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Combining species distribution modelling and environmental perceptions to support sustainable strategies for Amazon-nut (*Bertholletia excelsa* Bonpl.) planting and conservation

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Thesis presented to obtain the degree of Doctor in Science. Area: Applied Ecology

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"When one tugs at a single
thing in nature, he finds it attached
to the rest of the world". (John Muir)

SUMMARY

RESUMO

Combinando a modelagem de distribuição de espécies e percepções ambientais para fundamentar estratégias sustentáveis de plantio e conservação da Castanha-da-Amazônia (*Bertholletia excelsa* Bonpl.)

Os ecossistemas amazônicos vêm sendo impactados ao longo dos anos por diversos processos de uso e ocupação do território, os quais têm resultado em perdas de habitats e na fragmentação da paisagem nativa. Essas perturbações antrópicas, associadas às mudanças climáticas, têm consequências diretas sobre a distribuição e persistência das espécies in situ. Das 14.003 plantas da Amazônia reconhecidas taxonomicamente, somente 76 estão atualmente listadas pelo Ministério do Meio Ambiente brasileiro como espécies ameaçadas, embora acredita-se que esse número seja muito maior. Entre elas, a Castanha-da-Amazônia (*Bertholletia excelsa*), uma espécie de árvore nativa, reconhecida nacional e internacionalmente pela sua importância cultural, socioeconômica e nutricional, encontra-se classificada como vulnerável. Para nortear políticas públicas na conservação e no plantio dessa espécie, um profundo entendimento sobre o habitat disponível para ela, bem como a origem e escala das ameaças à esse ambiente, é necessário. A modelagem de distribuição de espécies é uma ferramenta que oferece predições espaciais robustas sobre a adequabilidade de habitat e tolerância das espécies, mas tem sido pouco utilizada no Brasil, sobretudo para espécies Amazônicas. Nesse contexto, esse estudo objetivou modelar a distribuição potencial da *B. excelsa* no bioma Amazônia, bem como conhecer os fatores que controlam sua distribuição. Para aprofundar essas análises, estudos de caso foram realizados com o objetivo de conhecer a percepção de atores sociais envolvidos com a espécie sobre as principais ameaças e potenciais soluções. Essa tese baseou-se em duas hipóteses: (i) existem áreas com maior adequabilidade para a ocorrência da Castanha-da-Amazônia que demandam diferentes objetivos, para conservação e para o plantio; (ii) se a população local é conciente da vulnerabilidade da espécie, ela pode indicar os fatores que geram essa condição. No capítulo 1, o habitat foi investigado por meio de simulações usando o algoritmo MAXENT. Um total de 3.325 ocorrências e 102 variáveis ambientais foram obtidas, e posteriormente organizadas por categorias climática, edáfica e geofísica. A resolução espacial escolhida foi de 30 arc-segundo (~1km). A multi-colinearidade entre as variáveis foi reduzida por meio da estatística multivariada associada ao conhecimento de especialistas, e as tendências nas ocorrência foram tratadas através da filtragem espacial. O melhor modelo foi selecionado usando métricas quantitativas e examinações visuais. As variáveis biofísicas mais importantes encontradas foram altitude (m), solos com fragmentos grosseiros (<2mm) e argila (%). Por fim, o modelo indicou que 2.3 million km^2 i.e., 32% da região amazônica é apropriado para *B.excelsa* crescer. No capítulo 2, os fatores que afetam a conservação e o plantio da espécie foram discutidos com comunidades, gestores e pesquisadores locais, totalizando 203 participantes. As técnicas de discussão em grupo focal, entrevistas individuais e questionários foram utilizadas para a coleta das informações. Os dados foram categorizados e as opiniões entre os diferentes grupos comparadas utilizando análises quali-quantitativas. Concluiu-se que atualmente existem 36 problemas responsáveis pela vulnerabilidade da espécie, dos quais 72% encontram-se no contexto ambiental e político. O desmatamento foi a principal forçante apontada, seguida pela desvalorização do fruto, falhas na fiscalização e falta de organização nas comunidades. Para os três grupos, as principais soluções foram voltadas para o contexto político. Os resultados obtidos nesse estudo contribuiem para aumentar o conhecimento ecológico da espécie, para demostrar a complexidade do uso sustentável na Amazônia, e orientar tomadores de decisão na seleção de áreas prioritárias para conservação e potenciais para o plantio.

Palavras-chave: Adequabilidade de habitat; Percepção ambiental; Espécies ameaçadas; Conservação

ABSTRACT

Combining species distribution modelling and environmental perceptions to support sustainable strategies for Amazon-nut (*Bertholletia excelsa* Bonpl.) planting and conservation

The amazon ecosystems have been compromised by historical forms of occupation and land-use causing habitat loss and forest fragmentation. These anthropogenic disturbances associated to climate changes have direct consequences on the distribution of species and their *in situ* persistence. Currently, 76 of 14.003 plants taxonomically identified in the Amazon have been listed by the Brasilian Ministry of the Environment as threatened species, though we believe this number to be much bigger in the reality. Among them, Amazon-nut (*Bertholletia excelsa*), a native tree species, national and internationally known for its cultural, social-economic and nutritional value has been classified as vulnerable. For developping of public policy turned to its management and conservation is fundamental to know the percentage of habitat available, as well as the nature and scale of threats to this environments. Species distribution modelling is an increasingly important tool for predicting habitat suitability and for understanding species environmental tolerances, but has been rarely used in Brazil, especially for Amazonian species. This study aimed to model the potential distribution of *B. excelsa* in the Amazon biome and to know the factors that control its distribution. To enhance our analysis, case studies were carried out with stakeholders aiming to know their perceptions about the main threats to the species and potential solutions.This research project was based on two hypotheses: (i) There is a suitable habitat to Amazon-nut which require different objectives for conservation and planting; (ii) If the local people are aware of the species vulnerability, they are able to point out the factors that cause this condition. In the chapter 1, habitat was investigated using MAXENT algoritm. We collected 3,325 Amazon-nut records and organized one hundred-and-two environmental variables into climatic, edaphic and geophysical categories at a spatial resolution of 30 arcs-second (~1km). Multi-colinearity between variables was dealt with multivariate statistics associated to expert's knowledge, and presence data biased with the spatial filtering. The best model was selected adopting quantitative metrics and visual examination. The most importante biophysic variables we identified were: altitude (m), coarse soil fragments (<2mm) and clay (%). Finaly, the best model indicated 2.3 million km^2 i.e., 32% of the Amazon basin has potential for *B.excelsa* to grow. In the chapter 2, the factors that affect Amazon-nut conservation and planting were discussed with local communities, public managers and researchers, totalyzing 203 participants. Focus groups, individual interviews and questionaire techniques were used to gather information. Data were categorized and the perceptions among stakeholders compared using quali-quantitative analyses. We found that there are currently 36 problems responsible for the species vulnerability and 72% of them belong to environmental and political contexts. Deforestation was the main problem mentioned, followed by fruit depreciation, control failures and lack of organization in the communities. For three groups of stakeholders, the main solutions were related to political context. The results obtained in this study contribute to increase ecological knowledge on the species, to demonstrate the complexity of sustainable use in the Amazon and to guide decisions makers in the selection of priority areas for conservation and potential planting.

Keywords: Habitat suitability; Environmental perception; Threatened species; Conservation

1. INTRODUCTION

Land-use and climate changes are both main threats to the world's biodiversity (Nobre et al., 2016; Pimm et al., 2014). Concerns arise because species extinction rates are exceptionally high, causing significant alterations in the functioning of the ecosystems and impacting on the service ecosystems provided to humanity (Cardinale et al., 2012). Consequently, governments have been signing international agreements to reduce these losses and to promote sustainable development in the last two decades (ONU, 2015).

An important indicator of sustainable forest management has been the extent of forest resources (FAO, 2016), which update us on land-use changes over time, and which are needed to elaborate and implement policies. However, few decisions have been taken previously examining the habitat availability per species to design strategies to maintain and recover populations, in spite of the ecological parameter being suggested as critical to guide restoration (Crouzeilles et al., 2015) and landscape connectivity plans (Saura & Pascual-Hortal, 2007).

The understanding of habitat is a cornerstone of management for plants and animals. One of the oldest and most fundamental concepts of ecology (Yapp, 1922), habitat implies more than vegetation, it is a place in which an organism can live. Indeed only certain combinations of conditions and resources allow a species to maintain a viable population (Begon, Townsend, and Harper, 2006). The spatial distribution within a habitat is determined by the interaction of physical and biological components (Odum, 2008). This is why, the recognition of the environmental patterns and the disturbances that influence them are essential for greater effectiveness on conservation planning.

In the Amazon forest, which hosts the richest biodiversity of the planet, only 14,003 species are taxonomically identified, 6,727 of them being trees (Cardoso et al., 2017), while estimates are approximately 50,000 for the former and 16,000 for the latter (Ter Steege et al., 2013). Unfortunately, ecological information are still incomplete or unavailable to science and governance, despite recent efforts to minimize impacts on endangered species in Brazil (Leite, 2017) and in Peru (Gamboa, Symingto, and Villanueva, 2017).

One of the key-species to evaluate both habitat suitability and availability is Amazon-nut[1] (*Bertholletia excelsa Bonpl.*, Lecythidaceae), because its trees population has been vulnerable to illegal activies in the Amazon for the last fourty years, mainly in southern and eastern of Amazon, in the region named "arch of deforestation" (Scoles et al., 2016).

[1] We adopted Amazon-nut than the more common name Brazil-nut for *Bertholletia excelsa*, because this species occurs in Brazil and others Amazonian countries. Its seeds are traded by Brazil, Bolivia and Perú.

Another reason is that its seeds are one the most important non-timber forest product traded in the region (Thomas et al., 2017). Fruit's success is recently attributed to health benefits offered by the seeds rich in selenium and other micronutrients (Cardoso et al., 2017). Moreover, it is almost exclusively collected by traditional communities in mature forests (Guariguata et al., 2017). In this kind of forest, the species ranked third of the top 20 accumulators of aboveground woody biomass (Fauset et al., 2015) and has positive interactions with amphibians and rodents (Camera & Krinski, 2014; Haugaasen et al., 2010).

Amazon-nut also has a broad and discontinuous distribution, leading to formation of groves in some areas (Salomão, 2009) and scattered trees in others (Wadt, Kainer, & Gomes-Silva, 2005). Although low regeneration levels were observed in old-growth forests (Scoles & Gribel, 2012), it has the potential to be managed in disturbed or regenerating forests areas (Guedes et al., 2014). Unfortunally, the Amazon-nut domestication has not been emplaced, even with scientific and technological advances to stimulate the planting (Müller, 1995; Wadt & Kainer, 2009). Nevertheless, species has been recommend to inclusion in several forms of Agroforest system due its good development and environmental services offered in degraded areas (Castro, Wandelli, & Campos, 2009).

While this species is protected by Peruvian (Law n°00729-81-AG, 1981), Bolivian (Law nº 27572, 2004), Brazilian (Law n° 5.975, 2006) and Colombian governments (Law n °49.072, 2014), its habitat has been suffering significant environmental alterations (Nobre et al., 2016), some of it in protected areas (Barber et al., 2014; Fearnside, 2017). It incites some specific questions:

What is the suitable habitat extension of *B. excelsa*? What are the factors that control its distribution? What is the habitat percentage inside and outside protected areas? What are local people thinking about the threats to this species? Has law been effective to protect the Amazon-nut against the recent land-use forms?

We hypothesized that:

(a) There is a suitable habitat to *B. excelsa* which require different objectives for conservation and planting in the Amazon;

(b) If the local people are aware of the species vulnerability, they are able to point out the factors that cause this condition;

Both natural and social sciences have developed a plurality of theories, methods and tools to help us answer the research questions (Bennett et al., 2017; Franklin et al., 2010). In this study, we investigated the *B. excelsa* distribution using the ecological modelling and environmental perception techniques.

