 (100%)
Conservation Units (Sustainable Use)	187,351	187,247 (100%)	186,206 (99%)	185,164 (99%)	184,123 (98%)
Conservation Units (Strict Protection)	265,279	265,245 (100%)	264,904 (100%)	264,563 (100%)	264,222 (100%)

Table 10. BAU scenario with relative rates (BAU-SRR): remaining forest in hectares and in percentages relative to 2019 in the different land categories.

Actors	Remaining forest (ha)				
	2019	2020	2030	2040	2050
Public land without destination	227,805	221,728 (97%)	169,198 (74%)	129,113 (57%)	98,525 (43%)
Indigenous Lands	846,582	846,526 (100%)	845,968 (100%)	845,411 (100%)	844,853 (100%)
Conservation Units (Sustainable Use)	187,351	187,245 (100%)	186,185 (99%)	185,132 (99%)	184,084 (99%)
Conservation Units (Strict Protection)	265,279	265,244 (100%)	264,889 (100%)	264,535 (100%)	264,181 (100%)

The deforestation trajectory by 2050 in both scenarios was similar, showing an increasing trend after 2020 in public land without destination and in sustainable-use conservation units. Indigenous Lands and strict protection conservation units maintained this trend through the simulated years. Strict-protection conservation units encompassed more deforestation than did those in the sustainable-use category by 2020, but after 2030 the pattern changed, and deforestation started to increase more in the sustainable-use conservation units (Fig. 10). Indigenous Lands showed more cumulative deforestation than did conservation units because of deforestation along the Transamazon Highway located in Indigenous Lands.

BAU scenario with absolute rates (BAU-SAR) **BAU scenario with relative rates (BAU-SRR)**

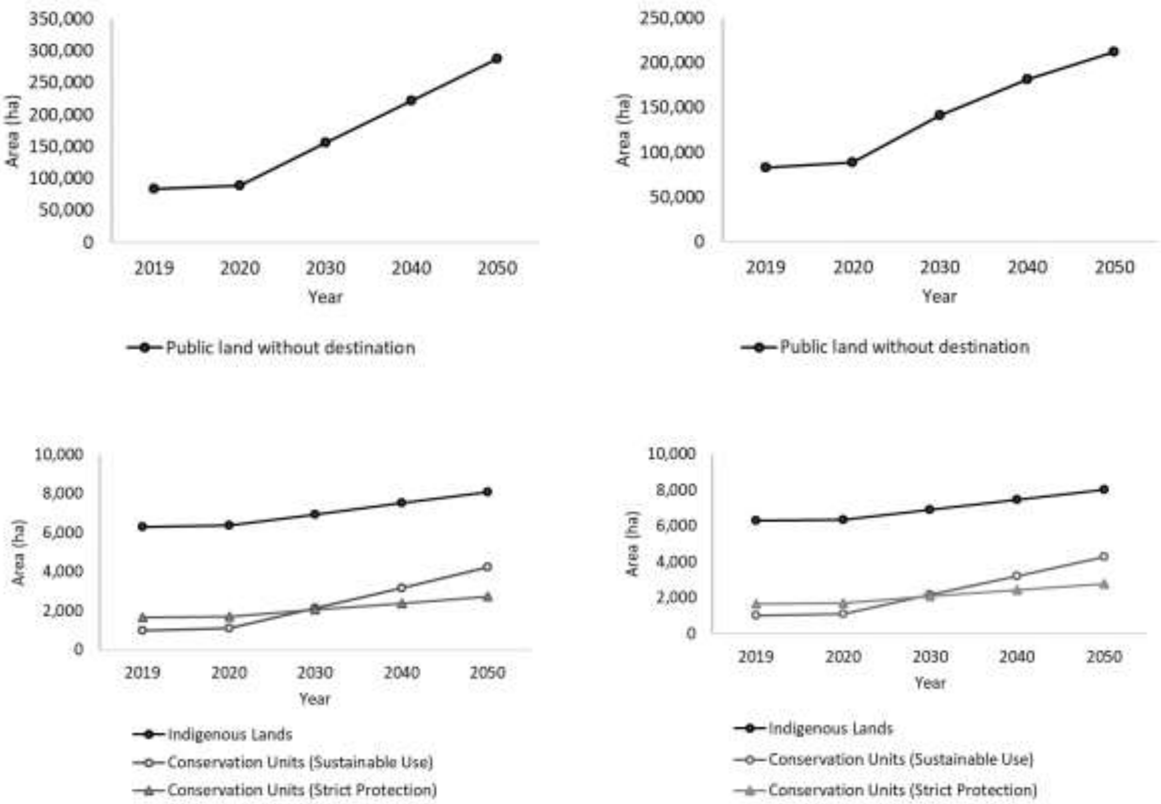


Fig. 10. Cumulative deforestation from 2019 to 2050 in simulated scenarios in the different land categories.

4. Discussion

4.1. Trajectory of deforestation by 2050

Based on the assumption used in our modeling we observed that in general, the business-as-usual scenario with absolute rates (BAU-SAR) has clearing through 2050 that is more intense than in the business-as-usual scenario with relative rates (BAU-SRR) for all actor types and land categories.

The rates of deforestation applied had an important role in amount of forest remaining at the end of the simulation in 2050. Intense deforestation by 2050 was found for actors with high rates, small landholdings and small forest areas in 2019 (i.e., non-concentrators, concentrators of 2 lots, smallholders and semi-smallholders). In addition, the location (e.g., near of previous deforestation and roads) also contributed to consolidate deforestation in the Matupi settlement, small and semi-small landholdings.

In general, actors with large areas of forest in their landholdings in the initial year of the simulation, as in the cases of medium landholders and largeholders, maintained this pattern through the end of simulation. In the case of largeholders, the relative rate (0.7%) applied seemed reasonable, since it was similar to rates observed in other areas that are more consolidated, such as the municipality of Colniza in Mato Grosso State for the period between 2008 and 2018. However, since in our study large landholdings are generally located far from pre-existing deforestation (i.e., consolidated cleared areas), and patches of simulated deforestation were only allocated in landholdings that showed an increment in deforestation during the historical reference period (2013-2018), the probability of clearing is very low for landholdings that did not show change in forest cover during the reference period.

Protected areas and the concentrator of 10 lots were the only land categories that maintained the same percentage of remaining forest from 2019 to 2050. In both scenarios: protected areas still had percentages of remaining forest ranging from 98% to 100% by 2050, and the concentrator of 10 lots maintained 97% forest cover by 2050. Protected areas are important instruments to restraining the advance of deforestation and of illegal land occupation, provided that conservation units and Indigenous Lands have appropriate monitoring law enforcement (Barber et al., 2014).

Another important difference in the simulation was found in areas of public land without destination, where from 2040 to 2050 the percentage of forest in the BAU-SAR simulation decreased from 39% to 10%, while in the BAU-SRR simulation the decrease was more gradual with the percentage of remaining forest decreasing from 57% in 2040 to 43% in 2050 (Tables 9 and 10). This is because in this land category, the absolute deforestation rate was high (6599.6 ha year^{-1}), and this rate was used during all of the simulated years. The simulation in this land category was more general, since the types of landholders are unknown in the public land without destination. If the coverage of the CAR registry in public lands increases in the future, we could include the effects of these actor types and the spatial configuration of simulated deforestation could be different.

The high percentage of forest loss in areas of public land without destination indicates the importance of the government assigning a destination for these areas and not allowing illegal occupation, since deforestation in this area is also associated with land grabbing (*grilagem*) and land conflicts. Landholders have been motivated to increase their deforestation in the present political context in Brazil, which has weakened environmental enforcement, frozen the creation of protected areas and applied policies to encourage occupation (e.g., granting land titles to illegal occupants). The government's promotion of the privatization of public land through the new land law (law 13,465 of July 2017), which grants amnesty to illegal occupations in public land carried out between 2005 and 2011, legalizing areas up to 2500 ha per individual. In addition, the policy has allowed the purchase of public land at prices below market price, which benefits land grabbers (Brito et al., 2019).

Previous studies have suggested areas of public land without destination should be given a designation. For example, Azevedo-Ramos and Moutinho (2018) suggested that a designation such as a settlement or a protected area could be assigned for undesignated forestlands through a detailed study and participatory consultation. But, until then, to protect these areas from land grabbing a moratorium on deforestation in public forest should be instituted. Brito et al. (2019) suggest that in areas of public land without destination the government should recognize the land claims of indigenous peoples, traditional communities and protect land for achieving conservation targets.

4.2. Matupi model limitations and future studies

The limitation of our model is related to the fact that we do not address the actors as individual agents, but as rather perform the analysis at the level of actor types (e.g., smallholders and largeholders). Only the concentrator of 5 lots and the concentrator of 10 lots, which represent two families that concentrate lots, were considered at the level of individuals in our model. Furthermore, the model has no interaction between the actors, which means that a medium landholder could not change to become a largeholder during the simulation.

Future improvement in the model could be achieved with the addition of functions to make the interaction between actors possible. For example, in the Matupi settlement, including the dynamics of large concentrators who buy multiple lots from non-concentrators would make deforestation patches change from small to large over the course of the simulation. In addition, it is important to include information in the model on each landholding legal reserve and area of permanent preservation.

The scenarios in the present study should be considered to be simplifications of the deforestation behavior of the different actors. We only showed a possible deforestation trajectory in the actors' landholdings and in each land category based on the deforestation patterns in recent years.

Future simulations could include a conservation scenario, where there is no clearing in the legal reserve in the landholdings, there is an increase in command-and-control actions that reduce the deforestation rates, and there is a designation of areas of public land without destination promoting the maintenance of forest rather than cattle ranching.

5. Conclusion

Modeling the deforestation patterns of different types of actors allowed us to better to understand and simulate the contributions of these actors to forest-cover loss.

The scenarios represent the future deforestation trajectory if the recent high deforestation rates continue in the coming years, with the rates in the two scenarios being expressed in different ways: in absolute and in relative terms. The business-as-usual scenario with relative rates resulted in a more gradual deforestation increase that slows through the years in comparison with the business-as-usual scenario with absolute rates.

One of the important factors in simulating the deforestation patterns of actors is related to estimating the clearing behavior of these actors in order to inform decision makers and to assist in formulating specific policies for each type of actor, especially those who most accelerate the spread of deforestation on the cattle-ranching frontier. This is needed to reduce deforestation pressure in areas with large amounts of forest and in protected areas.

This type of simulation used here is more refined than previous types, where the deforestation of different actors has been simulated homogeneously. This is due the fact that we can specify rates, probabilities of deforestation allocation and the sizes and shapes of deforestation patches that are specific to each type of actor.

Acknowledgments

We thank the National Institute for Research in Amazonia (INPA) (PRJ15.125), the National Institute of Science and Technology for the Environmental Services of Amazonia (INCT-SERVAMB), the National Council for Scientific and Technological Development (CNPq Proc. 573810/2008-7, 610042/2009-2), the Foundation for the Support of Research of the state of Amazonas (FAPEAM Proc. 708565) and the Brazilian Research Network on Climate Change (RedeClima) for financial and logistical support. The National Institute for Space Research (INPE) provided logistical support during the time that the first author spent at that institute processing and analyzing part of the data. Ana Paula Rezende of IDESAM (Institute for the Conservation and Sustainable Development of Amazonia) provided guidance for the fieldwork, and INCRA provided the 2011 Matupi settlement dataset. This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) (Finance Code 001).

References

Aldrich, S.P., Walker, R.T., Arima, E.Y., Caldas, M.M., Browder, J.O., Perz, S., 2006. Land-cover and land-use change in the Brazilian Amazon: Smallholders, ranchers, and frontier stratification. Econ. Geogr. 82, 265–288. https://doi.org/10.1111/j.1944-8287.2006.tb00311.x

Almeida, C.M., Batty, M., Monteiro, A.M.V., Câmara, G., Soares-Filho, B.S., Cerqueira, G.C., Pennachin, C.L., 2003. Stochastic cellular automata modeling of urban land use dynamics: Empirical development and estimation. Comput. Environ. Urban Syst. 27, 481–509. https://doi.org/10.1016/S0198-9715(02)00042-X

Almeida, C.M., Gleriani, J.M., Castejon, E.F., 2008. Using neural networks and cellular automata for modelling intra-urban land-use dynamics 22, 943–963. https://doi.org/10.1080/13658810701731168

Azevedo-Ramos, C., Moutinho, P., 2018. No man’s land in the Brazilian Amazon: Could undesignated public forests slow Amazon deforestation? Land use policy 73, 125–127. https://doi.org/10.1016/j.landusepol.2018.01.005

Barber, C.P., Cochrane, M.A., Souza Jr, C.M., Laurance, W.F. 2014. Roads, deforestation, and the mitigating effect of protected areas in the Amazon. Biol. Conserv. 177, 203-209. https://doi.org/10.1016/j.biocon.2014.07.004

Bell, A.R., 2011. Environmental licensing and land aggregation: An agent-based approach to understanding ranching and land use in rural Rondônia. Ecol. Soc. 16. https://doi.org/10.5751/ES-03947-160131

Bonham-Carter, G.F., Agterberg, F. P., Wright, D.F., 1989. Weights of evidence modelling: a new approach to mapping mineral potential, in: Agterberg, F P, Bonham-Carter, G.F. (Eds.), Statistical Applications in the Earth Sciences. Geological Survey of Canada, pp. 171–183.

Brazil, INCRA (Instituto Nacional de Colonização e Reforma Agrária). 2018a. Acervo fundiário do INCRA. http://acervofundiario.incra.gov.br/i3geo/geodados/AMAZONAS/ (Last access 23 August 2018).

Brazil, INCRA (Instituto Nacional de Colonização e Reforma Agrária). 2018b. SIGEF (Sistema de Gestão Fundiária). https://sigef.incra.gov.br/ (Last access 30 October 2018).

Brazil, INPE (Instituto Nacional de Pesquisas Espaciais). 2019. Taxas de desmatamento – Amazônia Legal. http://terrabrasilis.dpi.inpe.br/app/dashboard/deforestation/biomes/legal_amazon/increments. (Last access 30 November 2019).

Brazil, SFB (Serviço Florestal Brasileiro). 2018. Cadastro Ambiental Rural (CAR). SFB, Brasília, DF, Brazil. http://www.car.gov.br/publico/imoveis/index (Last access 1 November 2018).

Brito, B., Barreto, P., Brandão, A., Baima, S., Gomes, P.H., 2019. Stimulus for land grabbing and deforestation in the Brazilian Amazon. Environ. Res. Lett. 14, 064018. https://doi.org/10.1088/1748-9326/ab1e24

da Silva, V.V., Vettorazzi, C.A., Padovani, C.R., 2011. Assentamento rural e a dinâmica da paisagem. In: XV Simpósio Brasileiro de Sensoriamento Remoto. Curitiba. Anais do XV Simpósio Brasileiro de Sensoriamento Remoto – SBSR 2011. Instituto Nacional de Pesquisas Espaciais (INPE), São José dos Campos, SP, Brazil. pp. 7000-7006. Available at: http://marte.sid.inpe.br/col/dpi.inpe.br/marte/2011/07.28.19.56/doc/p0539.pdf (Last access 8 June 2018).