Species Distribution Modelling (SDM) has been an advantageous and widely used resource to assess habitat suitability or species tolerance since 1980s (Franklin, 2010). The principle of correlative models is to relate locations of a species with the environmental characteristics of these locations (Elith & Leathwick, 2009). The outputs or probability of presence, limited by environmental factors is projected geographical space, even in the areas where small samples are present. Currently, many techniques using statistical or machine learning approaches are available to make spatial prediction (Phillips et al., 2017). These models can be used in several applications, for example, to evaluate impact of climate changes (Franklin et al., 2013), invasive species (Václavick & Meentemeyer, 2012) and for the recolonization of threatened species (Cianfrani et al., 2010).

As far as stakeholders's perception is concerned, it has been recognized as an important and indispensable source of information to evaluate environmental issues (Villamor et al., 2014). Studies have demonstrated that in virtue of local or traditional knowledge, 'people are able to provide useful evidence' at all stages of the conservation process from planning to ongoing management (Nathan James Bennett, 2016), since the most of the drivers of environmental change are social (Newing et al., 2011). Perception is a multi-dimensional processes formed as a result of individual factors (e.g. sensory experiences, preferences, personal motivations, interpretations, actions, observations, etc.), as well as collective (e.g, culture, politics, socioeconomic, norms, etc) (Garling & Golledge, 1989, Bennett, 2016). In recent years, social data analyses have gained more authenticity through systematic protocols with computational support (Chandra & Shang, 2016; McGranahan, Fernando, and Kirkwood, 2017). These advances were not only developed to avoid mistakes, oversights, but also to reduce subjectivity as much as possible (Kruger et al 1998).

In this thesis, modelling was made on a large scale, i.e, Amazon biome geographical space, to develop a robust habitat model using statistical analysis supported by expert's knowledge. On a smaller scale, perception was examined in case studies with three group of local stakeholders (rural communities; public managers; and researchers), in two municipalities of Para State, where there are a high Amazon-nut vulnerability. Both techniques were explored aiming to discuss methodological aspects and increase ecological knowledge in order to support conservation and planting strategies for this species.

Objective

The main objective of this study was to establish the Amazon-nut (*Betholletia excelsa.*) spatial distribution and identify the main drives that guide or limit this distribution by ecological modelling and environmental perception techniques to support planting and conservation.

To achieve this objective, we stabilised the following specific objectives:

1. Organize a geodatabase with environmental variables and species presence data in a unique projected coordinate system;
2. Explore biotic and abiotic data using the most applied multivariate techniques;
3. Conduct simulations and fit models using the Maxent algorithm;
4. Evaluate a model-building process supported by experts' knowledge;
5. Map the extent of suitable habitat for Amazon-nut;
6. Describe environmental patterns that control species distribution;
7. Select municipalities to develop case studies;
8. Identify stakeholders involved with the species;
9. Conduct focal groups, individual interviews and questionnaires;
10. Describe stakeholder's perception on main problems that affect the habitat;
11. Compare critily communities, managers and researchers' perception;
12. Obtain their main solution for Amazon-nut planting and conservation.

Thesis Organization

This document is organized in two chapters. In chapter 1, we focus on developing a robust model of suitability habitat and investigating the most important environmental predictors that control Amazon-nut distribution. We examined the effects of model parameters, spatial filtering and chosen variables supported by expert knowledge. In Chapter 2, we discussed the factors that affect the Amazon-nut trees with local people (rural communities, public managers and researchers), exploring environmental perception techniques with focal group discussion, individual interviews and questionnaires. Both chapters have appendices as supplementary material to give further details on the subject studied.

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2. MODELLING HABITAT SUITABILITY OF AMAZON-NUT (*BERTHOLLETIA EXCELSA*) IN PANAMAZONIA: TESTING DIFFERENT STRATEGIES TO OPTIMIZE MODEL FIT

2. MODELLING HABITAT SUITABILITY OF AMAZON-NUT (*BERTHOLLETIA EXCELSA*) IN PANAMAZONIA: TESTING DIFFERENT STRATEGIES TO OPTIMIZE MODEL FIT

Abstract

Aim

Amazon-nut (*Bertholletia excelsa*) is a hyperdominant and protected tree species playing a keystone role in nutrient cycling and ecosystem service provision in Amazonia. Our main goal was to develop a robust habitat suitability model of Amazon-nut and to identify the most important predictor variables to support conservation and tree planting decisions.

Localization

Amazon region, South America.

Methods

We collected 3,325 unique Amazon-nut records and assembled >100 spatial predictor variables organized across climatic, edaphic and geophysical categories. We compared suitability models using variables (i) selected through statistical techniques; (ii) recommended by experts; and (iii) integrating both approaches (i and ii). We applied different spatial filtering scenarios to reduce overfitting. We additionally fine-tuned MAXENT settings to our data. The best model was selected through quantitative and qualitative assessments.

Results

Principal Component analysis based on expert recommendations was the most appropriate method for predictor selection. Elevation, coarse soil fragments, clay, slope and annual potential evapotranspiration were the most important predictors. Their relative contribution to the best model amounted to 75%. Filtering of the presences within a radius of 10 km displayed lowest overfitting, a satisfactory omission rate and the most symmetric distribution curve. Our findings suggest that under current environmental conditions, suitable habitat for Amazon-nut is found across 2.3 million km^2, i.e., 32% of the Amazon Biome.

Main conclusion

The combination of statistical techniques with expert knowledge improved the quality of our suitability model. Topographic and soil variables were the most important predictors. The combination of predictor variable selection, fine-tuning of model parameters and spatial filtering was critical for the construction of a reliable habitat suitability model.

Keywords

Habitat suitability, MAXENT, model evaluation, expert knowledge, Amazon conservation

2.1 Introduction

Range-wide management and conservation of socio-economically important tree species requires a comprehensive understanding of species habitat preferences and the magnitude and nature of anthropogenic and natural threats to their in situ persistence. However, in Amazonia such knowledge often remains diffuse, incomplete, and based on local experience rather than rigorous scientific data. Furthermore, existing knowledge on Amazonian forest species has been poorly integrated within conservation planning frameworks (Addison et al., 2013; Gardner et al. , 2009). As a result, biodiversity conservation strategies have failed to protect the majority of endemic species from vertebrate, arthropod and angiosperm groups in Brazil (Oliveira et al., 2017). The latter authors found that less than 40% of the estimated distribution area for some species fell inside protected areas. Conservation decision making processes in Amazonia can be greatly improved through the inclusion of species distribution models (SDMs) which is currently not the case in most Amazon countries.

The complexity of SDMs, both in terms of development and understanding, is a common constraint to their application in decision-making (Addison et al., 2013). Nonetheless, SDMs are an increasingly important tool for predicting habitat suitability and for understanding species environmental tolerances (Stolar & Nielsen, 2014). SDMs are also essential to guide field collections, as well as to inform or reinforce management, reforestation and conservation plans (Franklin, 2010). The value and importance of a well-constructed SDM has motivated an explosion of methods aimed at building more accurate models (Elith et al., 2011; Kuhnert, Martin, & Griffiths, 2010). However, few efforts have been made to develop a collaborative model-building process among modellers, ecologists, and decision-makers to improve model quality (Calixto-Pérez et al., 2018) and to facilitate clear communication of model results (Addison et al., 2013).

One of the most widely used methods of developing SDMs is MAXENT (Phillips et al., 2017). MAXENT is a correlative model based on the principle of maximum entropy to predict or infer species occurrence using presence-only data and environmental variables (Phillips, Anderson, & Schapire, 2006). The probability of occurrence is then modelled using a logistic equation fitted to available presence data and randomly chosen or target-group background data in a given study region (Phillips & Dudík, 2008). Several studies have highlighted that the performance of MAXENT models is influenced by (i) biases in occurrence data that cause overfitting and need to be removed (Kramer-Schadt et al., 2013) and (ii) the uncritical use of “default settings” (Phillips & Dudík, 2008). Indeed, there is growing evidence that the most appropriate MAXENT settings vary according to species and study area. However, only 3.7 % of articles published between 2013 and 2015 tested if the default regularization and feature class parameters were appropriate for their data (Morales, Fernández, & Baca-González, 2017; Radosavljevic & Anderson, 2014). When adequately fine-tuned, these parameters prevent the algorithm from fitting the input data too closely (Phillips & Dudík, 2008).

Errors can furthermore be introduced into MAXENT-based analysis through multi-collinearity among predictors that can inflate the variance and standard errors of regression parameter estimates. Careful selection of candidate predictor variables is therefore recommended (Dormann et al., 2013). Statistical analysis has been commonly used to address this issue, as for example through Principal Component Analysis (PCA) in the generation of multiple orthogonal synthetic variables and selection of the most representative axis and predictors (Everitt & Dunn, 2001). However, models using maximum entropy have also been improved by integrating expert knowledge in the predictor selection stage of model development (Porfirio et al., 2014).

An expert is someone who has gained knowledge through his/her life experience, education or trainning, and who is responsible for providing judgments (Mcbride & Burgman, 2012). Experts can contribute, for example, to the choice of variables to be included in the model based on their knowledge of a species’ life cycle (Porfirio et al., 2014), to determine geographic limits to the presumed species (Jones et al., 2012), to provide knowledge when empirical data are lacking yet management decisions are required (Kuhnert et al., 2010), or simply to provide feedback on model results . Expert-based information has been successfully used to improve management of environmental systems (Perera, Drew, & Johnson, 2012), but has been seldom used in the development of SDMs (Kuhnert et al., 2010; Porfirio et al., 2014).

Amazon-nut modelling distribution

MAXENT has been applied previously to model the distribution of the Amazon-nut (*Bertholletia excelsa*), specifically at Para State, Brazil (Albernaz & Avila-Pires, 2009). However, results from this study are limited in their utility for conservation planning due to paucity of presences used, the restricted spatial extent of analysis, and the limited diversity of environmental predictors considered. Thomas et al (2014) also examined Amazon-nut distribution using an ensemble modelling approach. Their goal was to assess the distribution of Amazon-nut habitat suitability across the Amazon basin and make projections to past and future climate conditions. They found that the current spatial distribution of this species was shaped by an initial period of range contraction in the Pleistocene, followed by range expansion in the Holocene resulting in its contemporary distribution. Although these findings are informative and compelling, the model of distribution of suitable habitat estimated showed a high degree of overfitting and had limited out of sample (OOS) predictive power. Such reduced predictive power was clearly observed at eastern amazon, where they had few records of presence.

Developing robust models with a high OOS for the Amazon-nut is now possible thanks to the availability of high-quality environmental data (e.g. Wordclim (Fick & Hijmans, 2017) and Soilgrid platforms (Hengl, et al. 2014)). Additionally, species occurrence data are being generated in scientific collaboration networks with standardized accessibility policies (e.g. Global Biodiversity Information Facility; https://www.gbif.org). Specifically for *B. excelsa*, a Brazilian project named MAPCAST "Mapping of Amazon-nut groves and socio-environmental and economic characterization of Amazon-nut production systems in the Amazon" was carried out from 2013 to 2018 (https://www.embrapa.br/en/projetos). It generated direct biological information and the formation of a group of specialists on this taxonomic group.

Amazon-nut (*Bertholletia excelsa*) is one of the largest and longest living hyperdominant tree species in Amazonia (Ter Steege et al., 2013). It ranked third in the top 20 accumulators of aboveground woody biomass in Amazonia (Fauset et al., 2015) and has provided critical ecosystem services to humans since pre-history (Roosevelt et al., 1996). Currently, the Amazon-nut is legally protected and one of the most important non-timber forest product (NTFP) in the Amazon basin, on which tens of thousands of local people depend, mainly in Brazil, Bolivia and Peru (Guariguata et al., 2017). Extensive research has been dedicated to evaluating the sustainability of nut harvesting (Bertwell et al., 2017), characterizing demographic and genetic structure within and among (Salomão, 2009; Sujii et al., 2015), and understanding the natural and human drivers of its current distribution (Thomas et al., 2015). Despite this rich body of work, surprisingly little is known about the environmental gradients that determine the species occurrence across its range in Amazonia.

In this paper, we develop a novel SDM using MAXENT with the goal of improving our understanding of the habitat extent and the environmental determinants of *B. excelsa* occurrence, in order to guide conservation and tree planting strategies. Given the importance of careful selection of potential predictor variables and removal of bias in SDMs (Boria et al., 2014; Franklin, 2010), we also address three methodological questions: 1) which strategy of predictor selection is most adequate to model *B. excelsa* habitat suitability?; 2) what are the best MAXENT settings based on the distribution of our data across Amazonia?; 3) what is the minimum distance between occurrence points to remove bias and fit robust models statistically and ecologically? Finally, we evaluated the usefulness of incorporating expert knowledge in predictor variable selection for enhancing the quality of SDM for *B. excelsa*.

2.2 Material and methods

2.2.1 Occurrence data

This study was conducted in the Amazonia biome (Fig. 1), the world's largest tropical rainforest, occupying 7.2 million of km^2 and shared by nine countries (Brazil, Bolivia, Ecuador, Peru, Venezuela, Columbia, Guyana, French Guyana, and Suriname). Amazon-nut's occurrence data (n=3,325) were collected from a diversity of sources: datasets provided by researchers acquired in field collection from research projects; data available from Emilio Goeldi Museum and Embrapa herbarium collections; Global Biodiversity Information Facility (GBIF) database; scientific publications and data recorded in field expeditions from 2015 to 2018 supported by São Paulo Research Foundation (see Table S1.1 of Appendix A).

2.2.2 Environmental data

Predictor variables were derived from globally available raster data at 30 arc-second spatial resolution (~ 1km). A total of 102 predictors were assembled for this study (Table S1.2). Nineteen bioclimatic variables were obtained from http://www.worldclim.org , which are based on interpolation data from 1950 to 2000 (Hijmans et al., 2005), and are widely used in ecological modelling (Franklin et al., 2017). From these layers, monthly potential evapotranspiration (PET), Aridity (ARI) and Soil-water content (SWC) layers were calculated and available by http://www.cgiar-csi.org/data.

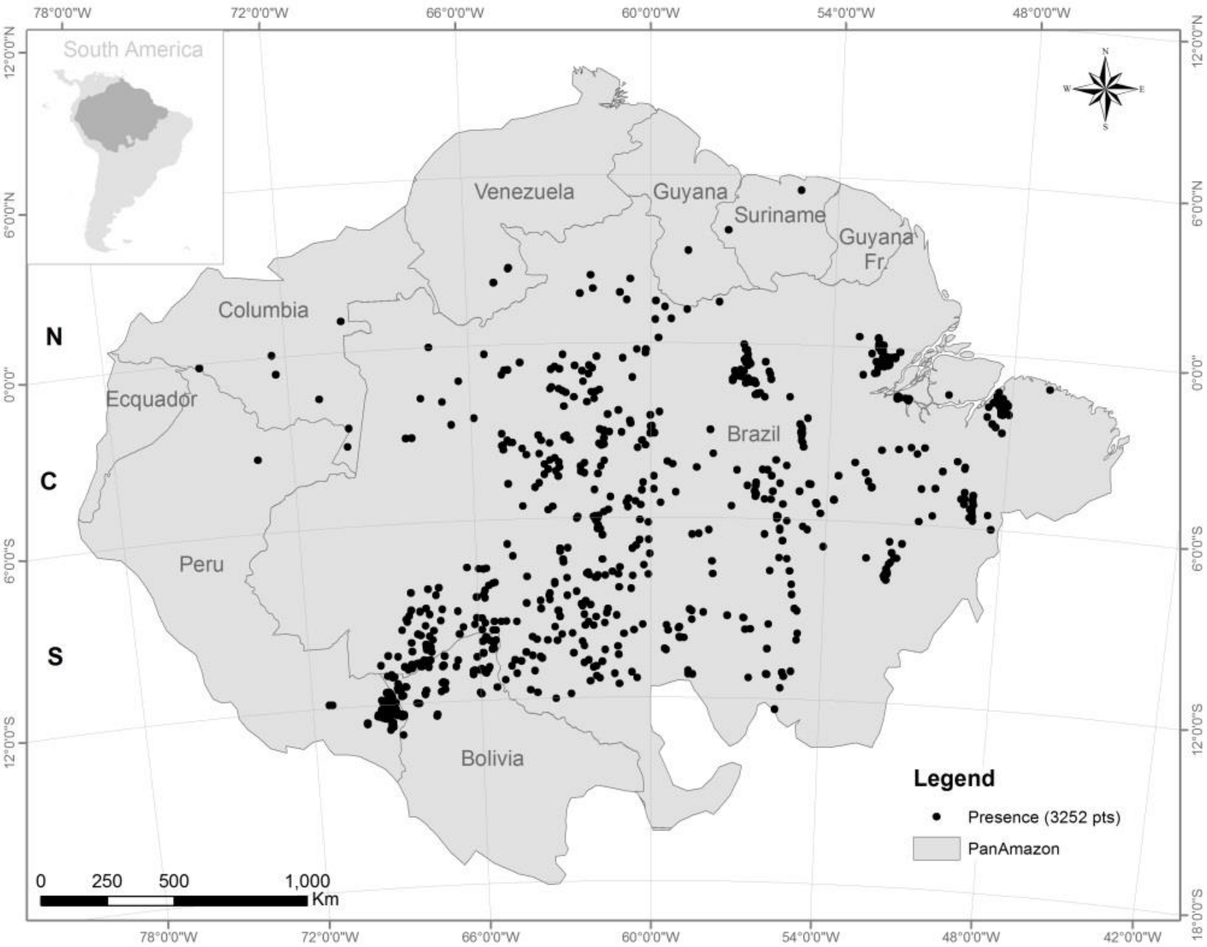


Figure1. a) Geographical localization of the Amazon in South America. The black points indicate the localization of the Amazon-nut (*Bertholletia excelsa*) observation points obtained to this study (3252). The Coordinate System adopted was Albers Equal Area Conic projected for continental areas.

Predictors for physical and chemical soil properties were obtained for seven depths (0 up to 200 cm) from https://www.soilgrids.org. Selected predictors included soil organic carbon (g kg^{-1}), soil pH x 10 in H_2O, sand, silt and clay fractions (%), bulk density (kg m^{-3}), cation-exchange capacity (cmol+/kg), and coarse fragments (%) (Hengl et al. 2014). To test for differences between soil variable means at different depths, we used ANOVA followed by post-hoc *Tukey tests* computed using the *multcompView* package for R (Graves et al., 2015). Prior to ANOVA, we verified the assumption of normality and homogeneity of data variance, using *Shapiro-Wilk* and *F tests*, respectively. To minimize multicollinearity among soil predictors, only layers with significantly different mean values were retained for further modelling. Boxplots are given in Fig S1.1 of Appendix A).

Global terrain elevation data (GMTED2010) were retrieved from the USGS / NASA database: https://topotools.cr.usgs.gov/gmted_viewer/. This data was used to derive topography and hydrological variables, such as slope, aspect, Compound Topographic Index, and Stream Power Index via ARCGIS 10.3. Geological data were also obtained from NASA https://daac.ornl.gov/SOILS/guides/Global_Soil_Regolith_Sediment.html. These variables provided estimates of the thickness of the permeable layers above bedrock like soil, regolith, and sedimentary deposit (Pelletier et al., 2016).

2.2.3 Removing bias

One source of inaccuracy in SDMs is sampling bias in presence data (Boria et al., 2014). For example, it has been shown that presences recorded near municipal centres are known to suffer from geocoding errors (Franklin et al., 2017). To minimize such potential biases, we removed all presences from within a radius of 5 km from municipal centres. Additionally, presences in Cerrado (dry-forest) areas within the Amazon biome were not used because there are few Amazon-nut occurrences found in these Cerrado patches and species persistence in these drier environments requires further investigation. Omission of samples from the Cerrado regions was also strongly suggested by experts consulted. After this first filtering, 3,252 occurrence records remained.

Bias also occurs when presence data are spatially clustered, often due to more frequent sampling in regions that are more accessible. Consequently, parts of the environmental space suitable for a species are overrepresented, while other parts are absent or poorly represented (Fourcade et al., 2014). Inconsistent spatial representation of potential species habitat can lead to overfitting (Radosavljevic and Anderson 2014) and biased inference. To address this problem, spatial filtering can be used to reduce overrepresentation and to improve model quality through minimizing both omission and commission errors (Boria et al., 2014; Kramer-Schadt et al., 2013).

To reduce biases and find optimal geographic distance, we filtered our Amazon-nut presence data through random rarefication of 3,252 presences considering minimum Euclidian distances between them of 3, 5, 10, 15 and 20 km. Filtering was implemented using the *Sdmtoolbox* ArcGIS toolbox (Brown, 2014). These distances were selected for two reasons: first, many of the presence points in our dataset were clustered at spatial resolutions below 1km, the grain size of our predictor variables. Second, to preserve environmental heterogeneity in the sampled sites with Amazon-nut (high variance and low bias) when assessed in geographic distances of meso-scale (1-10 km) or broad scale (>10 km). These experiments has been suggested in the literature (Boria et al., 2014).

2.2.4 Predictor selection

When developing SDMs, researchers often prioritize predictors associated with primary plant resources (e.g. water, temperature, and nutrients) or those related to human or natural disturbance (e.g., fire, insect outbreaks) (Guisan & Thuiller, 2005). However, problems may arise on the one hand because predictors choices may be subjective and on the other because subsets of predictors may be highly correlated. Automated model selection methods have been developed to address some of these subjectivity issues. These methods use different combinations of variables to find the 'best' model according to some objective measure, such as minimization of the Akaike Information Criterion (Burnham & Anderson, 2002). Despite the advances, it remains challenging to identify a meaningful and informative subset of SDM predictors (Galipaud et al., 2014), largely due to the confounding influence of multi-collinearity (Dormann et al., 2013).

Principal Component Analysis (PCA) has been suggested to reduce the dimensionality of predictor variables through the generation of multiple orthogonal synthetic variables (Everitt & Dunn, 2001). PCA summarize, in few dimensions or axes, most of variability of a dispersion matrix of original predictors (Legendre & Legendre, 1988). The downside is that PCA results can be difficult to interpret, especially when trying to determine which variables contribute meaningfully to each component (Vaughan & Ormerod, 2005). Eigenvector values are often used to identify the most important descriptors (Legendre & Legendre, 2012). However, also external information can be useful to interpretation of ecological structure. Expert knowledge previously considered to be subjective has recently been recognized for its vast potential to improve ecological models (Kuhnert et al., 2010; Porfirio et al., 2014). Here, we compare three methods for variable selection: one based on ordination (PCA), one based on expert knowledge, and another that combines both approaches.

Ordination-based variable selection

We used PCA to reduce collinearity and dimensionality in our large predictor dataset through the creation of mutually orthogonal synthetic predictors (Legendre & Legendre, 2012). PCA-derived synthetic predictors were calculated using environmental data covering the entire geographic space of the Amazon (Pan-Amazon) at spatial resolution of 30 arc seconds (~ 1km).

Prior to analysis, all predictors were standardized to zero mean and unit variance. Then we explored correlations between variables using Pearson's R. We grouped variables by category (i.e., climatic, edaphic, and geophysical) and submitted each group to a PCA. For each group we retained the sub-set of principal components accounting for 80% of the variance in the original data (Jolliffe, 1972).