Deadman, P., Brown, R., D., 1993. Modelling rural residential settlement patterns with cellular automata. J. Environ. Manage. 37, 147–160. https://doi.org/https://doi.org/10.1006/jema.1993.1011

Deadman, P., Robinson, D., Moran, E., Brondizio, E., 2004. Colonist household decision making and land-use change in the Amazon Rainforest: An agent-based simulation. Environ. Plan. B Plan. Des. 31, 693–709. https://doi.org/10.1068/b3098

Deng, M., 2010. A spatially autocorrelated weights of evidence model. Nat. Resour. Res. 19, 33–44. https://doi.org/10.1007/s11053-009-9107-z

Ferrante, L., Fearnside, P.M., 2019. Brazil's new president and 'ruralists' threaten Amazonia's environment, traditional peoples and the global climate. Environ. Conserv. 1–3. https://doi.org/10.1017/s0376892919000213

Gilbert, N., 2008. Agent-based models (No. 153). Sage. Available at: http://epubs.surrey.ac.uk/1580/1/fulltext.pdf Last access: 21 October 2019

Hagen, A., 2003. Fuzzy set approach to assessing similarity of categorical maps. Int. J. Geogr. Inf. Sci. 17, 235–249. https://doi.org/10.1080/13658810210157822

Hagen-Zanker, A., Lajoie, G., 2008. Neutral models of landscape change as benchmarks in the assessment of model performance. Landsc. Urban Plan. 86, 284–296. https://doi.org/10.1016/j.landurbplan.2008.04.002

Le, Q.B., Seidl, R., Scholz, R.W., 2012. Feedback loops and types of adaptation in the modelling of land-use decisions in an agent-based simulation. Environ. Model. Softw. 27–28, 83–96. https://doi.org/10.1016/j.envsoft.2011.09.002

Negret, P.J., Sonter, L., Watson, J.E.M., Possingham, H.P., Jones, K.R., Suarez, C., Ochoa-Quintero, J.M., Maron, M., 2019. Emerging evidence that armed conflict and coca cultivation influence deforestation patterns. Biol. Conserv. 108176. https://doi.org/10.1016/J.BIOCON.2019.07.021

Nepstad, D., McGrath, D., Stickler, C., Alencar, A., Azevedo, A., Swette, B., Bezerra, T., DiGiano, M., Shimada, J., Da Motta, R.S., Armijo, E., Castello, L., Brando, P., Hansen, M.C., McGrath-Horn, M., Carvalho, O., Hess, L., 2014. Slowing Amazon deforestation through public policy and interventions in beef and soy supply chains. Science. 344, 1118–1123. https://doi.org/10.1126/science.1248525

Nepstad, D., Soares-Filho, B., Merry, F., 2009. The end of deforestation in the Brazilian Amazon SEARCH 1. Science. 326, 1350–1351. https://doi.org/10.1126/science.1182108

Ramos, C.J.P., Graça, P.M.L.A., Fearnside, P.M., 2018. Deforestation dynamics on an Amazonian peri-urban frontier: Simulating the influence of the Rio Negro Bridge in Manaus, Brazil. Environ. Manage. 62, 1134–1149. https://doi.org/10.1007/s00267-018-1097-3

Roriz, P.A.C., Yanai, A.M., Fearnside, P.M., 2017. Deforestation and carbon loss in southwest Amazonia: Impact of Brazil's revised forest code. Environ. Manage. 60, 367–382. https://doi.org/10.1007/s00267-017-0879-3

West, T.A.P., Börner, J., Fearnside, P.M., 2019. Climatic benefits from the 2006–2017 avoided deforestation in Amazonian Brazil. Front. For. Glob. Chang. 2. https://doi.org/10.3389/ffgc.2019.00052

West, T.A.P., Grogan, K.A., Swisher, M.E., Caviglia-Harris, J.L., Sills, E., Harris, D., Roberts, D., Putz, F.E., 2018. A hybrid optimization-agent-based model of REDD+ payments to households on an old deforestation frontier in the Brazilian Amazon. Environ. Model. Softw. 100, 159–174. https://doi.org/10.1016/j.envsoft.2017.11.007

Chapter 4

Land-tenure concentration on a cattle-ranching frontier

Aurora Miho Yanai[1], Paulo Maurício Lima de Alencastro Graça[1,3], Maria Isabel Sobral Escada[2], Philip Martin Fearnside[1,3,4]

[1]Department of Environmental Dynamics, National Institute for Research in Amazonia (INPA), Av. André Araújo n° 2936, CEP 69067-375, Manaus, Amazonas, Brazil.

[2]Department of Image Processing, National Institute for Space Research (INPE), Av. Astronautas, n° 1758, CEP 12227-010, São José dos Campos, São Paulo, Brazil

[3]Brazilian Research Network on Climate Change (RedeClima)

[4]Corresponding author

Email addresses: yanai@inpa.gov.br; pmlag@inpa.gov.br; isabel@dpi.inpe.br; pmfearn@inpa.gov.br

Abstract

One of the factors driving Brazil's Amazon deforestation is land-tenure concentration, or the replacement of many small landholdings by a smaller number of larger holdings. Here we examine the complexity of land-tenure concentration and its relation to the increase of deforestation in the Santo Antônio do Matupi District, a cattle-ranching frontier in the southern portion of Amazonas State. We synthesize our findings from field observations and contribute to discussions on the issues surrounding land-tenure concentration, showing the difference between the clearing estimated in smallholders areas versus largeholders. Based on our previous studies, we also make suggestions on how decision makers could control and avoid land concentration.

1. **Why land-tenure concentration occurs?**

Land-tenure concentration in public lands is one of the main drivers responsible for increasing deforestation in cattle-ranching frontier areas in Amazonia. Estimates for Brazilian Amazonia as a whole have indicated that 36% of the deforestation detected in 2019 is related to land grabbing: 27% of the total was in public land without destination, 5% in Conservation Units (protected areas for biodiversity) and 4% in Indigenous Lands (Alencar et al., 2019; IPAM, 2019).

It is estimated that 9% to 13% of the land in Brazilian Legal Amazonia is vulnerable to speculation, where ranchers can easily occupy the land through "*grilagem*," or land grabbing (Bowman et al., 2012). Land grabbing is the illegal occupation of public lands using falsified land titles that are made to appear legal (Brazil, MMA, 2006).

Santo Antônio do Matupi District was identified as a land-speculation frontier, meaning that the area is profitable by land grabbing but not profitable if a rancher must buy the land. Thus, by occupying an area of public land at no cost and later selling it at market price allows the land grabber to invest in clearing a new forest area elsewhere (Bowman et al., 2012).

The land price in Santo Antônio do Matupi District is lower than in Rondônia State, thus attracting capitalized ranchers from this neighboring state. In Matupi District, ranches with substantial improvements (*benfeitorias*) located along the Transamazon Highway have been selling by R$10,000 per *alqueire paulista* (1 *alqueire paulista* = 2.42 ha), or US$1063/ha at an exchange rate of R$4.2/US$. In Rondônia the price per *alqueire paulista* is 4 times higher (R$40,000 per *alqueire paulista*, or US$4252/ha) (Ana Paula Rezende, personal communication, November 24, 2019).

2. **Why is the percentage of clearing in small landholdings higher than in large landholdings?**

In Santo Antônio do Matupi, both smallholders and largeholders have cattle ranching as their main economic activity. Although some smallholders have tried to produce agricultural crops for sale, the difficulty of transporting these products, the lack of assistance from the National Institute for Colonization and Agrarian Reform (INCRA) and the low profit make cattle a better source of income. Since cattle demand large areas of pasture, the pressure to clear most of a smallholder's available area (≤100 ha) is inevitable. In addition, our findings indicate that clearing in smaller landholdings occurred earlier than in larger landholdings because the smallholders are located in areas of consolidated deforestation near the Transamazon Highway, which were the first to be occupied.

When large ranchers decide to clear, large areas of pasture can be opened in a single year. However, in our study area we also found large landholdings with high percentages of forest remaining through the years. This occupation strategy could be related to the fact that (i) the land occupation was recent (~6 years), as we observed in some cases, but it could also suggest (ii) land speculation, where these larger actors have occupied land illegally and are waiting for a good opportunity to sell the land at a good price or to invest in pasture. Waiting for the value of land to increase can bring much higher financial returns than investing in “improvements” in the land, although, in order to secure the land-tenure the option is clearing for pasture (Fearnside, 2017).

Thus, in our study areas we found that the fact that smallholders have more clearing in terms of percentage in their landholdings in comparison with largeholders is related to size of landholding, year of first clearing and the distance between the landholding and the Transamazon Highway. A previous study also found that smaller and older landholdings hold less forest than larger and younger landholdings (Michalski et al., 2010).

When illegal occupation and clearing occur and there is no punishment this motivates new land grabbing and more clearing. This cycle tends to continue, and the land market tends to increase with the weakening of the public institutions responsible for controlling and monitoring deforestation.

3. How can land-tenure concentration be avoided?

Public institutions must make efforts to take effective control of areas of public lands without destination and agrarian reform lands. To avoid land-tenure concentration and illegal occupation it is important to strengthen command-and-control actions targeting those who illegally occupy land and concentrate lots. Rooting out corruption, which contributes to the land grabbing, has a substantial potential role in ending the land market on cattle-ranching frontiers.

Furthermore, it is necessary to strengthen government institutions to promote better technical and social assistance for settlers and smallholders by promoting socio-environmental alternatives in settlement projects with the aim of reducing pressure to cut forest for pasture. For example, in 2016 rural extension activities were being carried out in the Matupi settlement consisting of planting corn for animal feed, cultivation of coffee in and agroforestry project and implanting a rotational silvipastoral system (*sistema silvipostoril rotacionado*). However, only 36 families were approved by INCRA (20% of the 176 families settled by the agrarian-reform program: Brazil, INCRA, 2015) to receive credit for these activities and the period in which assistance was available for these activities was short.

Any new settlements to be created need to be of an environmental type (e.g., Sustainable Development Project) with policies to restrict support to low-impact activities. Environmental monitoring should be strengthened to avoid illegal clearing and land occupation by large ranchers. Law enforcement is important because, as we found in our previous study, the clearing and environmental settlements was similar to that in traditional settlements if the environmental settlement is located in the “arc of deforestation,” or the area along the southern and eastern edges of the Amazon forest in which most deforestation has occurred to date (Yanai et al., 2017).

One good alternative for supporting smallholders is to invest in tapping the value of the environmental services provided by the forest. For this, improvement in the quantification of the environmental services has substantial importance (Fearnside, 2018). A recent study estimated that the value of different types of ecosystem services of Brazilian forest could reach US$737 ha^{-1} $year^{-1}$, which represents a much higher value than is obtained from cattle ranching (US$40 ha^{-1} $year^{-1}$) (Strand et al., 2018; Vasconcelos, 2019).

We highlight the importance of having decision makers who understand the value of forest and are committed to forest protection and the sustainable use of forest resources. Economic policies must be created for Amazonia with a focus on strengthening alternatives for supporting small famers, such as small-scale crop production that does not require large areas and extraction of non-timber forest products (e.g., Brazil nuts). Policies that currently encourage the extensive cattle ranching that promotes deforestation must be discontinued.

References

Alencar, A., Moutinho, P., Arruda, V., Balzani, C., Ribeiro, J., 2019. Amazon Burning: Locating the Fires. Technical Memo from the Amazon Environmental Research Institute (IPAM) September 2019. Instituto de Pesquisa Ambiental da Amazônia (IPAM), Brasília, DF, Brazil. 12 pp. https://ipam.org.br/wp-content/uploads/2019/09/AmazonBurning_LocatingTheFires.pdf Last access: 27 November 2019.

Bowman, M.S., Soares-Filho, B.S., Merry, F.D., Nepstad, D.C., Rodrigues, H., Almeida, O.T., 2012. Persistence of cattle ranching in the Brazilian Amazon: A spatial analysis of the rationale for beef production. Land Use Policy 29, 558–568. https://doi.org/10.1016/j.landusepol.2011.09.009

Brazil, INCRA, 2015. Relatório de ATES apresentado em cumprimento a meta 2.3.1. Lote 01 – Apuí, Manicoré e Novo Aripuanã – AM. Contrato nº CRT. AM. 1000020/2014.

Brazil, MMA, 2006. A grilagem de terras públicas na Amazônia brasileira. Instituto de Pesquisa Ambiental da Amazônia (IPAM). Ministério do Meio Ambiente (MMA), Brasília, DF, Brazil. 108 pp. Available at:

https://www.mma.gov.br/estruturas/225/_arquivos/9___a_grilagem_de_terras_pblicas_na_amaznia_brasileira_225.pdf. Last access: 24 November 2019.

Fearnside, P.M., 2017. Deforestation and development of the Brazilian Amazon. Oxford Research Encyclopedia of Environmental Science. H. Schugart, Ed. Oxford University Press, New York. https://doi.org/10.1093/acrefore/9780199389414.013.102

Fearnside, P.M., 2018. Challenges for sustainable development in Brazilian Amazonia. Sustain. Dev. 26, 141–149. https://doi.org/10.1002/sd.1725

IPAM (Instituto de Pesquisa Ambiental da Amazônia), 2019. 35% do desmatamento na Amazônia é grilagem, indica IPAM. Available at: http://www.observatoriodoclima.eco.br/35-desmatamento-na-amazonia-e-grilagem-indica-ipam/. Last access: 20 November 2019.

Michalski, F., Metzger, J.P., Peres, C.A., 2010. Rural property size drives patterns of upland and riparian forest retention in a tropical deforestation frontier. Glob. Environ. Chang. 20, 705–712. https://doi.org/10.1016/j.gloenvcha.2010.04.010

Strand, J., Soares-Filho, B., Costa, M.H., Oliveira, U., Ribeiro, S.C., Pires, G.F., Oliveira, A., Rajão, R., May, P., van der Hoff, R., Siikamäki, J., da Motta, R.S., Toman, M., 2018. Spatially explicit valuation of the Brazilian Amazon forest's ecosystem services. Nat. Sustain. 1, 657–664. https://doi.org/10.1038/s41893-018-0175-0

Vasconcelos, M. 2019. R$ 7 trilhões por ano: os estudos que tentam calcular quanto a Amazônia, em pé, rende ao Brasil. BBC News. Available at: https://www.bbc.com/portuguese/brasil-50497413. Last access: 24 November 2019.

Yanai, A.M., Nogueira, E.M., de Alencastro Graça, P.M.L., Fearnside, P.M., 2017. Deforestation and carbon stock loss in Brazil's Amazonian settlements. Environ. Manage. 59, 393–409. https://doi.org/10.1007/s00267-016-0783-2

GENERAL CONCLUSION

The dynamic of forest cover loss in areas known as new deforestation frontier (e.g., Distrito de Santo Antônio do Matupi) is driven by the clearing behavior of different types of actors located in settlement project or in areas of public land without destination. Although the main reason to clearing could be similar between the types of actors (i.e., cattle ranching activity), the deforestation pattern in terms of the shape and clearing size is different between smallholders and large landholders. Land-tenure concentration in settlements and land occupation in areas of public land without destination increase the deforestation rates threatening the remaining public forest on the cattle-ranching frontier. Through the analysis of deforestation patterns is possible to associate the size, shape and the spatial location of deforestation patches with the different actor types. This helps to better understand the behavior of the different actors and their contribution to deforestation dynamics, both spatially and through time.

Actors in the Matupi settlement could be identified by the number of lots they concentrated. Lot concentration, whether by families or by individuals, influenced the speed of deforestation in the landholdings and undermines the purpose of agrarian reform program because only a few individuals are benefited. Thus, the social role of the agrarian-reform program in promoting equity in land distribution is not achieved, resulting in a negative social effect. The method used to identify and assess land-tenure concentration in the settlement project we studied could help government institutions such as INCRA to identify actors who concentrate lots and to monitor the land-tenure concentration in agrarian-reform settlements.

For actors located outside of the Matupi settlement we found that smallholders (<100 ha) and semi-smallholders (100-400 ha) had high percentages of their landholdings cleared in comparison with medium landholders (400-1500 ha) and largeholders (>1500 ha). Size of the landholding, year of first clearing and distance between the landholding and the Transamazon Highway were the main predictors of deforestation and demonstrated that smallholders and semi-smallholders had a greater role in deforestation in the past years than did medium landholders.