The predictors that maximally contributed to explaining variance in principal components were identified based on correlations between variables and PCA axes (loading and standard deviation). By means of graphics produced by means of the fviz_contrib function in the factorextra package for R (Kassambara & Mundt, 2017), we obtained the contribution of each variable to the overall axis expressed as a percentage. Only the variables whose contribution was greater than the average were retained. We iteratively recalculated a new PCA on this restricted set of predictors. Next, we applied collinearity tests at a 95 % confidence interval using mctest package for R (Ullah & Aslam, 2017). When, collinearity persisted, the variables for which Person R $> | 0.7|$ in the correlation matrix were rejected, following (Dormann et al., 2013). The variables retained following this procedure will be referred to as Group 1.

Expert-based variable selection

In 2016, we convened an expert panel in Amapa State, Brazil, composed of twelve researchers (PhDs and graduate students) with different types of expertise on Amazon-nut to a workshop titled "Maxent modelling and its application in the estimation of preferential areas of occurrence of B. excelsa", organized by the MAPCAST project. The panel was established to collect expert knowledge on the geophysical and biological factors influencing Amazon-nut distribution for incorporation in the SDM building process.

The 102 variables in the original database, as well as preliminary PCA results, were submitted to their appraisal. The panel of experts was specifically asked the following questions: Which variables should be included in the model? What is the maximal period during which the plant can be exposed to water and heat stress? Should all available depths of soil variables be used? Were the variables selected by PCA adequate to model B. excelsa? After analysis and discussion, the experts reached consensus and provided a list of what they considered to be the most important variables for the occurrence of Amazon-nut (Table S1.2). This variable set will be referred to as Group 2.

Combining both approaches, we also calculated a PCA from the set of variables selected by the expert panel. The variable set will be referred to as Group 3.

2.2.5 Setting and fitting models

We calibrated and projected all models using the ENMeval package for R (v. 0.2.2; Muscarella et al., 2014), which includes some of the latest functions developed to help modelers find parsimonious models using maximum entropy (v. 3.3.3k; Phillips et al., 2017). It allows dividing data sets for k-fold cross-validation, fine-tuning user-defined MAXENT settings, and provides multiple evaluation metrics (Muscarella et al., 2014).

Presence data were used to determine appropriate feature classes (FC) and regularization multiplier (β) parameters within MAXENT for our study area. Feature classes are functions (linear, quadratic, hinge, product, threshold and categorical) created by MAXENT for each environmental variable. By default, features choice is usually conditioned by the number of observations (n). When $n > 80$, all features are used and consequently, model complexity increases (Elith et al., 2011).To reduce complexity, users can specify FCs manually and adjust the level of regularization via the multiplier coefficient (β), which controls the smoothness of the distribution curve. By default, $\beta = 1$ is often selected, but studies have mentioned that higher values result in smoother models (Elith et al. 2011), while according to others, values of β above 4.00 may lead to decline in models quality (Radosavljevic & Anderson, 2014).

We sought to identify the best feature class and regularization parameters for our MAXENT model of Amazon-nut occurrence. As such, we examined five feature classes and combination thereof (L, H, T, LQ, LQP, LQH, LQHP, LQHPT, where L = linear, Q = quadratic, H = hinge, P = product and T = threshold), and four levels of regularization from 0.5 to 2.0, in increments of 0.5. We examined the suitability of these combinations of parameters for both filtered and unfiltered models of Amazon-nut occurrence for each of the three groups of candidate predictors. We used random k-fold cross-validation selection of training and testing data, adopting $k = 10$ to assess model accuracy (Kohavi, 1995). Overall, 576 models were run, taking 10,000 random pseudo-absences from the Pan-Amazonia background (Phillips & Dudík, 2008).

2.2.6 Model performance

Model performance was evaluated using the three metrics: a) the corrected Akaike Information Criterion (AICc) (Burnham & Anderson, 2002); b) the Area Under the Curve of the receiver operating characteristic (ROC) for the test data (AUCTEST) (Elith et al., 2011; James et al., 2017); and c) the 10 % training Omission Rate (OR10) (Fielding & Bell, 1997; Liu, White, & Newell, 2013). All metrics were calculated using the ENMeval package in R (Muscarella et al., 2014).

AICc quantifies model accuracy using maximum likelihood (Burnham & Anderson, 2002). It selects the model with the lowest expected information loss based on a number of parameters and can be used to compare nested models (Johnson & Omland, 2004). Advantageously, it is not affected by the method chosen for data partitioning, because it is calculated based on the full model (unpartitioned data set). Generally, models with ΔAICc <2 are considered to have substantial support (Burnham & Anderson, 2002). In MAXENT, AICc measure has been recently examined and used to compare regularization setting (Warren & Seifert, 2011).

AUC is a measure widely used to evaluate how well SDMs discriminate between actual presences and absences (Fielding & Bell, 1997). An AUC value of 0.5 indicates discrimination no better than random chance, whereas AUC equal to 1 indicates perfect discrimination. However, this measure is not recommended for distribution modelling based on presence-background data (Jiménez-valverde, 2012; Lobo, Jiménez-valverde, & Real, 2008) because it weighs omission and commission errors equally, and it does not provide direct information on overfitting (Radosavljevic & Anderson, 2014). Nevertheless, we believe that AUC results can be useful and calculated it for comparison with other metrics.

OR is other common measure of model performance, also named the false negative rates, is calculated from the confusion matrix (Fielding & Bell, 1997). When absence data are unavailable, it is the only error estimated (Liu et al., 2013). It indicates the proportion of occurrence data incorrectly predicted and can be compared with a theoretical expectation (Radosavljevic & Anderson, 2014). This proportion is essential for selecting a threshold, a cut-off value to transform non-binary into binary prediction (Liu et al., 2013). We used the 10 percentile training omission threshold as values above this proportion often indicate overfitting (Liu et al., 2013).

We compared all models with ΔAICc <2 using AUC and OR10 values to identify the most appropriate groups of predictors and filtering distance. Even based on these three metrics, it was not trivial to select the most appropriate spatial filtering distance. For this reason, we ran MAXENT using R dismo package just for the six best models (Hijmans et al., 2011). This resource was chosen because it offers a number of useful functions to complement our model evaluation, as nicheOverlap and evaluate.

We used the nicheOverlap function to compute Schoener's D statistic (Warren, Glor, & Turelli, 2008), which quantifies pairwise similarities among the best unfiltered and filtered models. Confusion matrices were also reevaluated using the evaluate function for constructing density curves, and determining the relative contributions of environmental variables, as well as different thresholds. Continuous maps were transformed into binary maps using the maximum sensitivity and specificity sum (max SSS threshold). This threshold has provided good results when reliable absence data are unavailable (Liu et al., 2013). Pixels with values equal to or higher than the threshold were considered suitable.

The final maps were examined visually by a group of six Amazon-nut experts who were asked to provide feedback on three aspects: 1) whether the model showed predictive power to identify underrepresented areas; 2) whether the distribution of the habitat of the B. excelsa had been well-represented; 3) whether the most important selected variables made ecological sense. This information was used in complement to the statistical metrics to discuss their utility, signs of overfitting and gaps in the suitability map. The model-building process is summarized in figure 2.

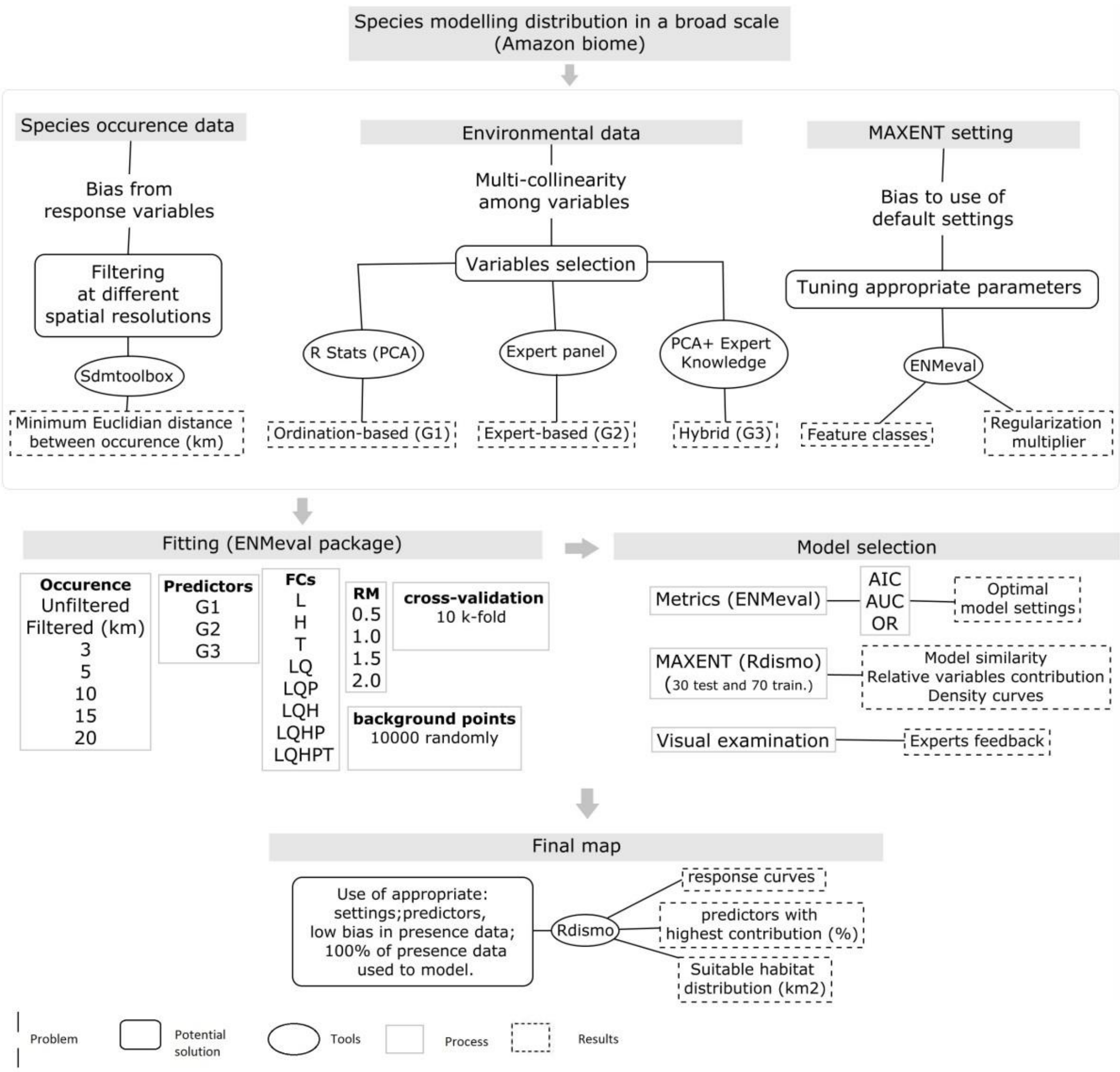


Figure 2. Summary of the model-building process executed to identify the suitable habitat for *B.excelsa* in the Pan-Amazon.

2.3 Results

2.3.1 Candidate predictor variables

For Group1, we identified moderate to high correlations among predictor variables within the climatic (Fig.3a), edaphic (Fig.3b) and geophysical (Fig.3c) predictor groups. For the set of 37 analysed climate variables, 87 % of the variance was explained by the first three ordination axes. For the soil (n = 43) and geophysical (n=10) predictors, four and five axes, respectively, were required to capture 80 % of the variance.

Following initial examination of PCA results, we retained 22 climate variables, 24 soil variables and five geophysical variables which have loadings on the respective PCA axes greater than average (Figs.3d-f). These variables were again submitted to a PCA which resulted in a new set of PCA scores by category. From this PCA 17 climatic variables, 16 soil variables and three geophysical variables had the highest contributions. Several of these variables remained correlated. To reduce multi-collinearity, we retained only variables with pairwise correlations (Pearson's r) < 0.7. Temperature of the Driest Quarter (0.93) and Evapotranspiration of driest quarter (0.81) had a stronger relationship with the first axis, whereas Soil Water Content of driest quarter had a stronger correlation with the second one (0.93). The soil and geophysical variables that were most correlated with the first three axes were bulk density (fine earth) in kg/m3, Soil pH x 10 in H2O, silt mass fraction %, aspect, hillslope valley-bottom and average soil, and sedimentary deposit-thickness. Additional details on ordination including factor loadings can be found in supporting information (Table S2.1).

For Group2, 29 environmental variables of the initial set of 102 were highlighted by experts (Table S1.2). They included only two soil depths, one superficial (0-5 cm) and the other deeper (100-200 cm), to represent variation of the soil variables. Among the climatic variables, temperature and soil water content of the driest quarter were indicated to represent stressful periods, as well as, annual precipitation because water supply is a determining factor for fruit production.

A PCA based on the variables selected by experts (Group 3) captured most of the variance in the first two ordination axes of climatic (86.8 %) and geophysical (90.0 %) predictors. Four climatic and two geophysical variables showed contributions above average: Mean temperature of driest quarter showed the highest correlation with the first axis (0.88), followed by mean temperature of the coldest quarter (0.85) and annual mean temperature (0.84), whereas the annual potential evapotranspiration had stronger relation with the second axis (0.88). The relation between the predictor variables and the first two principal components are visualized in Figs.4a-c.

Among the geophysical predictors, terrain elevation (0.86) and slope (0.89) were strongly associated with the first axis. For the soil variables, 83.5 % of the variance was explained by the first five axes, for which eight variables were above average: Coarse fragments > 2mm, Cation Exchange Capacity, Soil pH, sand mass fraction, clay mass fraction and silt mass fraction. Additional details on ordination of this group of predictors can be found in Appendix (Table S2.2).

2.3.2 Habitat suitability model

Values of AUC and omission rates of the best 18 models with lowest AICc (i.e. ΔAICc < 2) are illustrated in figure 5. All metrics are provided in Table S2.3.

Maxent settings

There was a high degree of variation in both *feature class* and *regularization multiplier* parameters among the best models. The most frequent regularization coefficient was β=1.5 (44%), followed by β=1 (39 %) and β=2.0 (17 %). LQHPT feature classes appeared in 56 % of the best models, including the final model.

Choice of variables

PCA based on expert recommendations (***Group 3***) was the most appropriate method to select predictors on both unfiltered and filtered model based on the metrics (Table S2.3). Among unfiltered models, the highest AUC (0.89) was obtained for ***Group 3*** and omission rates were within the expected 10 % (Fig.5a-b), but this model was considered unreliable due to overfitting caused by biased data used in calibration (Fig. 6).

Models based on all variables selected by experts (***Group 2***) had better discriminatory power than models based on the other groups, regardless of the scale of spatial filtering applied (3-20 km), with AUC values ranging from 0.80 to 0.86 (Fig. 5a). However, these models had omission rates between 12 and 17 %, i.e., rates above the expected theoretical threshold (10 %). This reflects low accuracy and predominance of false-negative errors in the confusion matrix. However, after removing multi-collinearity of the predictors selected by experts via PCA (***Group 3***), omission rates were reduced to 11 %, as well as overfitting (Table S2.3). Therefore, this group of variables was selected for modelling the distribution of Amazon-nut.

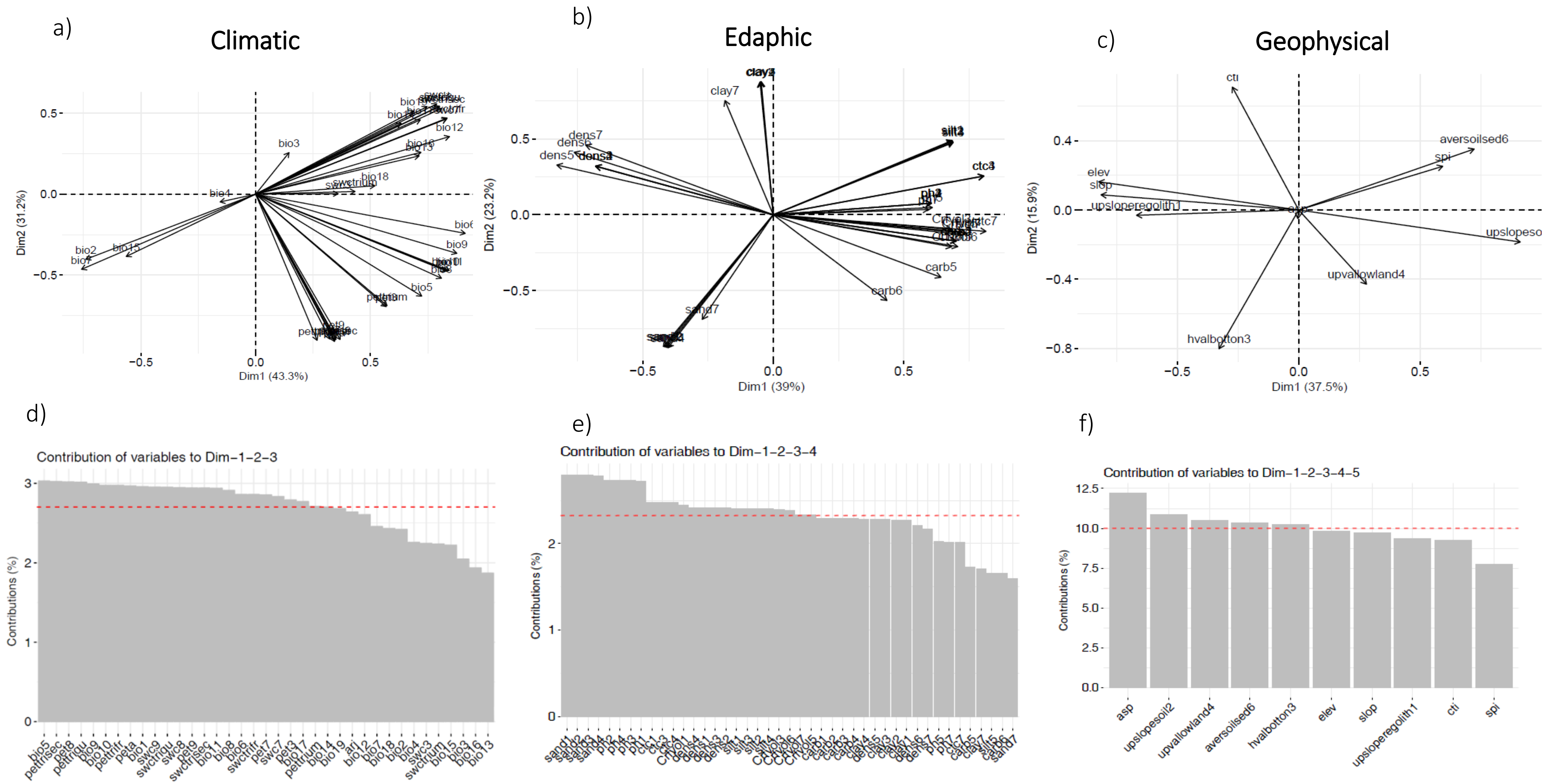


Figure 3. The first two principal axes of PCA for the environmental predictors in the Amazon geographical space (**group1**): a) 37 climate variables; b) 43 soil variables and c) 10 geophysical variables. Variables percentage of contribution in the principal components with the large variance of the data. The red dashed line indicates the expected average contribution: d) 22 climate variables; e) 24 soil variables and f) 5 geophysical variables were selected.

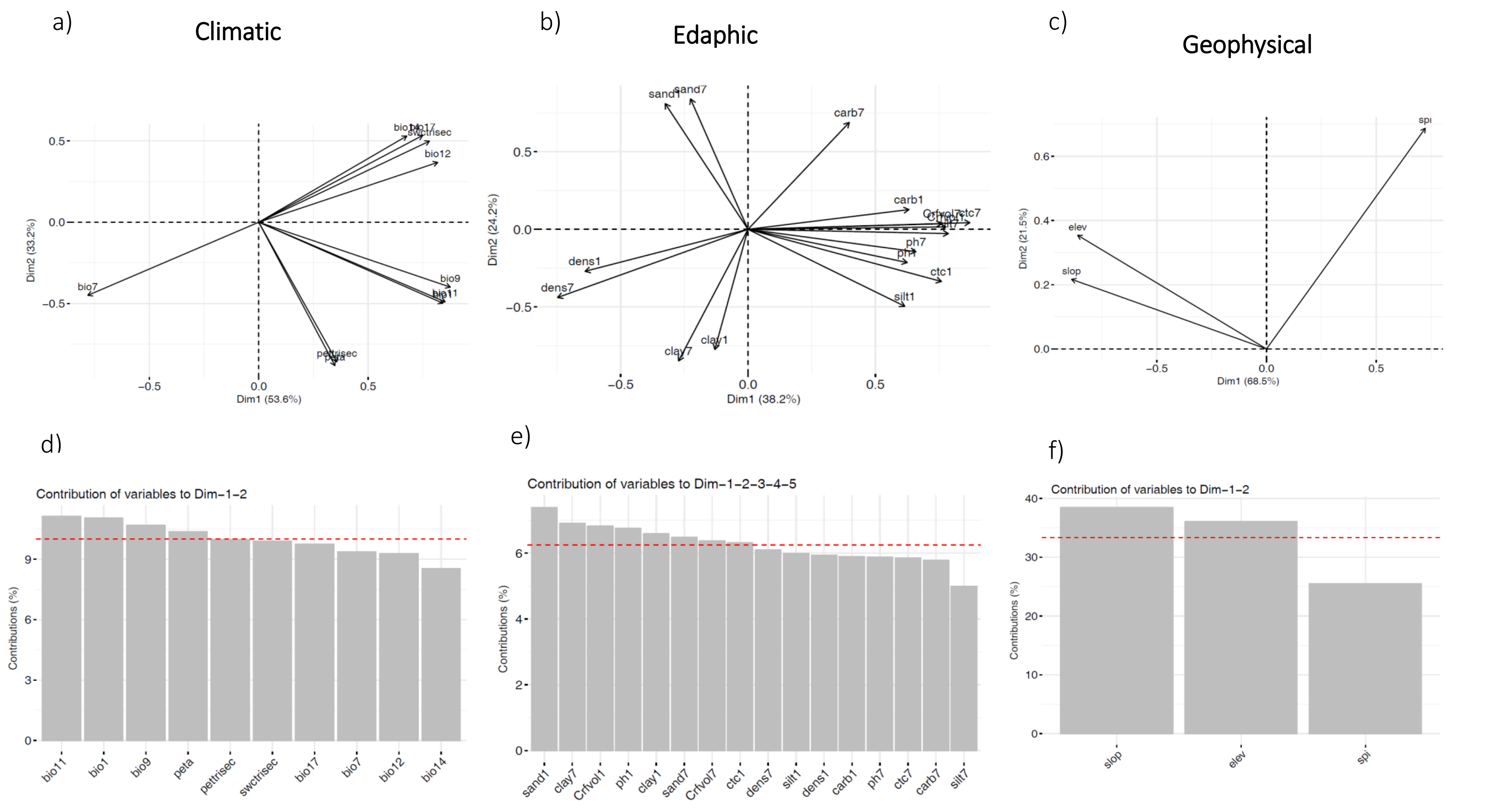


Figure 4. The first two principal axes of PCA for the environmental predictors proposed by experts in the Amazon geographical space (**group3**): a) 10 climate variables; b) 17 soil variables and c) 3 geophysical variables. Variables percentage of contribution in the principal components with the large variance of the data. The red dashed line indicates the expected average contribution: d) 4 climate variables; e) 8 soil variables and f) 2 geophysical variables were selected.