Deforestation modeling showed that the deforestation trajectory is different for each actor type and demonstrates the importance of considering the deforestation patterns of these actors in the modeling of deforestation. In general, actors with high deforestation rates, small landholdings, small percentages of remaining forest and who are located near of areas with high deforestation pressure have the potential to lose their remaining forest faster than actors with low deforestation rates and larger landholdings, high percentages of remaining forest in their landholdings and who are far from deforestation pressure.

The recent trends toward weakening command-and-control actions and environmental licensing, downgrading protected areas, freezing the creation of new protected areas, among other reversals in environmental governance, have increased deforestation in recent years in our study area and in the Brazilian Amazonia as a whole (Fearnside, 2016, 2018a,b). The coming years could follow the trend that we showed in our simulation if the government and public institutions do not take effective measures to control deforestation in settlement projects, in public lands without destination and in protected areas.

REFERENCES

Becker, B.K. 2005. Geopolítica da Amazônia. Estudos Avançados 19(53):71–86.

Brazil, INPE (Instituto Nacional de Pesquisas Espaciais), 2019. Projeto PRODES - Monitoramento da Floresta Amazônica Brasileira por Satélite. INPE, São José dos Campos, SP., Brazil. http://terrabrasilis.dpi.inpe.br/app/dashboard/deforestation/biomes/legal_amazon/rates. (Last access 31 October 2019).

Brazil, PR (Presidência da República). 1970. Decreto-Lei n°1.106 de 16 de junho de 1970. PR, Brasília, DF, Brazil.

Carvalho, W.D., Mustin, K., Hilário, R.R., Vasconcelos, I.M., Eilers, V., Fearnside, P.M., 2019. Deforestation control in the Brazilian Amazon: A conservation struggle being lost as agreements and regulations are subverted and bypassed. Perspect. Ecol. Conserv. 17, 122–130. https://doi.org/10.1016/j.pecon.2019.06.002

Coe, M.T., Muza, M.N., Powell, T.L., Wang, J., Imbuzeiro, H.M.A., Greenglass, N.L., Malhi, Y., Marthews, T.R., Saleska, S.R., Galbraith, D.R., Levine, N.M., Solorzano, L.A., Moorcroft, P.R., Costa, M.H., 2013. Deforestation and climate feedbacks threaten the ecological integrity of south-southeastern Amazonia. Philos. Trans. R. Soc. B Biol. Sci. 368, 20120155–20120155. https://doi.org/10.1098/rstb.2012.0155

dos Santos Silva, M.P., Câmara, G., Escada, M.I.S., Souza, R.C.M., 2008. Remote-sensing image mining: Detecting agents of land-use change in tropical forest areas. Int. J. Remote Sens. 29, 4803-4822. https://doi.org/10.1080/01431160801950634

Fearnside, P.M., 2016. Brazilian politics threaten environmental policies. Science 353, 746-748. https://doi.org/10.1126/science.aag0254

Fearnside, P.M., 2018a. Challenges for sustainable development in Brazilian Amazonia. Sustain. Dev. 26, 141-149. https://doi.org/10.1002/sd.1725

Fearnside, P.M., 2018b. Why Brazil's new president poses an unprecedented threat to the Amazon**.** *Yale Environment 360*, 8 November 2018. https://e360.yale.edu/features/why-brazils-new-president-poses-an-unprecedented-threat-to-the-amazon

Geist, H.J., Lambin, E.F., 2001. What drives tropical deforestation? A meta-analysis of proximate and underlying causes of deforestation based on subnational case study evidence. LUCC Report Series, 4. pp. 66-72. http://www.pik-potsdam.de/~luedeke/lucc4.pdf . (Last access 31 October 2019).

Kirby, K.R., Laurance, W.F., Albernaz, A.K., Schroth, G., Fearnside, P.M., Bergen, S., Venticinque, E.M., da Costa, C., 2006. The future of deforestation in the Brazilian Amazon. Futures 38, 432–453. https://doi.org/10.1016/j.futures.2005.07.011

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

Nepstad, D., McGrath, D., Stickler, C., Alencar, A., Azevedo, A., Swette, B., Bezerra, T., DiGiano, M., Shimada, J., Da Motta, R.S., Armijo, E., Castello, L., Brando, P., Hansen, M.C., McGrath-Horn, M., Carvalho, O., Hess, L., 2014. Slowing Amazon deforestation through public policy and interventions in beef and soy supply chains. Science 344, 1118–1123. https://doi.org/10.1126/science.1248525

Nogueira, E.M., Yanai, A.M., Fonseca, F.O., Fearnside, P.M., 2015. Carbon stock loss from deforestation through 2013 in Brazilian Amazonia. Glob. Chang. Biol. 21, 1271-1292. https://doi.org/10.1111/gcb.12798

Souza Jr., C.M., Siqueira, J. V., Sales, M.H., Fonseca, A. V., Ribeiro, J.G., Numata, I., Cochrane, M.A., Barber, C.P., Roberts, D.A., Barlow, J., 2013. Ten-year Landsat classification of deforestation and forest degradation in the Brazilian Amazon. Remote Sens. 5, 5493–5513. https://doi.org/10.3390/rs5115493

Strand, J., Soares-Filho, B., Costa, M.H., Oliveira, U., Ribeiro, S.C., Pires, G.F., Oliveira, A., Rajão, R., May, P., van der Hoff, R., Siikamäki, J., da Motta, R.S., Toman, M., 2018. Spatially explicit valuation of the Brazilian Amazon forest's ecosystem services. Nat. Sustain. 1, 657–664. https://doi.org/10.1038/s41893-018-0175-0

Zipperer, W.C., 1993. Deforestation patterns and their effects on forest patches. Landsc. Ecol. 8, 177-184. https://doi.org/10.1007/BF0012534

ANEXOS: Documentos de solicitação e disponibilização de dados do INCRA do projeto de assentamento Matupi

INPA | CDAM

MINISTÉRIO DA CIÊNCIA, TECNOLOGIA, INOVAÇÕES E COMUNICAÇÕES

BRASIL GOVERNO FEDERAL

Manaus, 22 de dezembro de 2016.

Ofício INPA/CDAM/ 05/2016

INCRA - SR(15)AM
ENTRADA: 23/12/16 Hrs 10:00
SR (15) A- P4290 :2016
Andamento: GAB
Responsável: Veronha D.

Ilmo Sr.
Sandro Freire Maia,
Superintendente Regional do INCRA – SR (15) Amazonas

Assunto: Solicitação do levantamento ocupacional das famílias do projeto de assentamento Matupi (PA Matupi).

Prezado Superintendente,

Ao tempo de cumprimentá-lo, venho por meio deste, solicitar o levantamento ocupacional atualizado das famílias localizadas no PA Matupi. O levantamento será utilizado para identificar espacialmente a localização das famílias residentes no referido assentamento e para confirmar informações de assentados que concentram lotes, obtidas previamente a partir da análise dos padrões de desmatamento dentro do PA Matupi utilizando imagens de satélites.

Este estudo faz parte da tese de doutorado em andamento da aluna do Programa de Ciências de Florestas Tropicais do INPA, Aurora Miho Yanai Nascimento, vinculada ao Laboratório de Agroecossistemas associado à Coordenação de Dinâmica Ambiental (CDAM). A tese da aluna tem o intuito de compreender a dinâmica de desmatamento dos atores locais do distrito de Matupi e analisar como esses atores respondem à ação de fiscalização.

Ressalta-se que esses dados serão utilizados somente para fins científicos e didáticos. Espera-se que esse estudo contribua para um melhor entendimento dos processos de desmatamento e que possa subsidiar políticas públicas específicas para os diferentes atores localizados em uma região de fronteira agropecuária como o distrito de Matupi.

Av. André Araújo, 2.936 - Petrópolis - CEP 69067-375 – Manaus/AM
Fones: + 55 92 3643–1826/1910

INPA | CDAM
MINISTÉRIO DA CIÊNCIA, TECNOLOGIA, INOVAÇÕES E COMUNICAÇÕES
BRASIL GOVERNO FEDERAL

Sem mais para o momento, fico à disposição para quaisquer esclarecimentos.

Atenciosamente,

Paulo Maurício Lima de Alencastro Graca, Dr.
Coordenador de Dinâmica Ambiental-INPA

Av. André Araújo, 2.936 - Petrópolis - CEP 69067-375 – Manaus/AM
Fones: + 55 92 3643–1826/1910

MINISTÉRIO DO DESENVOLVIMENTO AGRÁRIO- MDA
INSTITUTO NACIONAL DE COLONIZAÇÃO E REFORMA AGRÁRIA - INCRA
SUPERINTENDÊNCIA REGIONAL DO AMAZONAS-SR (15)/AM
AV. ANDRÉ ARAÚJO, 901 – ALEIXO – MANAUS/AM - CEP:69.060-001
TELEFONES: (92) 3194-1300 TELEFAX (92) 3642-3445

OFÍCIO/INCRA/SR(15)/AM/D/D2/Nº 06/2016

Manaus, 29 de dezembro de 2016.

Ao Senhor
Paulo Maurício Lima de Alencastro Graça
Coordenador de Dinâmica Ambiental - INPA
Av. André Araújo, 2.936 –Petrópolis – CEP: 69067-375
Manaus - AM

Ref.: Solicitação do levantamento ocupacional das famílias do PA Matupi

Prezado Senhor,

Em atendimento à solicitação feita através do Ofício INPA/CDAM/05/2016, encaminhamos um DVD contendo informações solicitadas, conforme abaixo relacionadas.

Qde	Pasta	Conteúdo	Assunto
1	Levantamento Ocupacional 2011	Diagnósticos Relatório fotográfico geral Relatórios por vicinais: Boa Esperança, Bom Futuro, Maravilha, Matupiri e Nova Vida	Levantamento Ocupacional realizado pelo Incra em 2011
2	ATES INCRA	Diagnósticos Final e Inicial Relatório Inicial de Atividades	Levantamento de ocupação de assentados realizado pela Prestadora, de Assistência Técnica, contratada pelo Incra
3	Mapas PA Matupi	Base de dados Atividades produtivas Desmatamento	Mapas de desmatamento e produção confeccionados pela prestadora de Assistência Técnica contratada pelo Incra

Atenciosamente,

Kellia Jane Fernandes dos Santos
Chefe da D-2 SR(15)/AM
Portaria INCRA Nº 610/2016

Recebido em: 29/dez/2016.

SUPPLEMENTARY MATERIAL

Chapter 1: Deforestation dynamics in Brazil's Amazonian settlements: Effects of land-tenure concentration

Additional information on Materials and Methods

Classification of deforestation patterns

Fifteen landscape metrics were calculated by GeoDMA. These were examined both in raw form and after being normalized using the minimum and maximum values.

In the second classification period (2000-2016), we could not specify the type of actor exactly in several cases involving large polygons because polygons with the "large irregular" pattern (n = 37 polygons) covered large areas and we do not have information about all actors covered by this pattern. In two polygons we found that parts of the polygons belonged to non-concentrating landholders. In the "small geometric" category (n = 29), 3 samples were from non-concentrating landholders, and for the remaining 26 samples we do not have information about the type of actor, but the sizes and shapes of the clearings are similar to the others in the dataset. All cases of the "small irregular" pattern (n = 23), these clearings were in areas where landholders do not concentrate lots.

After the first classification (~1994-1999) we had to manually reclassify 7 polygons from "large irregular" to "small geometric," where 4 polygons were used as samples in the classification. In addition, 1 polygon classified as "large irregular" was manually reclassified to "small irregular." We performed the reclassification because these polygons did not reflect the "large irregular" pattern (i.e., large polygons that covered more than one lot and that were located along access roads). The actor type is unknown for these reclassified polygons (and these polygons therefore were not used in the analyses that included actor types).

For the second classification period (2000-2016), concentrators of two lots had 12 polygons sampled and concentrators of three to ten lots had 10 polygons sampled. We had fewer samples of the "large geometric" pattern because the number of polygons available for use as samples was lower in comparison to the "small irregular" and "small geometric" patterns.

Estimation of lot concentration in 2011 and deforestation rates by landholders

In three cases of concentration (two cases encompassing two lots on the Maravilha access road and one encompassing three lots on Bom Futuro access road) we lacked information on the period that the family members occupied the lots; in these cases, we considered the group of lots to be concentrated based on the spatial distribution of deforestation polygons through 2011 in the landholding as a whole.

Generally, there is one community lot per access road, but on the Triunfo and Matupiri access roads we identified two community lots in each access road, while in the Maravilha, Bom Futuro and Santa Luzia access roads there are no community lots.

Table S1. Confusion matrix for classification from ~1994 to 1999. Values refer to numbers of samples (polygons) in training step and in the validation step. Total number of samples shown in bold.

	Pattern	Large irregular	Small geometric	Small irregular	Total	*Error of omission*
Reference	Large irregular	22; 15 **(37)**	-	-	37	-
	Small geometric	1; 3 **(4)**	16; 9 **(25)**	-	29	13.8%
	Small irregular	-	-	14; 9 **(23)**	23	-
	Total	41	25	23	89	
	Error of commission	9.8%	-	-		

Table S2. Confusion matrix for classification from 2000 to 2016. Values refer to numbers of samples in the training step and the validation step. Total number of samples shown in bold.

	Pattern	Large geometric	Small geometric	Small irregular	Total	*Error of omission*
Reference	Large geometric	12; 9 **(21)**	1; 0 **(1)**	-	22	4.6%
	Small geometric	-	39; 26 **(65)**	1; 0 **(1)**	66	1.5%
	Small irregular	-	-	37; 25 **(62)**	62	-
	Total	21	66	63	150	
	Error of commission	-	1.5%	1.6%		

Table S3. Deforestation rate per lot from 1995 to 2011 for each actor category.

Actor category	Total no. of lots	Mean annual rate per lot	SD	Mean total deforestation per lot (1995-2011)
Families concentrators of 2 lots	66	2.0	0.8	34.7
Individuals concentrator of 2 lots	28	2.5	0.8	43.3
Families concentrators of 3 lots	12	3.0	0.5	50.7
Families concentrators of 4 lots	12	2.4	0.7	40.9
Individuals concentrators of 4 lots	16	1.8	1.0	30.5
Family concentrator of 5 lots	5	1.2	0.2	21.0
Family concentrator of 10 lots	10	2.4	0.6	40.5
Individuals and family concentrators of non-neighboring lots	3	1.2	0.7	21.2
Non-concentrators	364	1.7	0.8	29.5

Table S4. P-values in pairwise tests in comparing actor categories. Values in bold indicate significant differences ($p < 0.05$). FC: Family concentrator; FCs: Families concentrators and ICs: Individual concentrators.