Spatial filtering

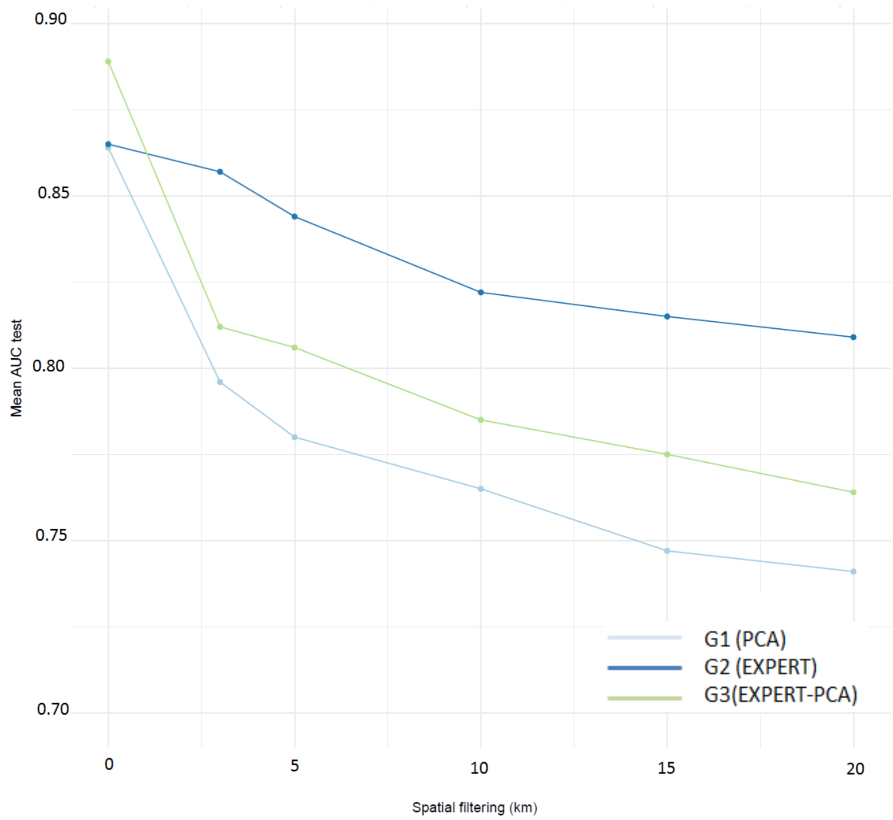
Unfiltered models were found to perform better than filtered models on the basis of AUC (Fig.5). However, through visual examination of the maps we noted strong signs of overfitting to training data for the former models (Fig.6), confirming that poorly fitted models with biased samples can have good discriminatory power (Lobo et al., 2008), but may be nonetheless overfit.

In figure 6, the probabilistic maps suggested that overfitting was reduced with spatial filtering improving model quality. We highlighted two areas with high density of presence data in unfiltered and filtered models, and detected adjustment of biases and increase of the area extension predicted in the filtered model toward the most likely suitable habitat of *B. excelsa* at the Amazon scale. However, our results expressed high similarity between filtered models using rarefied data from 3 to 20 km based on results of Schoener's D comparisons (Table S2. 4).

The minimum distance between occurrence points was also highlighted through density curves. The unfiltered model showed signs of highly clustered data, featuring three peaks in the distribution curve, while in filtered models curves were bell-shaped with a single peak (Fig.S2.1). The model simulated with 10 km of distance between records achieved a higher peak in the interval of 0.5 to 0.8 than other filtered models, as well as satisfactory discrimination power via AUC test (0.8) and lower omission rate (0.11).

The final model and the most the most important predictors are shown in figure 7. This model was fit using records of Amazon-nut distributed spatially filters at 10 km resolution. This final model was tuned with regularization multiplier ($\beta = 1.5$), feature classes combination (LQHPT), group 3 predictors and 557 presence points. The minimum probability of occurrence was limited by the Max SSS threshold of 0.5, representing an omission rate of 11%. The five predictors with highest contribution highlighted by MAXENT were elevation (19.4 %), coarse soil fragments >2mm in % (18.3 %), clay mass fraction % (18.2 %), slope (11.9 %) and annual potential evapotranspiration (6.9 %). Our results suggest that under current environmental conditions, suitable habitat for Amazon-nut is found across 2.3 million km2, or 32 % of the Amazon Biome.

a)



b)

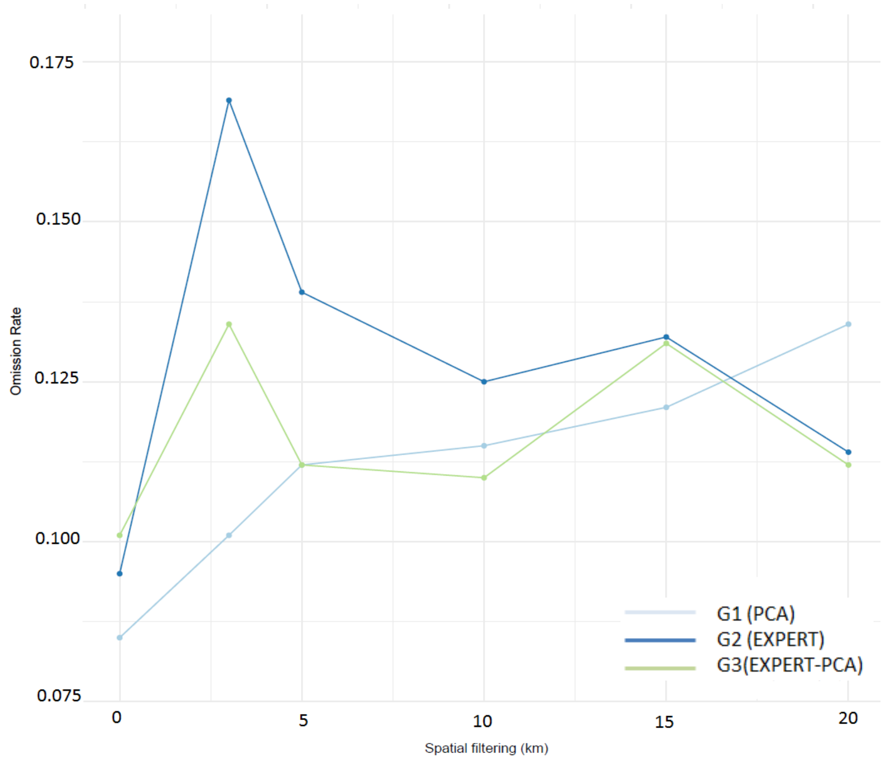


Figure 5. Results of the receiver operating characteristic (ROC) for the test data (AUC test) and omission rates (OR) in the 18 best models with lowest AICc (i.e. ΔAICc < 2) classified by group of predictors. a) AUC and b) OR. For each data-partitioning approach we adopted 10 interactions (k=10).

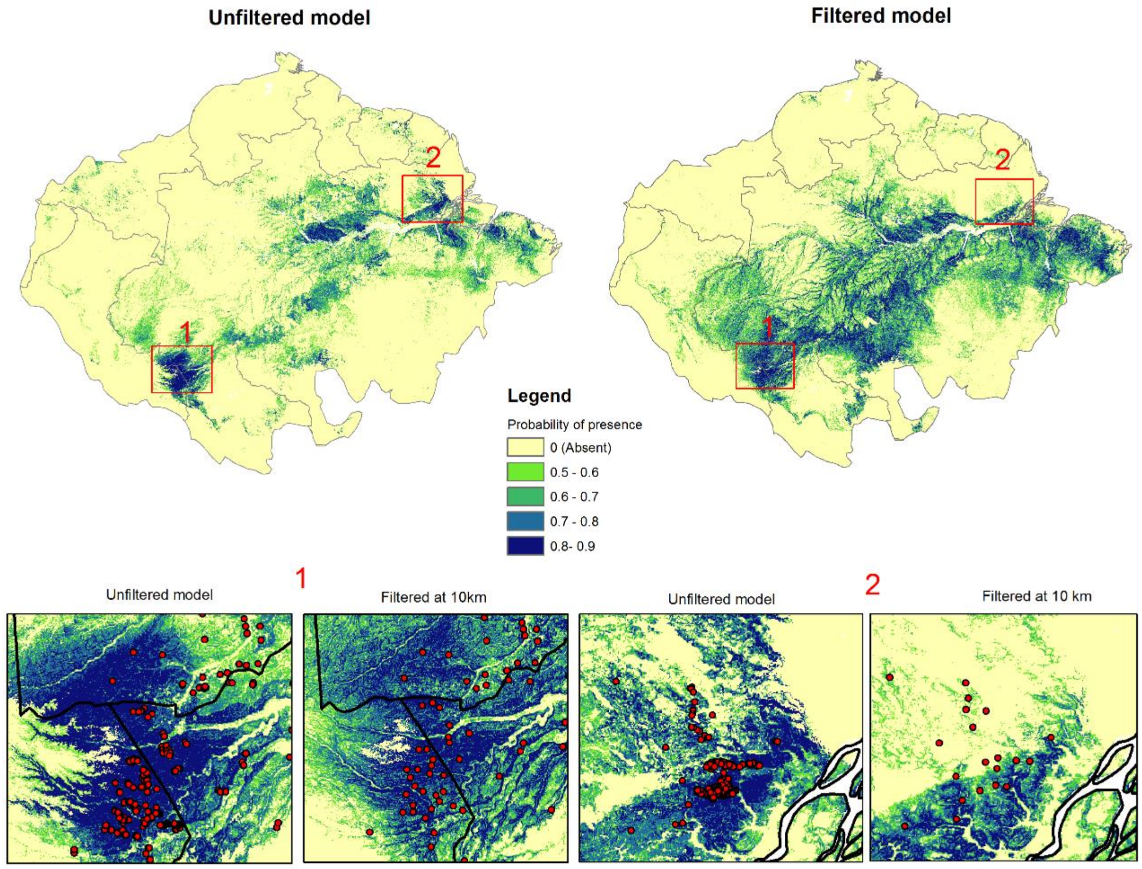


Figure 6. The best unfiltered and filtered models to estimate the *B. excelsa* habitat based on current environmental conditions (group 3 of predictors). We highlighted for two areas where we had high density of sampled points (red points). Area1: At the border between Brazil, Peru and Bolivia. Area 2: Southern Amapa State, Brazil.

2.4 Discussion

2.4.1 Amazon-nut habitat suitability

The main objectives of this study were to identify a robust habitat suitability model for Amazon-nut and to investigate the most important predictors that control its spatial distribution. To do so we explored >100 potential predictors, reduced bias in the presence data, determined optimal MAXENT settings, and evaluated models using different sets of predictors. We contrasted models with variables selected using state-of-the art statistical approaches with those recommended by a panel of experts. The best model we retained indicates that 32 % of the Amazon biome (2.3 million km2) is potentially suitable for B. excelsa. This area is far greater than that suggested by previous studies (1.3 million km2), in which the authors (Thomas et al., 2014), highlighted that some areas along the Tocantins River and in Southeastern Amazonia may have been underrepresented. Our model identified that these and other areas in the Eastern Amazon are suitable (Fig.7).

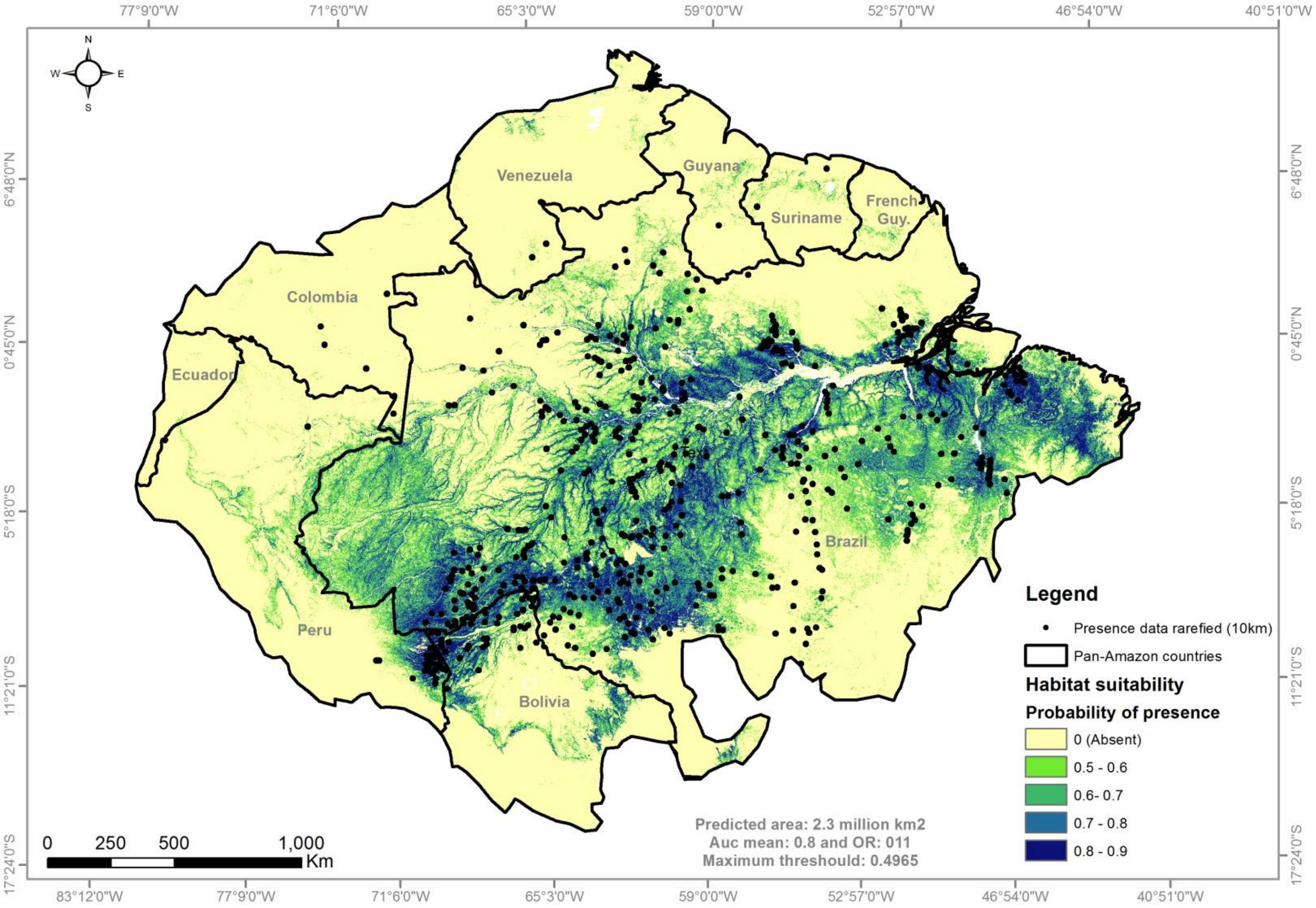


Figure 7. Distribution of suitable habitat for *B. excelsa* in the Pan-Amazon to a probability of presence > 0.5 (Max sss threshold).

With respect to the most important predictors that control its spatial distribution (Fig. 8), our results are similar to those found in other studies. In Peru, seed production was found to be positively correlated with clay content and negatively with sand content (Thomas et al. 2017). In Brazil, Guerreiro et al. (2017) found that the species has a preference soils with a clayey to very clayey texture. However, none of the previous studies identified the presence of coarse soil fragments > 2mm as being relevant to the distribution of this species, despite its known occurrence in high stem densities on lateritic soils which contain coarse fragments (Müller, 1995; Salomão, 2009) and often are rich in iron oxide and aluminium (Horbe & Da Costa, 2005). Concerning chemical attributes, soil influence on Amazon-nut fruit production has been shown to be positively associated with cation exchange capacity (Kainer, Wadt, & Staudhammer, 2007). However, other studies found highly productive trees in areas with higher levels of exchangeable Al and low soil pH, confirming that species can also be productive in acidic, less fertile areas (Costa, Tonini, & Filho, 2017).

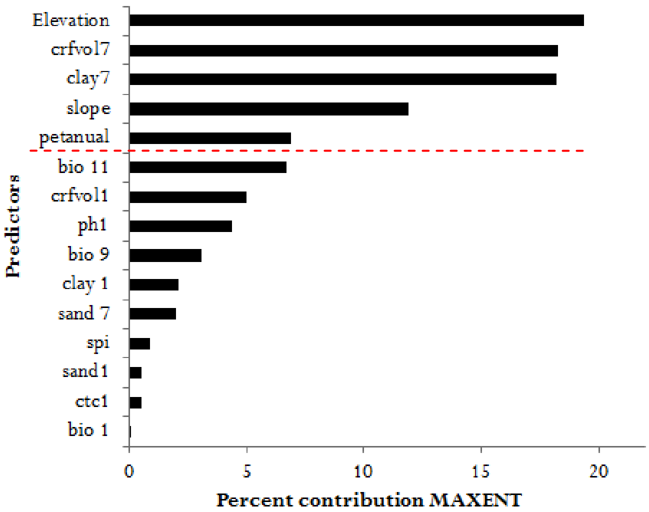


Fig 8. Percent of contribution of the variables in the final model. Dashed red line indicates five biggest contributions to Amazon-nut distribution. Elevation (19.4%), coarse fragments volumetric >2mm in % (18.3%), clay mass fraction % (18.2%), slope (11.9%) and Annual Potential evapotranspiration (6.9%).

Among topographic predictors, elevation was one of the strongest determinants of Amazon-nut habitat suitability. In the map, species probability of occurrence was lower at higher altitudes, as in the northern and southern extremes of the Amazon basin. Amazon-nut trees have been recorded from sea level to ~ 400 m above sea level (ASL) (Thomas et al., 2014). Our data included specimens found up to 562m ASL in the south of Para, Brazil. In addition, our model indicates that many lowland areas were suitable for *B. excelsa*, in contrast to the prevailing notion that this species prefers upland areas (Scoles & Gribel, 2012). Indeed, seed production *B. excelsa* has been shown to be lower when trees were close to rivers (Thomas, et al. 2017). The unexpected inclusion of lowland areas as suitable Amazon-nut habitat was discussed with experts.

Some experts emphasized that several islands in the Amazon estuary should not have been classified as suitable, because they are often flooded and have soils rich in silt, with growth condition adverse those where the species is commonly found. Others experts suggested that although Amazon-nut occurrence in areas prone to flooding is rare, it can happen. They reported an example in the *lago capanã grande* reserve, in Manicoré, Amazonas, where the local community affirms that the Amazon-nut trees in flooded areas are more productive than those found in non-flooded areas thanks to the presence of river sediments. Amazon-nut population observed closer to the river has been recently associated to dispersal by humans (Thomas et al., 2014). For future studies, we recommend a more detailed investigation about Amazon-nut suitability in periodically flooded areas using environmental data at finer spatial resolutions (< 1 km). Also, taking into account frequency and duration of floodings.

Climate was less important than soil and topography to Amazon-nut habitat suitability. This was unexpected given the known importance of climate to spatial patterns in floristic diversity across Amazonia (da Silva et al., 2011). However, our findings are similar to those of a recent study that highlighted the relative importance of edaphic conditions to plant occurrence in Amazon (Figueiredo et al., 2017). We attributed this result to recognized importance of soil attributes to Amazon-nut ecology and productivity (Costa et al., 2017; Kainer et al., 2007). Moreover, we highlight that the percent contribution values ranked by MAXENT is determined by how much of variation a model with only that variable explains, it consider environmental variables separately (Bradie & Leung, 2017). A low variation in climate predictors was confirmed though our PCA analysis, in which the number of principal components required to explain 80% of variance was smaller for climatic than for edaphic predictors (Table S2.2).

Despite low variation, the annual potential evapotranspiration was the fifth predictor retained for our final model. Derived from climatic variables, this predictor represents the amount of soil water lost by evaporation and transpiration from plants into the atmosphere under given conditions (Zomer, Trabucco, Straaten, & Bossio, 2006). Inclusion of this variable in the final model makes ecological sense as the Amazon-nut is an emergent tree that receives a high level of solar radiation. Consequently, Amazon-nut trees are highly vulnerable to drought and water loss. It has been noted that this species is most vulnerable to drought during the dry season, and that dry and warm conditions negatively affect seed production (Thomas et al., 2017).

The above reflections were supported by experts consulted who believe that the model was adequate to representing Amazon-nut habitat suitability. Although, some areas were deemed underpredicted in Venezuela, Guyana and Colombia. This was attributed to limited presence data obtained in these countries. In Brazil, the country that contains the greatest percentage of habitat for this species (91%), many micro-regions classified as suitable were confirmed by experts. These micro-regions were mainly in Amazonas (micro-region of Purus, Madeira, medium and low Rio Negro); Southern of Amapá (micro-region of Mazagao); Pará (micro-region of Santarém, Óbidos, Itaituba, Tome-Açu, Marabá); and Rondonia (Microregion of Porto velho). Experts also identified areas that were not suitable for *B. excelsa*, although the model identified them to be as. These micro-regions were found Roraima (Roraima) and Cruzeiro do Sul (Acre). According to these experts, this was not a commission error inherent to model because there are Amazon-nut trees planted and growing in arboretums and nurseries, but not in natural forest in the Cruzeiro do Sul, for example. These potential areas not occupied can be justified by ecological factors, such as dispersal limitations of the species.

2.4.2 Methodological aspects

This study sought to identify the most suitable predictors to model Amazon-nut. Our results demonstrated that a hybrid strategy based on statistical modelling and expert opinion allowed identifying the best model of habitat suitability for B. excelsa. This finding reinforces that the relationships among original predictors should be understood not only through their statistical behaviour, but also by the ecological role they play in the species distribution. Although PCA is a highly informative ordination technique and has been extensively applied in community ecology since 1954 (Legendre & Legendre, 2012), interpretation of outputs requires biological knowledge (Janekovi & Novak, 2012).

Detailed biological knowledge is still scarce or incomplete for many if not most Amazonian plant species. Therefore expert-based information has been proposed as an alternative approach to identifying meaningful predictors in habitat suitability modelling (Calixto-Pérez et al., 2018). Our findings showed that PCA was effective in reducing omission error rates, data collinearity and dimensionality, as well as preserving maximum variance, when applied to a set of variables pre-selected by experts, following Dormann et al. (2013). recommendations. Therefore, among 29 variables chosen by experts, fifteen were selected via PCA and used to fit our model. Five of them had a contribution of 75% in the best model found ensuring statistical and ecological representativeness.

Even using the best set of predictors, we observed that the discriminatory ability of filtered models measured by AUC was gradually reduced at larger filtering distances. Ironically, our most biased model (poorly fitted) received the highest highest AUC value. Similar results were found by Radosavljevic & Anderson (2014). This was expected, because the AUC has been shown to be insufficient for model evaluation when no true absence data are available (Jiménez-valverde, 2012; Lobo et al., 2008). Through visual interpretation, we identified clear positive effects of spatial filtering on reducing overfitting (Fig. 6), supporting previous research (Kramer-Schadt et al., 2013). However, the challenge was to define at which distance the filtering became too strict, because statistically there was high similarity between filtered models from 3 to 20 km. We addressed this problem by comparing metrics and density curves (Table S2.4 and Fig. S2.1).