	FC of 10 lots	FCs of 2 lots	FCs of 3 lots	FCs of 4 lots	FC of 5 lots	FC and ICs of non-neighboring lots	ICs of 2 lots	ICs of 4 lots
FCs of 2 lots	0.0950							
FCs of 3 lots	**0.0290**	**0.0003**						
FCs of 4 lots	1.0000	0.1139	**0.0373**					
FC of 5 lots	**0.0166**	**0.0237**	**0.0018**	**0.0060**				
FC and ICs of non-neighboring lots	**0.0341**	0.1488	**0.0113**	**0.0424**	0.5486			
ICs of 2 lots	1.0000	**0.0109**	0.0786	0.7339	**0.0007**	**0.0210**		
ICs of 4 lots	0.1873	0.2785	**0.0037**	0.0898	0.3623	0.5755	**0.00624**	
Non-concentrators	**0.0030**	**0.0044**	**0.0000**	**0.0039**	0.0749	0.2861	**0.0000**	0.7907

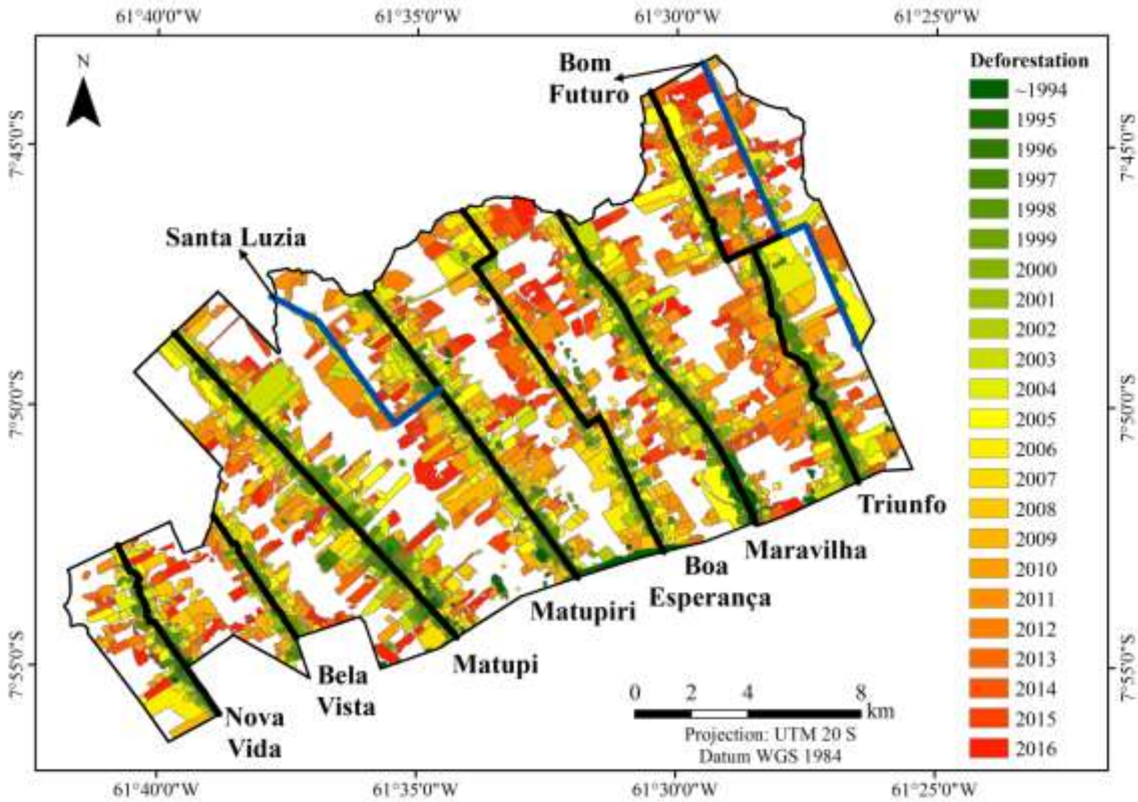


Fig. S1. Lots and access roads in the Matupi settlement, showing deforested areas and dates of deforestation.

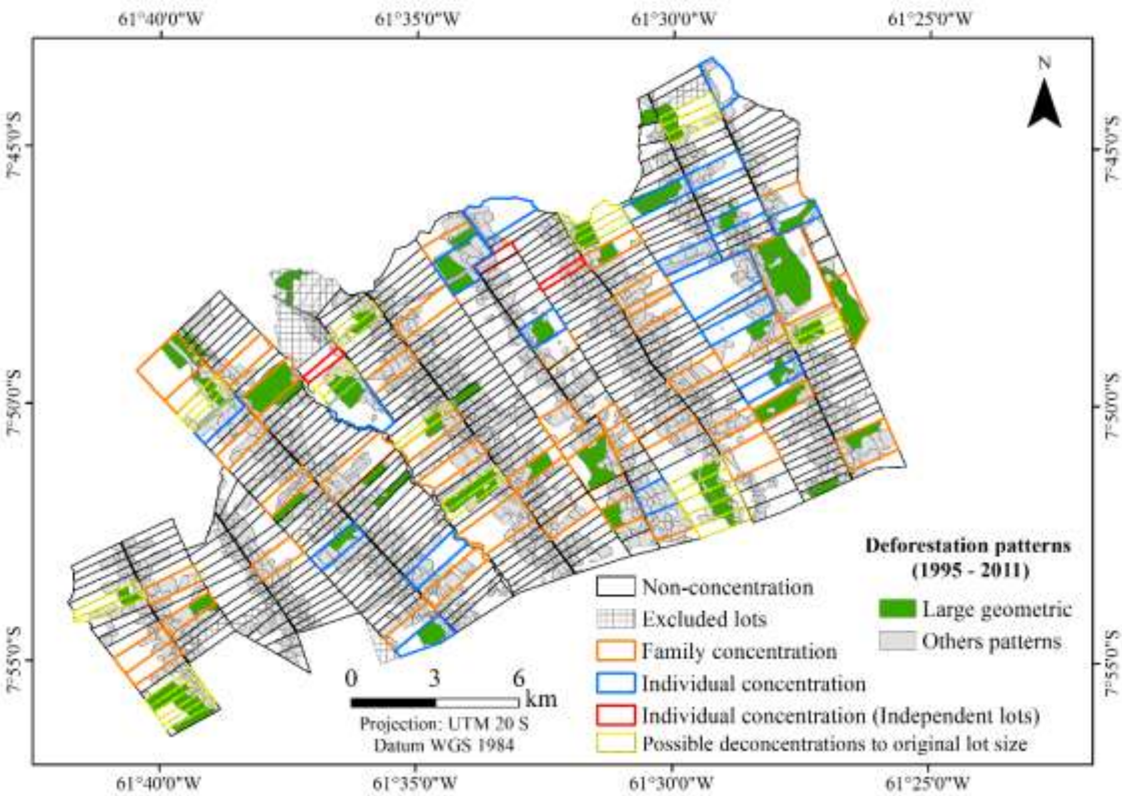


Fig. S2. The Matupi settlement indicating 30 lots held by non-concentrators that had portions of large geometric deforestation patches spanning more than one lot in 2011. This suggests fragmentation of previously concentrated landholdings.

SUPPLEMENTARY MATERIAL

Chapter 2: Brazil's Amazonian deforestation actors: Clearing behavior on a cattle-ranching frontier

Additional Information on Materials and Methods

The Brazilian Rural Environmental Registry (CAR = Cadastro Ambiental Rural)

Through June 2019, 543,489,672 ha of Brazilian territory had been registered in the CAR system (5,040,807 landholdings), representing 63.8% of the total area of Brazil. In Amazonas State, 49,772 landholdings had been registered in the CAR system, encompassing an area of 54,496,772 ha, or 34.7% of the state (Brazil, SFB, 2019).

The CAR is a public dataset, although the names of landholders are sensitive information. In the CAR dataset for Manicoré and Novo Aripuanã municipalities we spatially identified the landholdings of actors in Matupi District. Thus, through the intersection between the landholdings and the deforestation data, we could evaluate the area cleared, where the cleared area was spatially distributed and when the clearings were made, which makes it possible to monitor the speed of land-use change in the landholdings. The link between actor type and the sizes of patches of clearing can contribute to evaluating if an actor's behavior is changing through the time or if it changed in a specific period (e.g., whether the speed of deforestation increases when governance is low).

Since the landholding registry is self-declared we could not determine whether a large landholding was divided into several small landholdings. In addition, the validation process for landholding boundaries is still an issue because we could only indicate precision levels at which an error results either in overlap between two or more landholdings or in a land-tenure conflict.

Since the landholding registry can be rectified, it is reasonable to use the most-recent record for each landholding. Thus, the overlapped landholdings indicated in previous versions of the registry can be excluded.

Overlap between landholdings and land categories (conservation units and settlements)

The intersection between landholdings and protected areas is important issue, as it warns of the possibility of threats to forest that is under protection. We found medium and large landholdings in an Indigenous land and in a conservation unit.

The tolerance threshold for conservation units and settlements with landholdings are those of Carvalho (2017):

- Landholdings > 15 Fiscal Modules (FMs): 3% of a landholding;
- Landholdings > 4 FMs and ≤ 15 FMs: 4% of a landholding;
- Landholdings ≤ 4 FMs: 10% of a landholding.

For our study area 1 FM = 100 ha.

References:

Carvalho, N.S. 2017. Texto guia: Análise Geo: Sobreposição do IR. Universidade Federal de Lavras (UFLA), Lavras, MG, Brazil. 129 pp.

Brazil, SFB (Serviço Florestal Brasileiro). 2019. Cadastro Ambiental Rural (CAR). SFB, Brasília, DF, Brazil. http://www.car.gov.br/publico/imoveis/index (Last access 4 June 2019).

Supplementary tables and figures

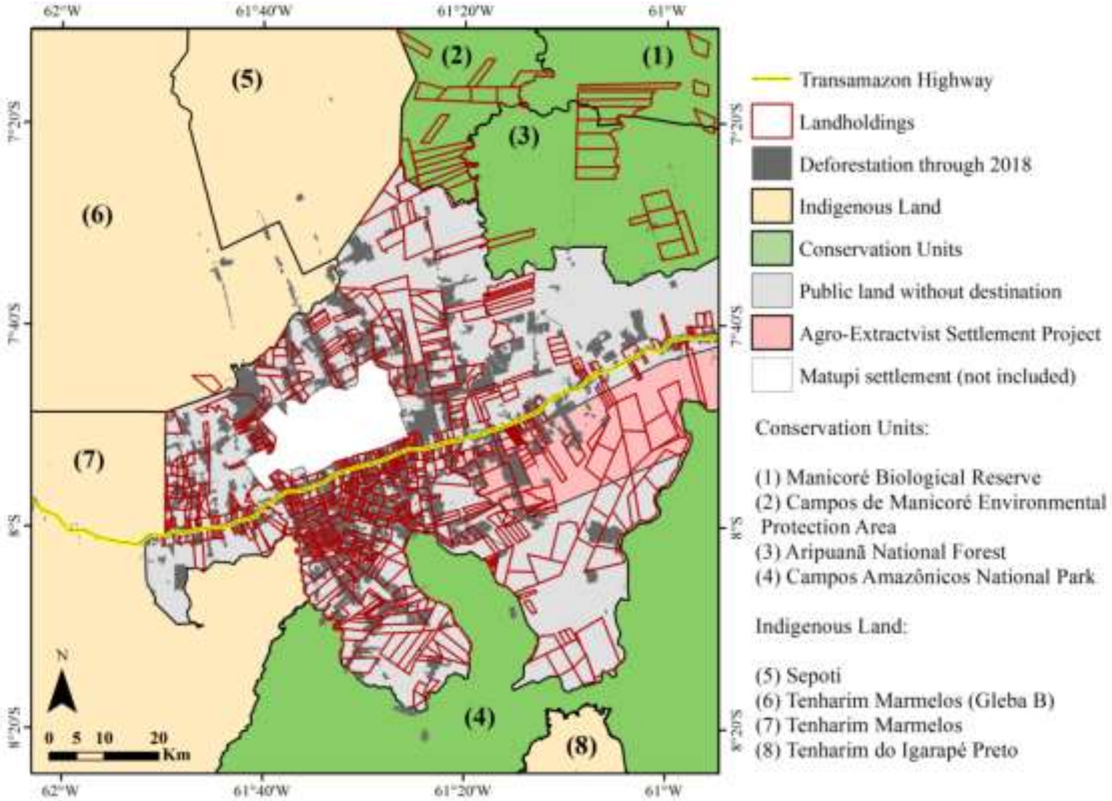


Fig. S1. Distribution of protected areas, landholdings and deforestation in the study area.

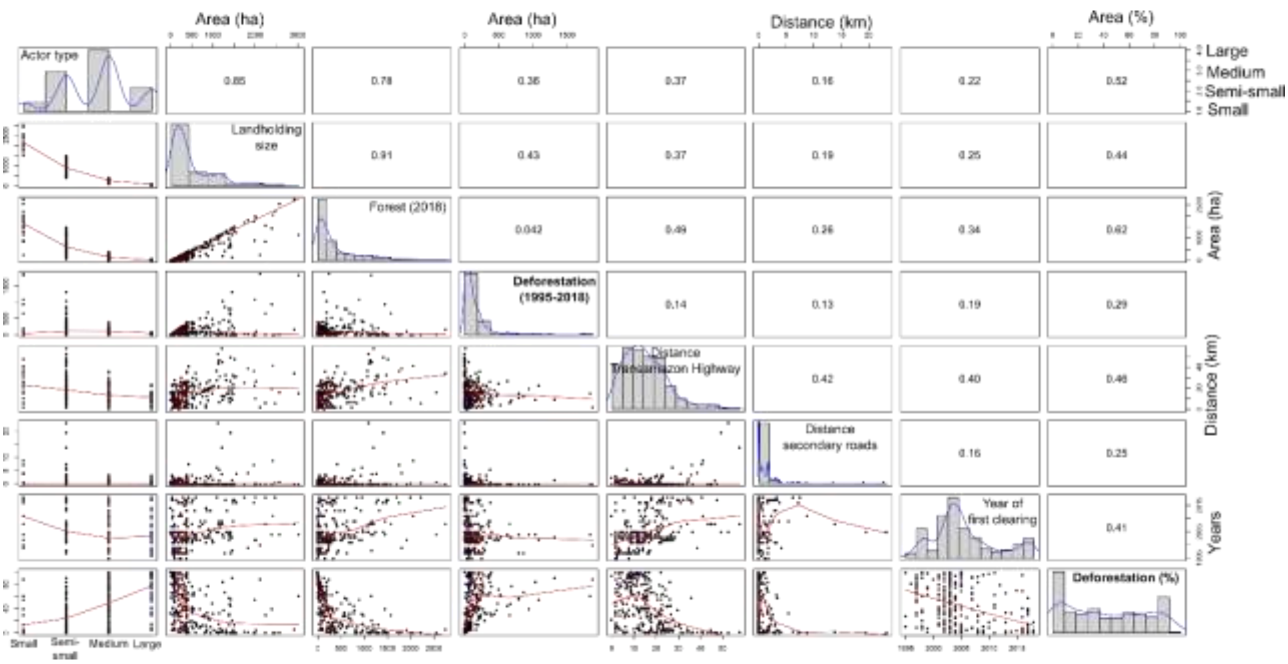


Fig. S2. Correlation matrix of dependent and predictor variables. The dependent variables are in bold.

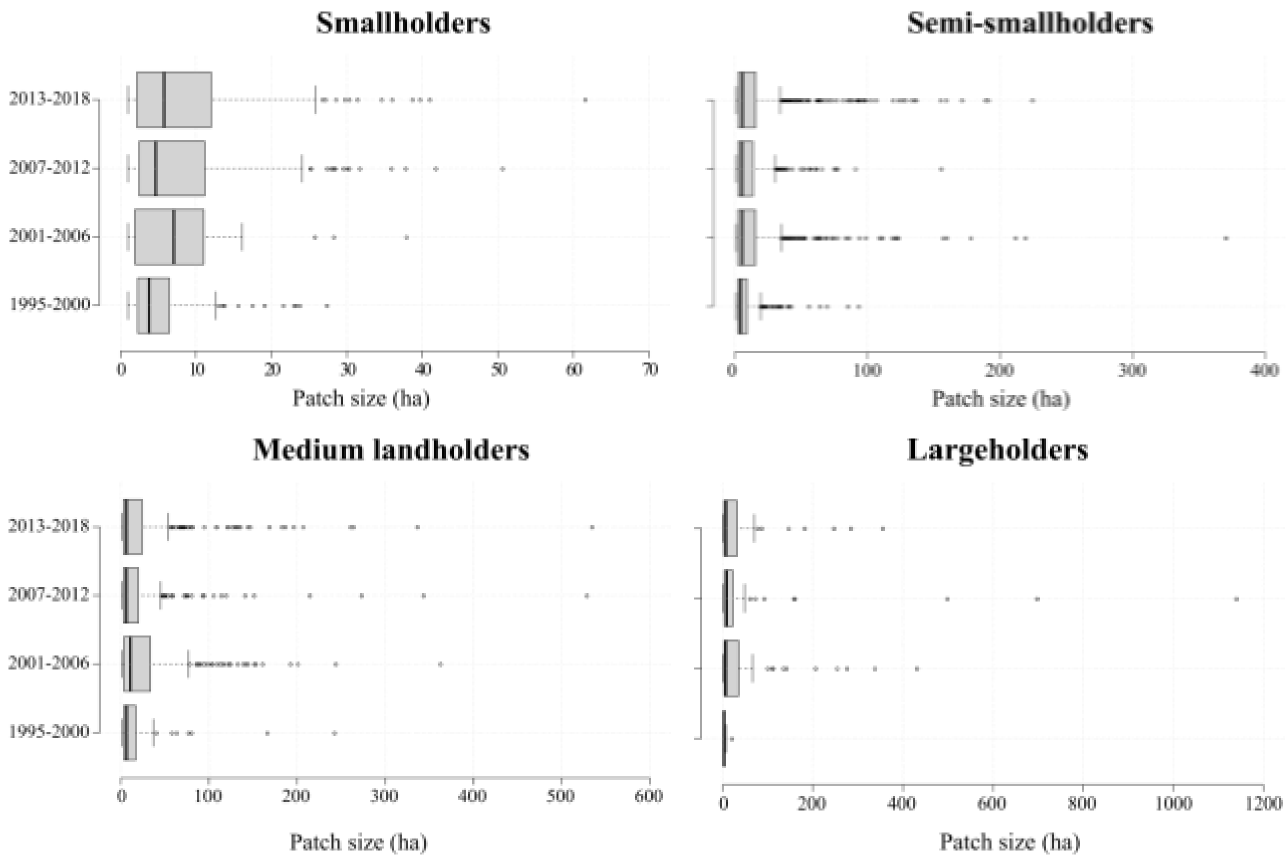


Fig. S3. Distribution of polygon sizes (≥ 1 ha) in year intervals for each actor type.

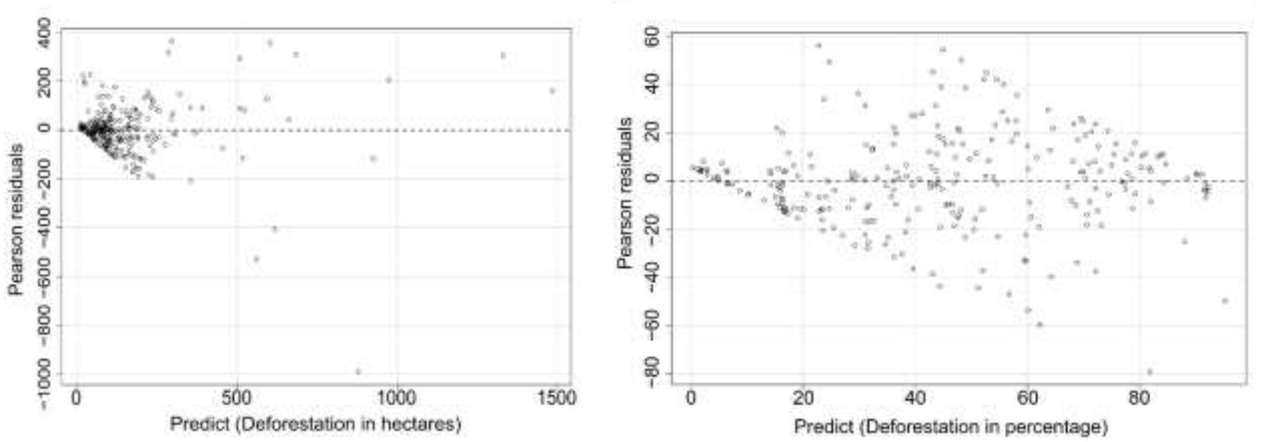


Fig. S4. Pearson residuals of predicted deforestation in terms of total area cleared (left) and in percentage of clearing (right).

Table S1. Hydrography (water courses) and non-forest vegetation in the landholdings of each actor type.

Actor type	Total area (ha)	Hydrography (ha)	Non-forest (ha)
Largeholders	82,112	81 (0.1%)	4,471 (5.4%)
Medium landholders	123,237	188 (0.2%)	1,227 (1.0%)
Smallholders	74,537	5 (0.0%)	0
Semi-smallholders	10,109	43 (0.1%)	336 (0.5%)
Total area	**289,995**	**317 (0.1%)**	**6,035 (2.1%)**

Table S2. Coefficients estimated for deforestation models (Equations 1 and 2).

Variables	**Deforestation (ha)**		**Deforestation (%)**	
	Coefficients	Probability test	Coefficients	Probability test
B_0	-16,590	0.002	2,406	0.005
B_1	57.050	< 0.001	0.519	0.581
B_2	8.341	0.001	-1.166	0.007
B_3	-7.315	< 0.001	-0.855	< 0.001
B_4	-0.028	< 0.001	-0.000267	0.568

SUPPLEMENTARY MATERIAL

Chapter 3: Simulating the deforestation patterns of actors on a cattle-ranching frontier

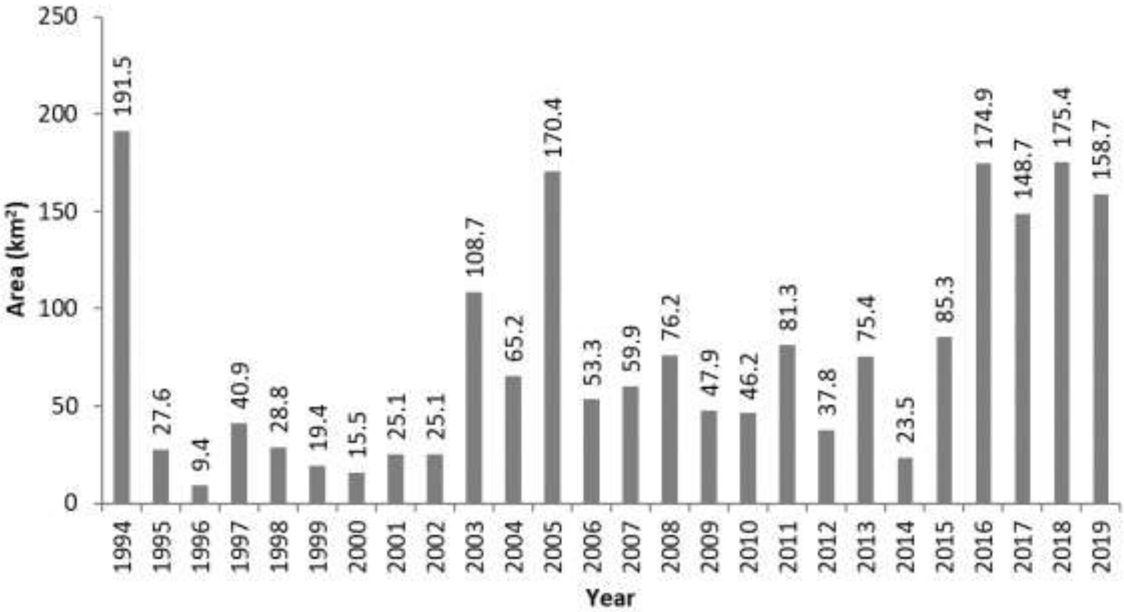
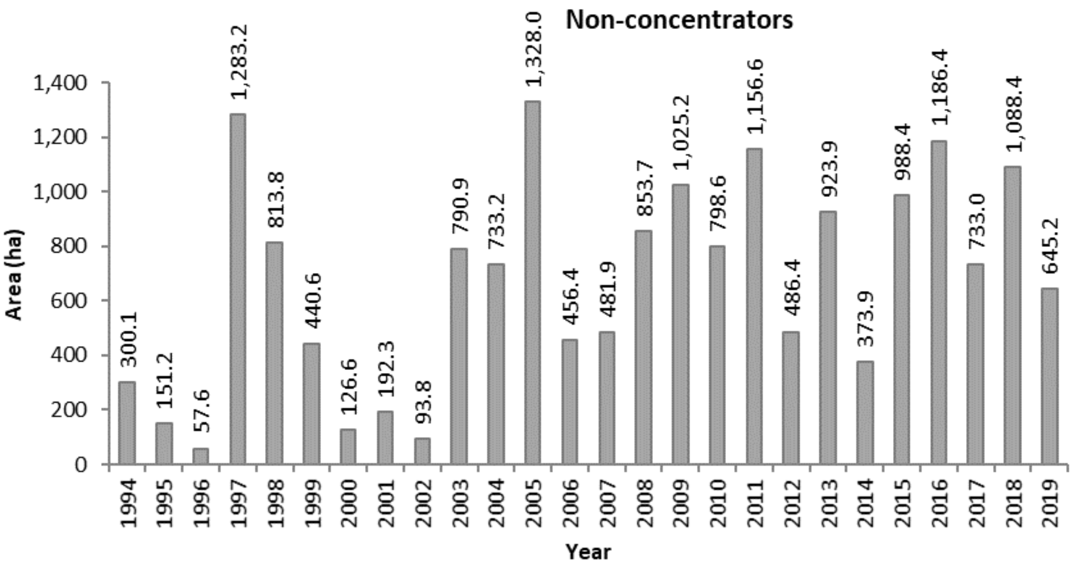
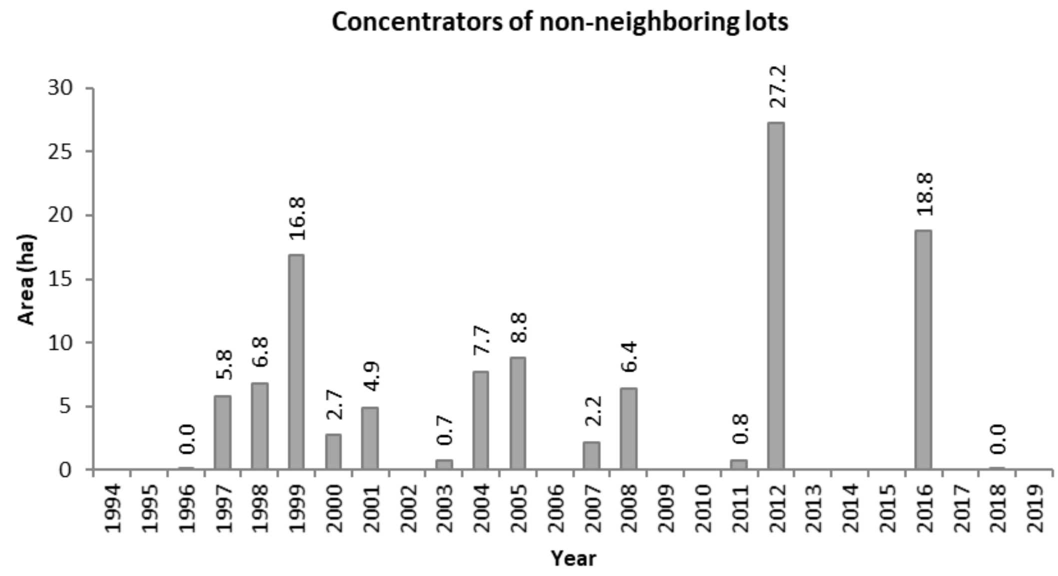
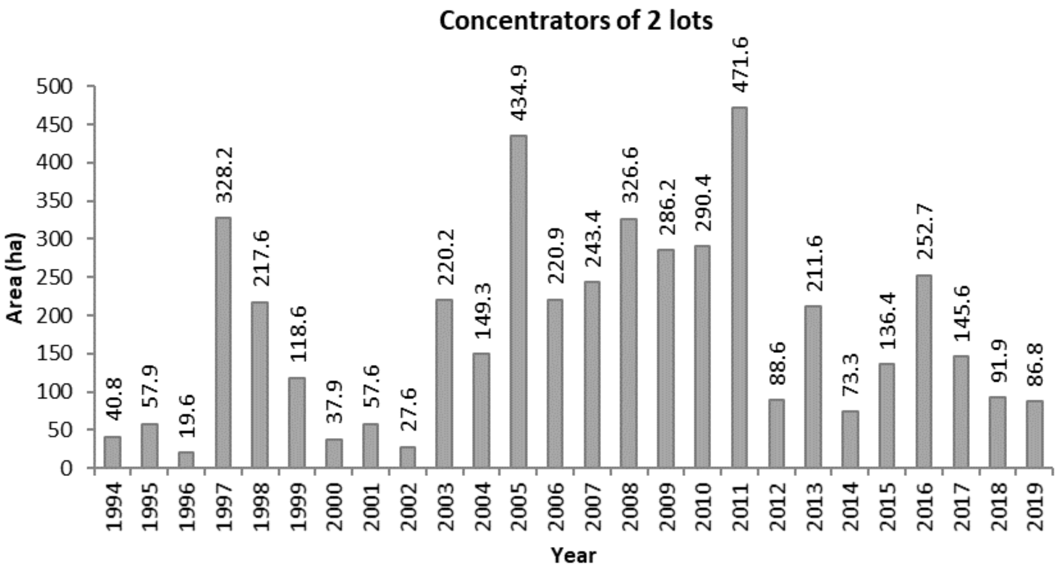
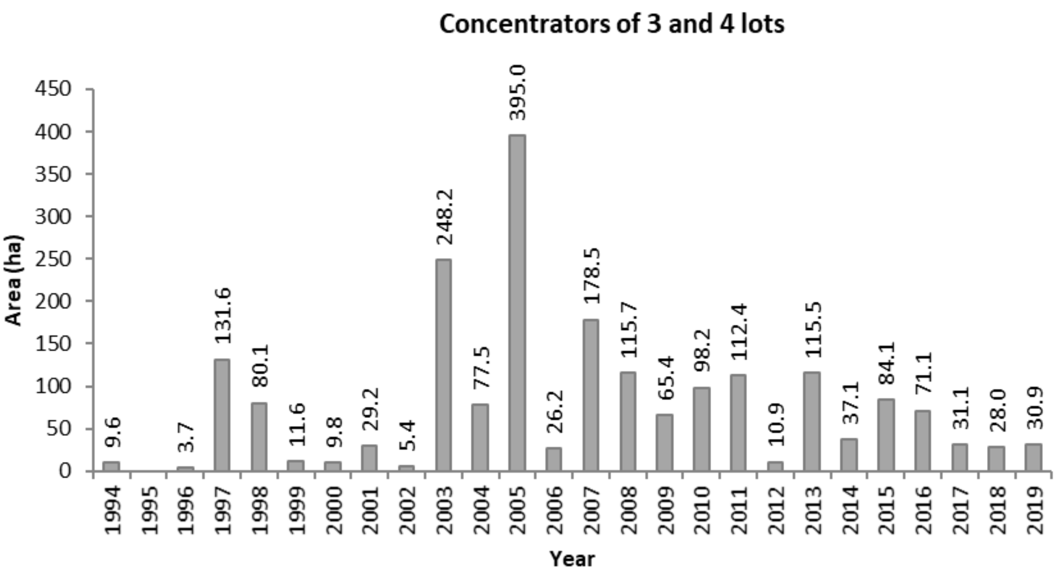


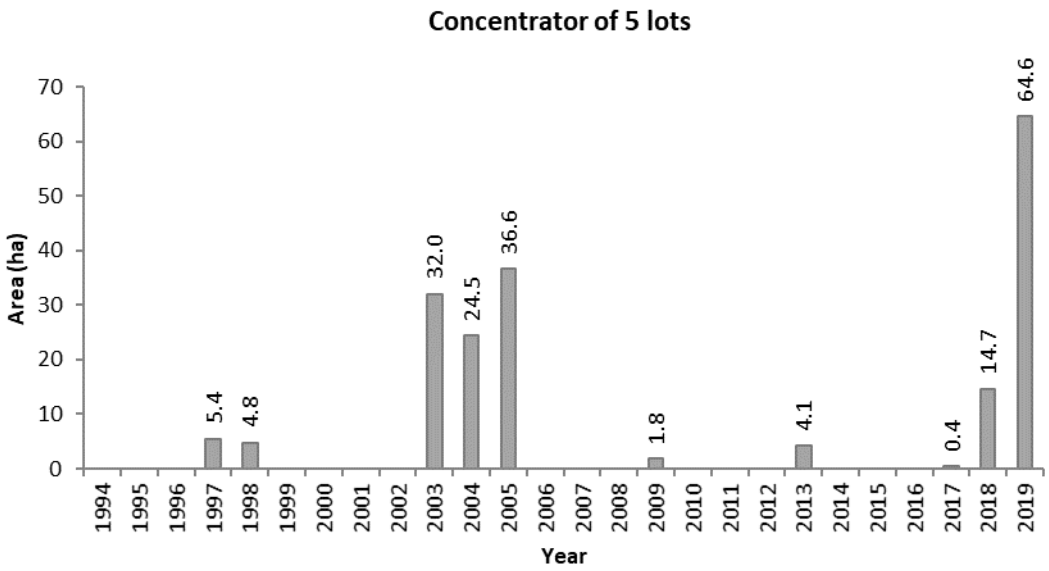
Fig. S1. Cumulative deforestation through 1994 and annual deforestation from 1995 to 2019 for the study area as a whole.




Concentrators of non-neighboring lots
Area (ha)
Year
0
5
10
15
20
25
30
0.0
5.8
6.8
16.8
2.7
4.9
0.7
7.7
8.8
2.2
6.4
0.8
27.2
18.8
0.0
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019


Concentrators of 2 lots
Area (ha)
Year
0
50
100
150
200
250
300
350
400
450
500
40.8
57.9
19.6
328.2
217.6
118.6
37.9
57.6
27.6
220.2
149.3
434.9
220.9
243.4
326.6
286.2
290.4
471.6
88.6
211.6
73.3
136.4
252.7
145.6
91.9
86.8
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019


Concentrators of 3 and 4 lots
Area (ha)
Year
0
50
100
150
200
250
300
350
400
450
9.6
3.7
131.6
80.1
11.6
9.8
29.2
5.4
248.2
77.5
395.0
26.2
178.5
115.7
65.4
98.2
112.4
10.9
115.5
37.1
84.1
71.1
31.1
28.0
30.9
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019



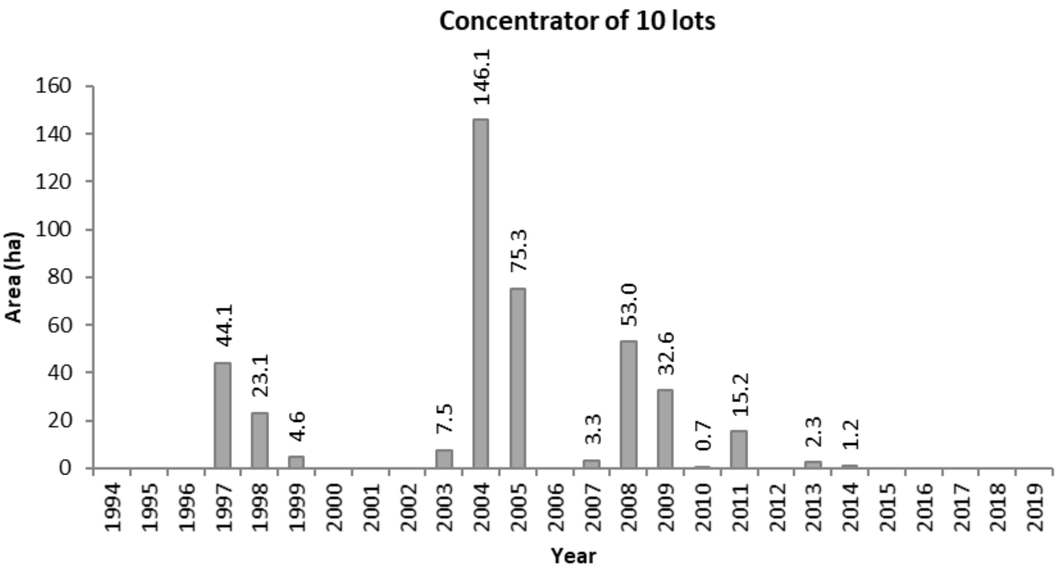
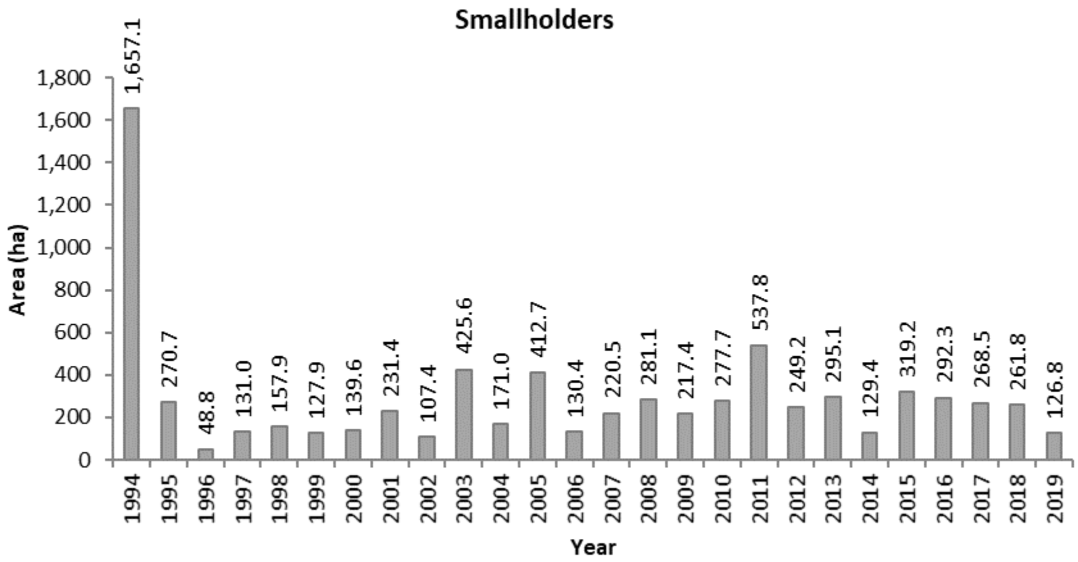
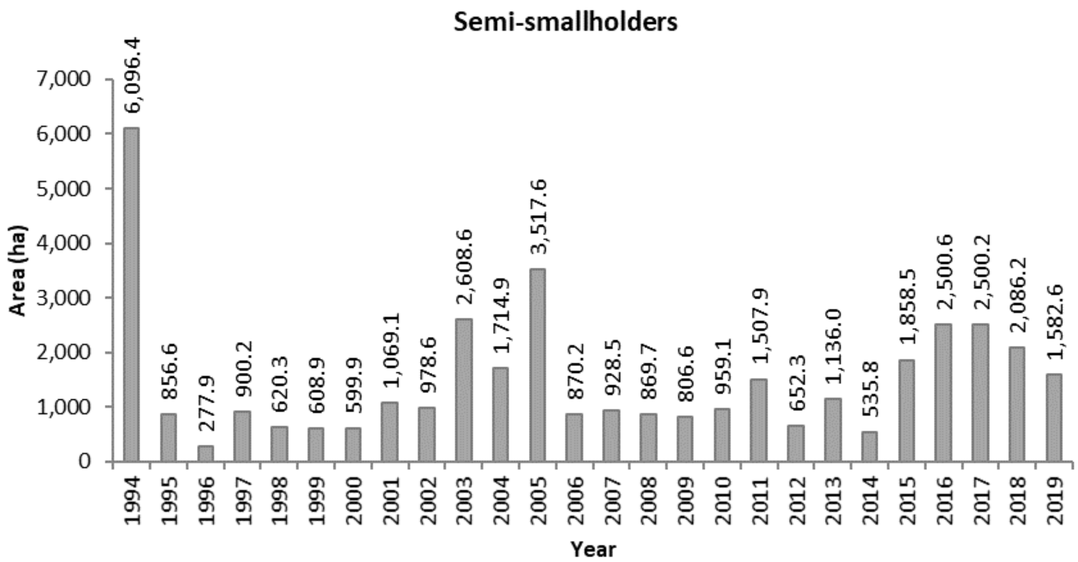
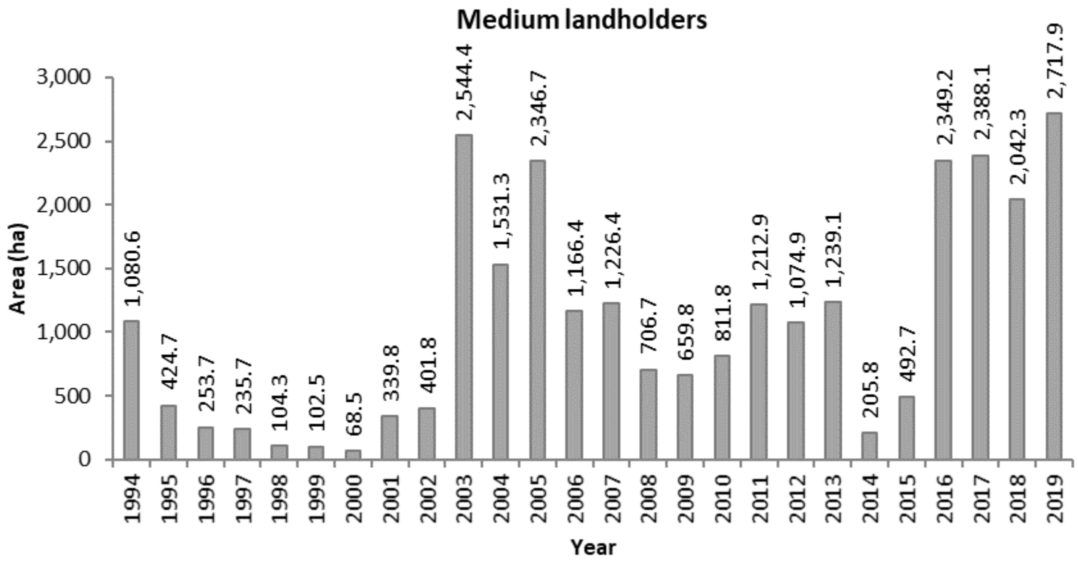


Fig. S2. Cumulative deforestation through 1994 and annual deforestation from 1995 to 2018 for the Matupi settlement.


Smallholders
Area (ha)
Year
1,800
1,600
1,400
1,200
1,000
800
600
400
200
0
1,657.1
270.7
48.8
131.0
157.9
127.9
139.6
231.4
107.4
425.6
171.0
412.7
130.4
220.5
281.1
217.4
277.7
537.8
249.2
295.1
129.4
319.2
292.3
268.5
261.8
126.8
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019


Semi-smallholders
Area (ha)
Year
7,000
6,000
5,000
4,000
3,000
2,000
1,000
0
6,096.4
856.6
277.9
900.2
620.3
608.9
599.9
1,069.1
978.6
2,608.6
1,714.9
3,517.6
870.2
928.5
869.7
806.6
959.1
1,507.9
652.3
1,136.0
535.8
1,858.5
2,500.6
2,500.2
2,086.2
1,582.6
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019



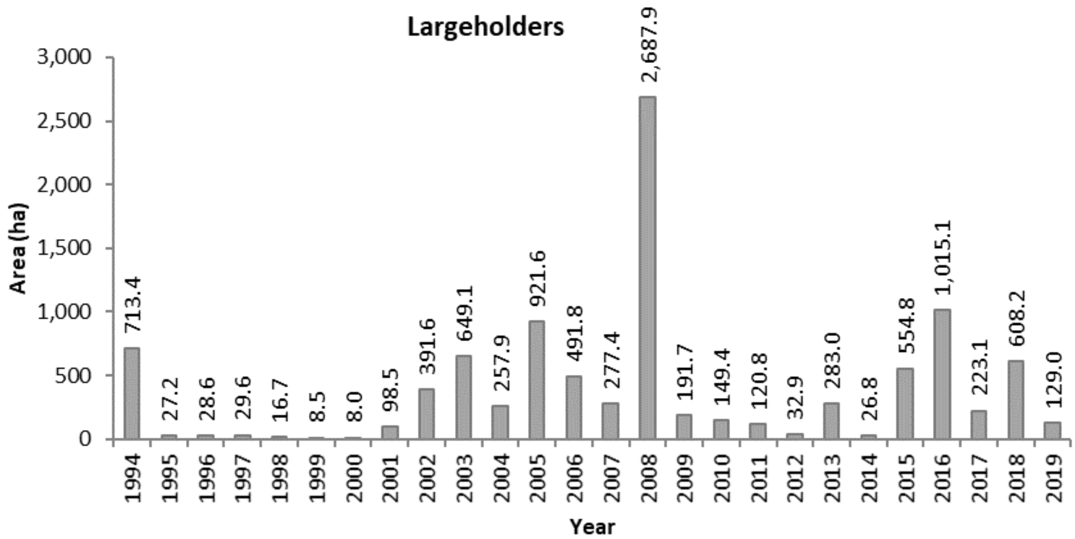
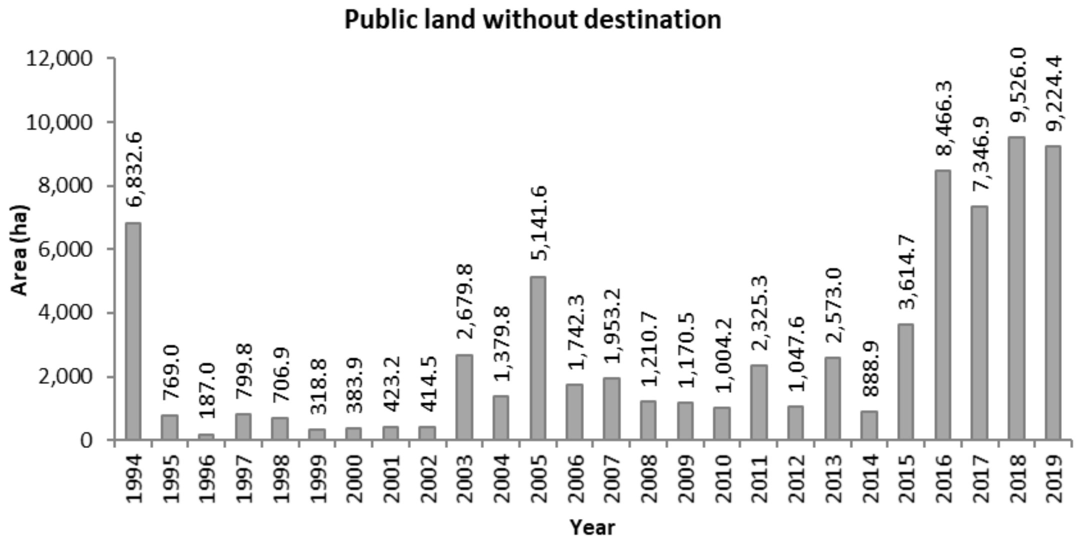
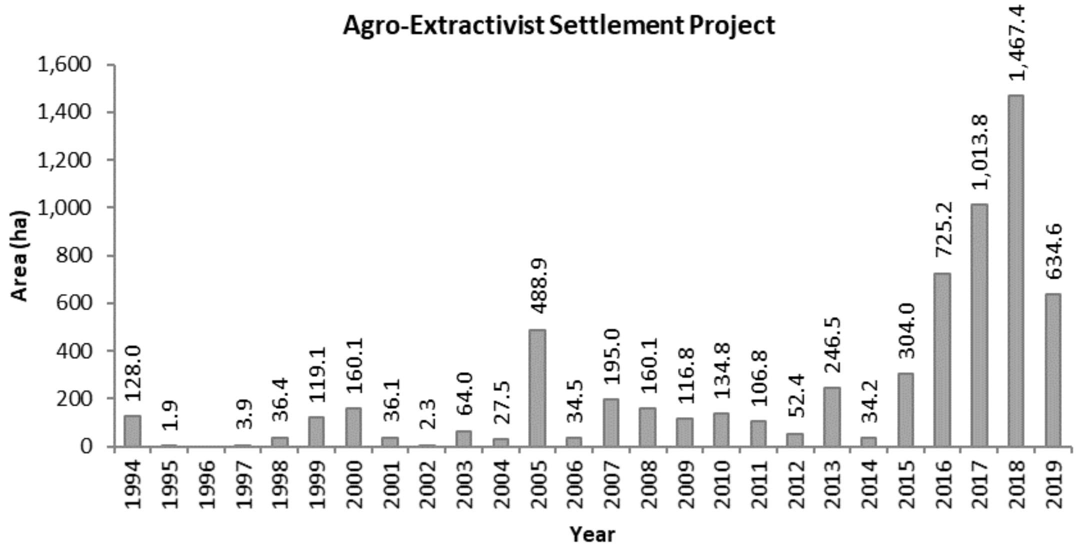
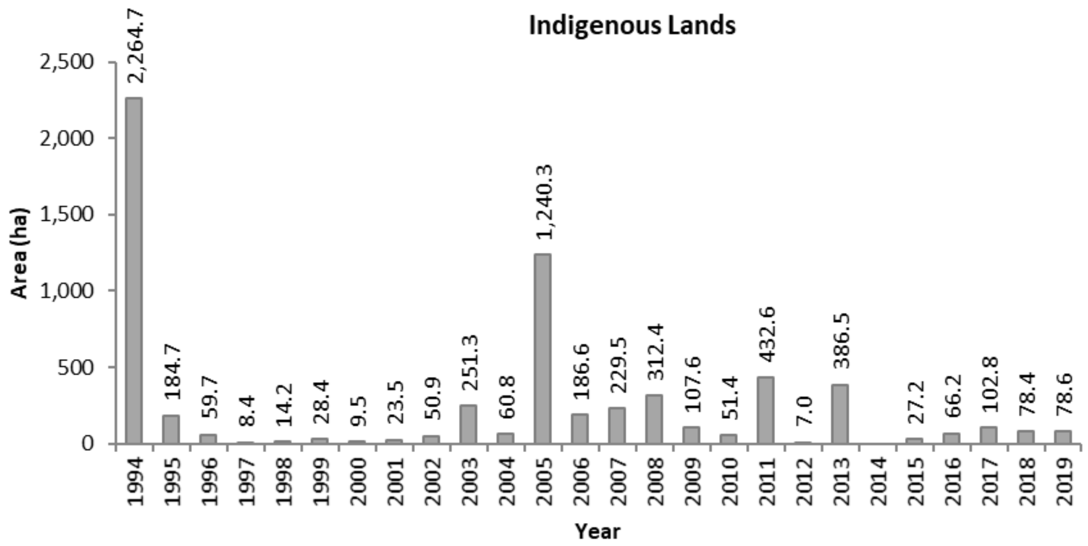
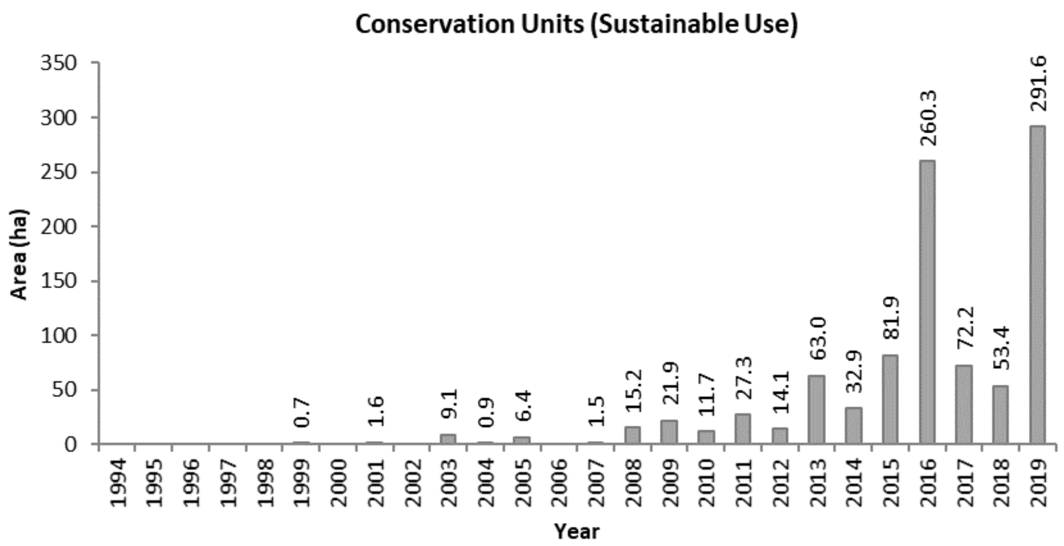


Fig. S3. Cumulative deforestation through 1994 and annual deforestation from 1995 to 2018 for landholdings outside the settlement.


Public land without destination
Area (ha)
Year
12,000
10,000
8,000
6,000
4,000
2,000
0
1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019
6,832.6
769.0
187.0
799.8
706.9
318.8
383.9
423.2
414.5
2,679.8
1,379.8
5,141.6
1,742.3
1,953.2
1,210.7
1,170.5
1,004.2
2,325.3
1,047.6
2,573.0
888.9
3,614.7
8,466.3
7,346.9
9,526.0
9,224.4


Agro-Extractivist Settlement Project
Area (ha)
Year
1,600
1,400
1,200
1,000
800
600
400
200
0
1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019
128.0
1.9
3.9
36.4
119.1
160.1
36.1
2.3
64.0
27.5
488.9
34.5
195.0
160.1
116.8
134.8
106.8
52.4
246.5
34.2
304.0
725.2
1,013.8
1,467.4
634.6


Indigenous Lands
Area (ha)
2,500
2,000
1,500
1,000
500
0
2,264.7
184.7
59.7
8.4
14.2
28.4
9.5
23.5
50.9
251.3
60.8
1,240.3
186.6
229.5
312.4
107.6
51.4
432.6
7.0
386.5
27.2
66.2
102.8
78.4
78.6
1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019
Year


Conservation Units (Sustainable Use)
Area (ha)
350
300
250
200
150
100
50
0
0.7
1.6
9.1
0.9
6.4
1.5
15.2
21.9
11.7
27.3
14.1
63.0
32.9
81.9
260.3
72.2
53.4
291.6
1994 1995 1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019
Year

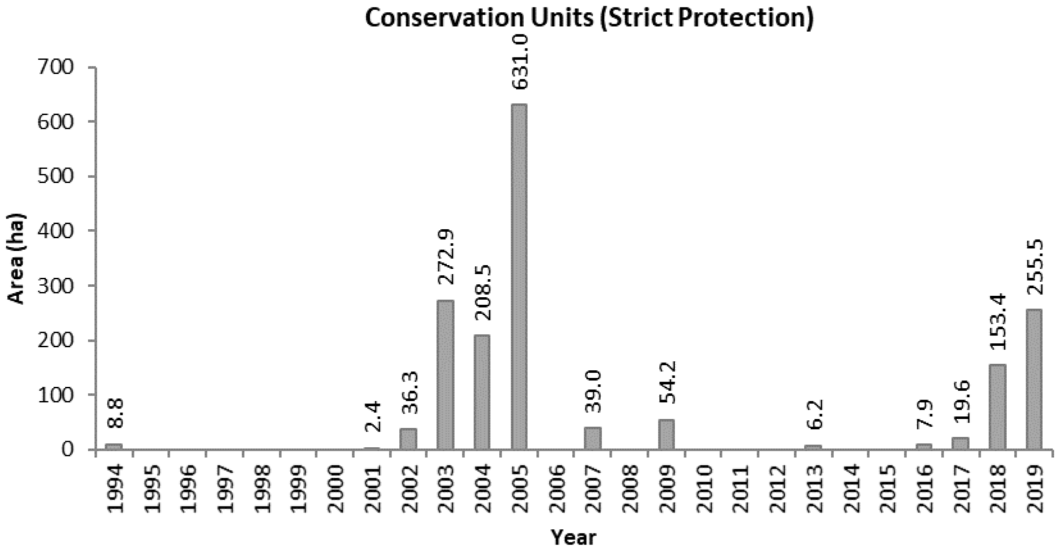


Fig. S4. Cumulative deforestation through 1994 and annual deforestation from 1995 to 2018 for different land categories.

Table S1. Values of minimum similarity for each region using *absolute rates* in the Matupi model and in the null model. Values ≥ 50% in the Matupi model are indicated in green and in the null model in orange.

Window size	Non-concentrators		Conc. 2 lots		Conc. 3 and 4 lots		Conc. 5 lots		Conc. 10 lots		Conc. Non-neighboring lots		Smallholders		Semi-smallholders		Medium landholders		Lergeholders		Public land		Indigenous Lands		Cons. Units (Sustainable Use)		Cons. Units (Strict Protection)	
	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model
1	0.57	0.50	0.68	0.28	0.80	0.53	0.16	0.16	0.23	0.00	0.68	0.11	0.70	0.36	0.47	0.28	0.23	0.17	0.53	0.09	0.31	0.22	0.06	0.02	0.28	0.09	0.04	0.00
3	0.63	0.55	0.76	0.34	0.87	0.56	0.23	0.29	0.50	0.00	0.89	0.14	0.75	0.40	0.51	0.31	0.26	0.19	0.55	0.10	0.33	0.24	0.07	0.03	0.36	0.11	0.05	0.00
5	0.69	0.61	0.78	0.39	0.89	0.59	0.27	0.44	0.75	0.00	0.89	0.14	0.78	0.43	0.54	0.34	0.29	0.21	0.57	0.11	0.35	0.27	0.08	0.03	0.39	0.14	0.06	0.00
7	0.73	0.65	0.79	0.44	0.91	0.62	0.32	0.59	0.83	0.00	0.89	0.14	0.81	0.46	0.56	0.36	0.31	0.23	0.60	0.12	0.37	0.29	0.09	0.04	0.42	0.17	0.06	0.00
9	0.77	0.70	0.80	0.49	0.92	0.64	0.35	0.70	0.83	0.00	0.89	0.14	0.83	0.49	0.59	0.39	0.34	0.25	0.62	0.13	0.39	0.32	0.10	0.05	0.45	0.20	0.06	0.00
11	0.81	0.74	0.81	0.52	0.93	0.66	0.39	0.80	0.83	0.00	0.89	0.14	0.85	0.51	0.61	0.41	0.36	0.27	0.63	0.13	0.40	0.34	0.11	0.05	0.47	0.23	0.06	0.01
13	0.83	0.77	0.82	0.56	0.94	0.68	0.43	0.88	0.83	0.00	0.94	0.20	0.86	0.53	0.63	0.43	0.38	0.29	0.65	0.14	0.41	0.36	0.12	0.06	0.49	0.26	0.07	0.01
15	0.85	0.80	0.83	0.59	0.94	0.69	0.47	0.94	0.83	0.08	0.98	0.26	0.87	0.55	0.65	0.45	0.40	0.30	0.67	0.15	0.43	0.37	0.13	0.06	0.50	0.29	0.07	0.01
17	0.87	0.82	0.84	0.61	0.94	0.70	0.50	0.97	0.83	0.17	1.00	0.26	0.88	0.57	0.67	0.47	0.42	0.32	0.69	0.16	0.44	0.39	0.14	0.06	0.52	0.31	0.07	0.01
19	0.88	0.84	0.85	0.64	0.95	0.70	0.54	0.98	0.83	0.17	1.00	0.26	0.88	0.59	0.69	0.49	0.44	0.33	0.71	0.17	0.45	0.40	0.16	0.07	0.53	0.32	0.08	0.01
21	0.89	0.86	0.86	0.66	0.95	0.71	0.58	0.98	0.83	0.17	1.00	0.26	0.89	0.60	0.70	0.51	0.45	0.35	0.72	0.18	0.46	0.42	0.17	0.07	0.55	0.33	0.08	0.01
23	0.90	0.87	0.86	0.68	0.95	0.72	0.61	0.98	0.83	0.25	1.00	0.26	0.89	0.62	0.71	0.52	0.47	0.36	0.74	0.19	0.47	0.43	0.19	0.08	0.56	0.34	0.08	0.02
25	0.91	0.89	0.87	0.70	0.96	0.73	0.65	0.98	0.83	0.33	1.00	0.26	0.89	0.63	0.73	0.54	0.49	0.38	0.76	0.20	0.48	0.45	0.20	0.08	0.58	0.34	0.09	0.02
27	0.92	0.90	0.88	0.71	0.96	0.73	0.69	0.99	0.83	0.42	1.00	0.26	0.90	0.65	0.74	0.55	0.50	0.39	0.78	0.20	0.49	0.46	0.22	0.08	0.59	0.35	0.09	0.02
29	0.93	0.91	0.88	0.72	0.96	0.73	0.73	0.99	0.83	0.50	1.00	0.26	0.90	0.66	0.75	0.56	0.52	0.40	0.79	0.21	0.50	0.47	0.23	0.08	0.60	0.35	0.09	0.02
31	0.94	0.92	0.89	0.73	0.96	0.74	0.76	0.99	0.83	0.50	1.00	0.26	0.90	0.68	0.76	0.58	0.53	0.41	0.81	0.22	0.51	0.49	0.23	0.08	0.61	0.35	0.09	0.02
33	0.95	0.93	0.89	0.74	0.96	0.74	0.80	0.99	0.83	0.50	1.00	0.26	0.90	0.69	0.77	0.59	0.54	0.42	0.83	0.23	0.52	0.50	0.24	0.08	0.61	0.35	0.09	0.02
35	0.96	0.94	0.89	0.75	0.96	0.75	0.84	0.99	0.83	0.50	1.00	0.26	0.90	0.70	0.78	0.60	0.55	0.44	0.84	0.24	0.52	0.51	0.25	0.08	0.62	0.36	0.09	0.02
37	0.97	0.95	0.89	0.75	0.96	0.76	0.88	0.99	0.83	0.50	1.00	0.26	0.91	0.71	0.79	0.61	0.57	0.45	0.86	0.25	0.53	0.52	0.26	0.08	0.63	0.36	0.10	0.02
39	0.97	0.96	0.90	0.76	0.96	0.76	0.91	0.99	0.83	0.50	1.00	0.26	0.91	0.72	0.80	0.62	0.58	0.46	0.87	0.26	0.54	0.53	0.26	0.08	0.63	0.36	0.10	0.02
41	0.98	0.96	0.90	0.77	0.97	0.77	0.95	1.00	0.83	0.67	1.00	0.26	0.91	0.73	0.81	0.63	0.59	0.47	0.88	0.27	0.55	0.55	0.27	0.08	0.64	0.36	0.10	0.02

43	0.98	0.97	0.90	0.78	0.97	0.78	0.98	1.00	0.83	0.67	1.00	0.26	0.91	0.74	0.82	0.65	0.59	0.48	0.89	0.28	0.55	0.56	0.28	0.08	0.64	0.37	0.10	0.02
45	0.98	0.97	0.91	0.79	0.97	0.78	0.99	1.00	0.83	0.67	1.00	0.26	0.91	0.75	0.83	0.66	0.60	0.49	0.90	0.28	0.56	0.57	0.29	0.08	0.64	0.37	0.10	0.02
47	0.99	0.98	0.91	0.80	0.97	0.78	1.00	1.00	0.83	0.75	1.00	0.26	0.92	0.75	0.84	0.67	0.61	0.50	0.90	0.29	0.56	0.58	0.30	0.08	0.64	0.37	0.11	0.02
49	0.99	0.98	0.91	0.81	0.97	0.78	1.00	1.00	0.83	0.83	1.00	0.26	0.92	0.76	0.84	0.68	0.62	0.51	0.91	0.29	0.57	0.59	0.30	0.08	0.64	0.37	0.11	0.02
51	0.99	0.98	0.91	0.82	0.97	0.78	1.00	1.00	0.83	0.83	1.00	0.26	0.92	0.77	0.85	0.69	0.63	0.52	0.91	0.30	0.58	0.60	0.31	0.08	0.65	0.38	0.12	0.02
53	0.99	0.98	0.91	0.83	0.97	0.78	1.00	1.00	0.83	0.83	1.00	0.26	0.92	0.78	0.86	0.70	0.63	0.53	0.91	0.30	0.58	0.60	0.32	0.08	0.65	0.38	0.12	0.02
55	0.99	0.98	0.91	0.84	0.97	0.79	1.00	1.00	0.83	0.83	1.00	0.26	0.92	0.79	0.86	0.71	0.64	0.54	0.91	0.31	0.59	0.61	0.33	0.08	0.65	0.38	0.13	0.02
57	0.99	0.99	0.91	0.85	0.97	0.79	1.00	1.00	0.83	0.83	1.00	0.29	0.93	0.80	0.86	0.72	0.65	0.55	0.92	0.31	0.59	0.62	0.34	0.08	0.65	0.39	0.13	0.02
59	0.99	0.99	0.91	0.87	0.97	0.80	1.00	1.00	0.83	0.83	1.00	0.35	0.93	0.81	0.87	0.73	0.65	0.56	0.92	0.32	0.60	0.63	0.35	0.08	0.65	0.39	0.14	0.02
61	0.99	0.99	0.91	0.88	0.97	0.80	1.00	1.00	0.83	0.83	1.00	0.41	0.93	0.82	0.87	0.74	0.66	0.57	0.92	0.32	0.60	0.64	0.36	0.08	0.65	0.40	0.15	0.03
63	1.00	0.99	0.92	0.89	0.97	0.80	1.00	1.00	0.83	0.83	1.00	0.47	0.93	0.82	0.87	0.74	0.67	0.58	0.92	0.32	0.61	0.65	0.36	0.08	0.65	0.40	0.16	0.03
65	1.00	0.99	0.92	0.90	0.97	0.81	1.00	1.00	0.83	0.83	1.00	0.51	0.93	0.83	0.88	0.75	0.68	0.59	0.92	0.33	0.61	0.66	0.37	0.08	0.65	0.40	0.17	0.03
67	1.00	0.99	0.92	0.91	0.97	0.81	1.00	1.00	0.83	0.83	1.00	0.55	0.94	0.83	0.88	0.76	0.68	0.60	0.92	0.33	0.62	0.67	0.38	0.08	0.65	0.40	0.18	0.03
69	1.00	1.00	0.92	0.92	0.97	0.82	1.00	1.00	0.83	0.83	1.00	0.59	0.94	0.83	0.88	0.77	0.69	0.61	0.92	0.34	0.62	0.67	0.38	0.09	0.65	0.40	0.19	0.03
71	1.00	1.00	0.92	0.93	0.97	0.82	1.00	1.00	0.83	0.83	1.00	0.63	0.94	0.84	0.89	0.78	0.70	0.61	0.92	0.34	0.63	0.68	0.39	0.09	0.65	0.40	0.20	0.03

Table S2. Values of minimum similarity for each region using *relative rates* in the Matupi model and in the null model. Values ≥ 50% in the Matupi model are indicated in green and in the null model in orange.

Window size	Non-concentrators		Conc. 2 lots		Conc. 3 and 4 lots		Conc. 5 lots		Conc. 10 lots		Conc. Non-neighboring lots		Smallholders		Semi-smallholders		Medium landholders		Lergeholders		Public land		Indigenous Lands		Cons. Units (Sustainable Use)		Cons. Units (Strict Protection)	
	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model	Model	Null model
1	0.56	0.49	0.66	0.39	0.72	0.31	0.19	0.18	0.62	0.00	0.80	0.32	0.70	0.39	0.45	0.28	0.23	0.16	0.56	0.14	0.31	0.21	0.03	0.00	0.26	0.09	0.12	0.06
3	0.62	0.54	0.73	0.43	0.79	0.36	0.27	0.28	1.00	0.08	0.84	0.32	0.75	0.42	0.49	0.31	0.26	0.18	0.58	0.15	0.34	0.24	0.04	0.00	0.32	0.12	0.15	0.06
5	0.67	0.60	0.75	0.45	0.83	0.41	0.31	0.39	1.00	0.17	0.88	0.32	0.78	0.44	0.52	0.34	0.28	0.20	0.60	0.16	0.36	0.26	0.04	0.00	0.35	0.15	0.17	0.07
7	0.72	0.65	0.77	0.46	0.84	0.45	0.35	0.49	1.00	0.17	0.88	0.32	0.81	0.47	0.55	0.36	0.30	0.22	0.62	0.17	0.37	0.28	0.05	0.00	0.37	0.17	0.19	0.08
9	0.76	0.69	0.78	0.48	0.86	0.48	0.39	0.59	1.00	0.17	0.88	0.32	0.83	0.49	0.58	0.38	0.32	0.24	0.64	0.18	0.39	0.31	0.06	0.00	0.40	0.20	0.21	0.10

11	0.80	0.73	0.79	0.49	0.87	0.50	0.43	0.68	1.00	0.17	0.88	0.32	0.84	0.50	0.60	0.40	0.34	0.26	0.66	0.19	0.40	0.33	0.07	0.00	0.42	0.23	0.23	0.11
13	0.83	0.76	0.80	0.50	0.89	0.51	0.46	0.76	1.00	0.17	0.92	0.33	0.86	0.52	0.62	0.42	0.36	0.28	0.68	0.20	0.42	0.35	0.07	0.01	0.44	0.26	0.25	0.12
15	0.85	0.79	0.81	0.51	0.90	0.53	0.50	0.81	1.00	0.17	0.95	0.36	0.87	0.54	0.64	0.44	0.38	0.30	0.69	0.21	0.43	0.36	0.08	0.01	0.47	0.29	0.27	0.13
17	0.87	0.82	0.82	0.52	0.91	0.54	0.54	0.86	1.00	0.17	0.96	0.36	0.88	0.56	0.66	0.46	0.39	0.32	0.71	0.22	0.44	0.38	0.09	0.01	0.49	0.32	0.29	0.14
19	0.88	0.84	0.82	0.53	0.92	0.54	0.58	0.91	1.00	0.17	0.96	0.36	0.88	0.57	0.68	0.48	0.41	0.34	0.73	0.24	0.45	0.39	0.09	0.01	0.51	0.34	0.30	0.15
21	0.89	0.86	0.83	0.54	0.92	0.54	0.61	0.95	1.00	0.17	0.96	0.36	0.89	0.59	0.69	0.50	0.42	0.35	0.74	0.25	0.46	0.41	0.10	0.01	0.53	0.35	0.32	0.16
23	0.90	0.88	0.84	0.55	0.93	0.54	0.65	0.97	1.00	0.17	0.96	0.36	0.89	0.60	0.71	0.52	0.44	0.37	0.76	0.26	0.47	0.42	0.10	0.01	0.55	0.35	0.34	0.18
25	0.91	0.89	0.85	0.56	0.93	0.54	0.68	0.98	1.00	0.17	0.96	0.36	0.89	0.61	0.72	0.53	0.45	0.38	0.78	0.27	0.48	0.43	0.11	0.01	0.56	0.36	0.36	0.19
27	0.92	0.91	0.86	0.56	0.94	0.55	0.72	0.98	1.00	0.17	0.96	0.36	0.89	0.62	0.73	0.55	0.46	0.39	0.79	0.28	0.49	0.45	0.11	0.01	0.58	0.36	0.37	0.20
29	0.93	0.92	0.86	0.57	0.94	0.55	0.76	0.98	1.00	0.33	0.96	0.36	0.90	0.63	0.75	0.56	0.48	0.40	0.81	0.29	0.50	0.46	0.12	0.01	0.59	0.36	0.39	0.20
31	0.93	0.93	0.88	0.58	0.94	0.55	0.80	0.99	1.00	0.33	0.96	0.36	0.90	0.64	0.76	0.57	0.49	0.42	0.82	0.30	0.51	0.47	0.13	0.01	0.61	0.36	0.41	0.21
33	0.94	0.94	0.89	0.58	0.94	0.56	0.84	0.99	1.00	0.33	0.96	0.36	0.90	0.65	0.77	0.58	0.50	0.43	0.84	0.31	0.52	0.48	0.13	0.01	0.62	0.36	0.42	0.22
35	0.95	0.95	0.90	0.59	0.94	0.57	0.88	0.99	1.00	0.42	0.96	0.36	0.91	0.67	0.78	0.60	0.51	0.44	0.86	0.32	0.53	0.50	0.14	0.01	0.64	0.37	0.43	0.23
37	0.96	0.95	0.90	0.59	0.95	0.58	0.91	0.99	1.00	0.50	0.96	0.36	0.91	0.68	0.79	0.61	0.52	0.45	0.87	0.33	0.54	0.51	0.14	0.01	0.65	0.37	0.43	0.25
39	0.96	0.96	0.91	0.60	0.95	0.59	0.95	0.99	1.00	0.67	0.96	0.36	0.91	0.69	0.80	0.62	0.53	0.46	0.88	0.34	0.54	0.52	0.14	0.01	0.66	0.37	0.44	0.26
41	0.97	0.97	0.92	0.61	0.95	0.60	0.98	0.99	1.00	0.83	0.96	0.36	0.92	0.70	0.81	0.63	0.54	0.47	0.89	0.35	0.55	0.53	0.15	0.02	0.66	0.38	0.45	0.27
43	0.97	0.97	0.92	0.61	0.95	0.61	0.99	1.00	1.00	0.83	0.96	0.36	0.92	0.71	0.81	0.64	0.55	0.47	0.89	0.36	0.56	0.54	0.15	0.02	0.67	0.38	0.45	0.28
45	0.97	0.98	0.93	0.62	0.95	0.63	0.99	1.00	1.00	0.83	0.96	0.36	0.92	0.72	0.82	0.65	0.56	0.48	0.89	0.36	0.57	0.56	0.16	0.02	0.68	0.39	0.46	0.29
47	0.98	0.98	0.93	0.63	0.95	0.64	0.99	1.00	1.00	1.00	0.96	0.36	0.93	0.73	0.83	0.66	0.57	0.49	0.89	0.37	0.57	0.57	0.16	0.02	0.68	0.39	0.46	0.30
49	0.98	0.98	0.93	0.64	0.95	0.65	1.00	1.00	1.00	1.00	0.96	0.36	0.93	0.74	0.84	0.67	0.58	0.50	0.90	0.38	0.58	0.58	0.17	0.03	0.68	0.40	0.47	0.31
51	0.98	0.98	0.94	0.65	0.95	0.67	1.00	1.00	1.00	1.00	0.96	0.36	0.93	0.75	0.84	0.68	0.59	0.51	0.90	0.38	0.59	0.59	0.18	0.04	0.68	0.40	0.47	0.31
53	0.98	0.98	0.94	0.66	0.95	0.68	1.00	1.00	1.00	1.00	0.96	0.36	0.94	0.76	0.85	0.69	0.60	0.52	0.90	0.39	0.59	0.60	0.18	0.05	0.68	0.40	0.47	0.31
55	0.99	0.99	0.94	0.67	0.95	0.69	1.00	1.00	1.00	1.00	0.96	0.36	0.94	0.77	0.86	0.70	0.61	0.53	0.90	0.39	0.60	0.61	0.19	0.05	0.69	0.40	0.48	0.31
57	0.99	0.99	0.94	0.68	0.95	0.70	1.00	1.00	1.00	1.00	0.96	0.37	0.94	0.78	0.86	0.71	0.61	0.53	0.90	0.39	0.61	0.62	0.20	0.06	0.69	0.41	0.48	0.31
59	0.99	0.99	0.94	0.68	0.95	0.71	1.00	1.00	1.00	1.00	0.98	0.41	0.94	0.79	0.87	0.71	0.62	0.54	0.90	0.40	0.61	0.63	0.21	0.07	0.69	0.41	0.48	0.31
61	0.99	0.99	0.94	0.69	0.95	0.71	1.00	1.00	1.00	1.00	1.00	0.45	0.94	0.80	0.87	0.72	0.63	0.55	0.90	0.40	0.62	0.64	0.22	0.08	0.69	0.41	0.48	0.31
63	1.00	0.99	0.94	0.70	0.95	0.72	1.00	1.00	1.00	1.00	1.00	0.48	0.94	0.80	0.87	0.73	0.63	0.56	0.90	0.41	0.62	0.64	0.23	0.08	0.69	0.41	0.48	0.31
65	1.00	0.99	0.94	0.70	0.95	0.73	1.00	1.00	1.00	1.00	1.00	0.49	0.94	0.81	0.88	0.74	0.64	0.56	0.90	0.41	0.63	0.65	0.24	0.09	0.69	0.41	0.49	0.31

67	1.00	0.99	0.94	0.71	0.95	0.74	1.00	1.00	1.00	1.00	1.00	0.49	0.94	0.81	0.88	0.75	0.65	0.57	0.90	0.42	0.64	0.66	0.25	0.09	0.69	0.41	0.49	0.31
69	1.00	1.00	0.94	0.71	0.95	0.75	1.00	1.00	1.00	1.00	1.00	0.49	0.94	0.81	0.88	0.76	0.65	0.58	0.91	0.42	0.64	0.67	0.27	0.10	0.69	0.41	0.49	0.31
71	1.00	1.00	0.94	0.71	0.95	0.76	1.00	1.00	1.00	1.00	1.00	0.49	0.94	0.81	0.88	0.76	0.66	0.59	0.91	0.43	0.65	0.68	0.28	0.10	0.69	0.41	0.50	0.31

Table S3. Comparison between observed and simulated deforestation in the calibration phase.

Region	Deforestation observed in 2019 (ha)	Absolute rates			Relative rates		
		Simulated deforestation (ha)	Difference between observed and simulated in area (ha) and percentage		Simulated deforestation (ha)	Difference between observed and simulated in area (ha) and percentage	
Non-concentrators	14,959	15,182	-223	-1.5%	14,951	8	0.1%
Concentrators of 2 lots	4,212	4,252	-40	-0.9%	4,240	-28	-0.7%
Concentrators of 3 and 4 lots	1,913	1,926	-13	-0.7%	1,922	-10	-0.5%
Concentrator of 5 lots	178	126	52	29.1%	127	51	28.5%
Concentrator of 10 lots	387	387	0	0.0%	387	0	0.0%
Concentrator of non-neighboring lots	92	89	3	3.7%	94	-2	-2.2%
Smallholders	6,680	6,720	-40	-0.6%	6,747	-67	-1.0%
Semi-smallholders	36,007	36,318	-311	-0.9%	36,081	-74	-0.2%
Medium landholders	26,529	25,328	1,201	4.5%	25,363	1,166	4.4%
Largeholders	9,796	10,033	-237	-2.4%	10,128	-332	-3.4%
Public land	83,170	78,154	5,016	6.0%	79,352	3,817	4.6%
Indigenous Lands	6,305	6,285	19	0.3%	6,275	30	0.5%
Conservation Units – Sustainable Use	998	801	197	19.7%	816	182	18.3%
Conservation Units – Integral Protection	1,674	1,447	227	13.5%	1,456	218	13.0%