The minimum distance of 10 km between presence data was considered appropriate to the adopted scale. Models using data filtered in this way displayed the highest peak in density curve in the interval of 0.5 to 0.8, satisfactory discrimination power via AUC test (0.8) and lower omission rate (0.11). The same distance has been used and recommended in other studies of highly heterogeneous areas (Boria et al., 2014; Kramer-Schadt et al., 2013). However, 10 km does not represent a distance between populations or groves, it was only chosen in order to reduce geographical bias existing in the data. If AUC would have been the only evaluation metric, it would have been misleading. But, together with other metrics and visual evaluation, this index was useful, because the biased models with highest AUC were used as reference to compare with other metrics.

Regarding Maxent settings, the variation of feature class and regularization multiplier between experiments led us to conclude that these parameters should be fine-tuned on a species and dataset-specific basis (Radosavljevic & Anderson, 2014). However, contrary to our expectations, the data were well-fitted to the combinations of all feature classes, usually suggested as default (Phillips & Dudík, 2008), when we compared to more simplified functions. Similar results were found by (Elith et al., 2011), when comparing models with all features to those using the hinge function, with no differences in the predictive ability of either model were found. For the regularization multiplier, values ranged from 1 to 2 among the 18 best models. This corresponds with the optimal range obtained by Radosavljevic & Anderson (2014).

2.5 Conclusion

We found that 2.3 million km^2 of the Amazon region is potentially suitable for *B. excelsa* based on the existence of suitable environmental condition. However, the real occupied habitat by this species is smaller due to other, generally unknown, ecological processes such as predation, pollination, and natural dispersal limitation (Hutchinson, 1957).

Although in the past the human-dispersal have strongly contributed to expand species distribution in the habitat (Thomas et al., 2015), currently rapid land-use changes have caused fragmentation and habitat loss in the Amazon (Nobre et al., 2016), which has direct effects on Amazon-nut occurrence. Natural and human factors, as well as their consequences on the species distribution must be urgently assessed to ensure its conservation.

Our findings show that the commonly used statistical techniques for predictor variable selection, although powerful, can be complemented and improved by expert knowledge. Expert knowledge was also essential in the visual examination and validation of the final suitability map. Therefore, we suggest that expert opinion should be considered more frequently in the process of building species distribution models to get reliable models for an effective conservation.

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3. LOCAL COMMUNITIES, PUBLIC MANAGERS AND RESEARCHERS ENGAGED TO DISCUSS OBSTACLES TO PLANTING AND CONSERVATION OF THE *BERTHOLLETIA EXCELSA* IN THE AMAZON

3. Local communities, public managers and researchers engaged to discuss obstacles to planting and conservation of the *Bertholletia excelsa* in the Amazon

Abstract

Aim
The sustainable use of biodiversity has been a great challenge in the Amazon region, where nature has to coexist with intense land and water use. The Amazon people have seen key-species threatened in many ways. Our goal was to identify the perception of local stakeholders about problems that impact Amazon-nut (Ber*tholletia excels*a) and to know their solutions for species planting and conservation. Although, Amazon-nut is legally protected, its population has been declining in some regions.

Localization
Communities and public managers (State of Pará) and Researchers (Brazilian Amazon)

Methods
We conducted focus groups, individual interviews and questionnaires for capturing perspectives of three local groups: communities, public managers and researchers. Focal group discussions were performed separately to maintain the interaction within the groups. We adapted some participative techniques to encourage reflections and produce collective information, such as problem ranking. All the material was recorded, transcribed, and then analysed through quantitative and qualitative methods. Frequency of words was used as a measure to help us identify codes that captured key-concepts on the reported problems. Using RQDA R package, the codes were assigned into categories that emerged in the discussion. The relation between codes and categories were described in broader contexts: environmental, economic, political, social and cultural. Additionally, we compared the main problems and solution perceived among stakeholders.

Results
We found thirty-six obstacles that affect the presence, use and conservation of Amazon-nut. Among them, deforestation was the most important cited drive (59 times), followed by fruit depreciation (48), failure of control (41) and difficulties of organization of the communities (36). Overall, environmental and political contexts were the most complex, responsible for 72% of the listed problems. Failure in the control, weak technical knowledge and lack of incentive from the government for planting were considered the main problems by communities and public managers, whereas for researchers the organizational and market access problems are much more impeditive than technical problems. Solutions presented by groups were highly dependent upon government actions. They believe that the forest will reduce even more, if management and planting is not encouraged.

Main conclusion
Three groups of stakeholders recognized the complexity of problems that threaten Amazon-nut trees in protected and non-protected areas. Deforestation was the main problem mentioned, but it has only been happening because of other associated factors. People's perception was an important source of information to help us identify them. Our findings suggest that people should be consulted and included in the decision to improve the governance and conservation in the Amazon.

Keyword: Environmental perception; Focus group; Conservation; Brazilian Amazon; Amazon-nut

3.1 Introduction

Rapid land-use changes have altered climate, economic and demographic patterns in the Amazon, without due attention to social and environmental dimensions (Nobre et al., 2016). Unfortunately, the disordered occupation process, low rates of the human development index, unsustainable extraction of forest and mineral products, and the subordination of markets to agricultural commodities are still typical scenarios in this region (Barbanti, 2015). Beyond these historical conditions, Amazon people have been living with the possible implementation of 79 energy infrastructure projects (Fearnside, 2006a). Some were recently executed, such as Belo Monte Dam causing severe environmental and social impacts (Fearnside, 2018). This development process is not compatible with this region that has a key role for biologic conservation, fresh-water security, cultural heritage and regional and global climate stability.

Brazilian governments have made many efforts to control illegal deforestation in the Amazon. The Plan for Prevention and Control of Deforestation in Legal Amazon (Plano de Prevenção e Controle do Desmatamento na Amazônia Legal - PPCDAm) has achieved positive results since it was implemented in 2004 (Mello & Artaxo, 2017). However, there are still many challenges to incorporate sustainable alternatives to large economic activities (Fearnside, 2018) and to those generated from socio-biodiversity resources (Pedrollo & Kinupp, 2015). Studies have shown that an effective governance require a collective process of monitoring, reflection, debate and decision to guide policies for sustainable development (Meadowcroft & Farrell, 2005). Understanding local and regional particularities and providing evidence on experienced problems demand knowledge of the perceptions from different social actors.

Environmental perception[1] has intensely been studied through psychology and geography (Garling & Golledge, 1989), but only in the last 20 years has been recognized for its high potential to improve conservation studies and practices (Bennett et al., 2017). This is why natural science was traditionally used as the only source of information to guide conservation action, based on species biology and ecosystems characterization (Mascia et al., 2003).

[1] Theory of Perception according to pysicology can be explained through two lines of thinking “Theory of copy” and “Theory of behavior”. In the first one, ‘perception is a psychophysics process, resulted in a copy of the environment (experience, idea, or representation)’. In the second, ‘perception is resulted of a complex behavior, that is interrelated with many others (self knowledge, purpose, thinking, problems resolution)’ (Lopes and Abib, 2002). In this work, we do not discussed how the perception among different local stackholerds was formed, we just used perception like form of thinking about their reality.

After a long period, conservation scientists have realized that 'conservation interventions are product of human decision and require changes in human behavior' (Mascia et al., 2003). Although, many efforts have been made to improve the interdisciplinary communication, the conservation field still remains fragmented (Sandbrook et al., 2013). Advances have been made when two different points of view are reconciled: conservationists need to develop social science expertise (Newing et al., 2011) and social scientists need to become more involved with the environmental theme (Sandroni & Carneiro, 2016). The dialogue between these sciences is urgently needed to adapt methodologies to support conservation plans, mainly for threatened and endangered species and with high socio-cultural value.

Bertholletial excelsa (Amazon-nut) is certainly the most popular tree species of Amazon local communities, due to its products and ecosystem services offered to humans since pre-history (Roosevelt et al., 1996; Thomas et al., 2014). In the last decades, it became a 'cornerstone of Amazonian conservation' due to related ecological, social and political aspects (Guariguata et al., 2017). Ecologically, in old-growth forest, Amazon-nut trees can reach 60 meters in height and 4 meters in Diameter at breast height (Müller, 1995). Their stem usually grow erect and is unbranched (Salomão, 2009) and they occur in large trees dominance and have a low regeneration rate (Scoles & Gribel, 2012). Therefore, it is the third of the top 20 accumulators of aboveground woody biomass in Amazonia (Fauset et al., 2015). However, in the last fourty years its population has declined in some regions due to anthropogenic causes (Scoles et al., 2016). Furthermore, the Amazon-nut was classified as vulnerable by the International Union for Conservation of Nature and Natural Resources (IUCN, 2018), while socially, in the last years, its seed (or nuts) have been highly valued by national and international trade for its nutritional value: high selenium levels and other micronutrients such as magnesium, copper, and zinc (Cardoso et al., 2017).

For centuries, this forest product has been harvested by thousands of traditional people and small communities, becoming a source of income and food, as well as a way maintain cultural traditions (Salomão, 2014). Ecological studies indicated that low harvesting levels may play a positive role in species recruitment and dispersal (Ribeiro et al., 2014). This non-timber forest product extractivism can be a tool to promote sustainability, since allows people and natural resources coexistence. Politically, protected areas (indigenous lands and conservation units) have been an important instrument to slow down deforestation. However, they play a larger role in the sustainable use of natural resource, with Amazon-nut been a key-species to promote this function.

The potential for multiple uses offered by Amazon-nut trees have led to an increase in the different stakeholder's groups[2] interested in the species, such as traditional people, small farmers, cosmetic and food industries, researchers, government and non-government organizations. These social actors have different expertise and points of view, which may generate or confirm known scientific evidences. Accordingly, studies have suggested that a range of evidences combining social and natural sciences should be incorporated in conservation policies (Bennett, 2016). To help us define the main problems that affect Amazon-nut and access the potential solutions to solve them, we chose three local stakeholders groups: communities, public managers and researchers, because they have direct and indirect interest in this species. Here we present a set of methodological aspects, difficulties and results obtained from these stakeholders' responses, our fieldwork experience and analytical interpretation of these results, regarding our target species.

3.2 Material and methods

3.2.1 Study area and participants

This study was conducted with human residents and workers of the Amazon biome, in South America. Primary[3] and secondary[4] stakeholders were identified as belonging to three groups: Communities (C), public managers (PM) and researchers (RE). Although the Amazon-nut is present throughout the biome Amazon, Brazil was chosen because encompasses the largest percentage of suitable habitat (91%) for the species grow (Tourne, under submission). Also, this habitat has been intensively threatened, mainly in southern and eastern Amazon, where land-cover changes have been multiplying (Nobre et al., 2016). We selected two municipalities located in State of Pará, Acará and Marabá (Fig. 1), based on landscape occurrence of Amazon-nut trees, history of extractivism, high nuts productivity in the past

[2] Stakeholders would be 'individuals and groups who hold some kind of "stake" or interest in the resource' (FAO, 1998).
[3] Primary stakeholders would be 'those with a direct interest in the resource, either because they depend on it for their livelihoods or they are directly involved in its exploitation in some way' (FAO,1998).
[4] Secondary stakeholders would be 'those with a more indirect interest, such as those involved in institutions or agencies concerned with managing the resource' (FAO, 1998).

and low at present, high deforestation rates, presence of distinct traditional people and small communities inside and outside protected areas, and logistic facility to develop fieldwork with limited resource. All fildwork expeditions were funded with FAPESP Doctoral technical reserve.

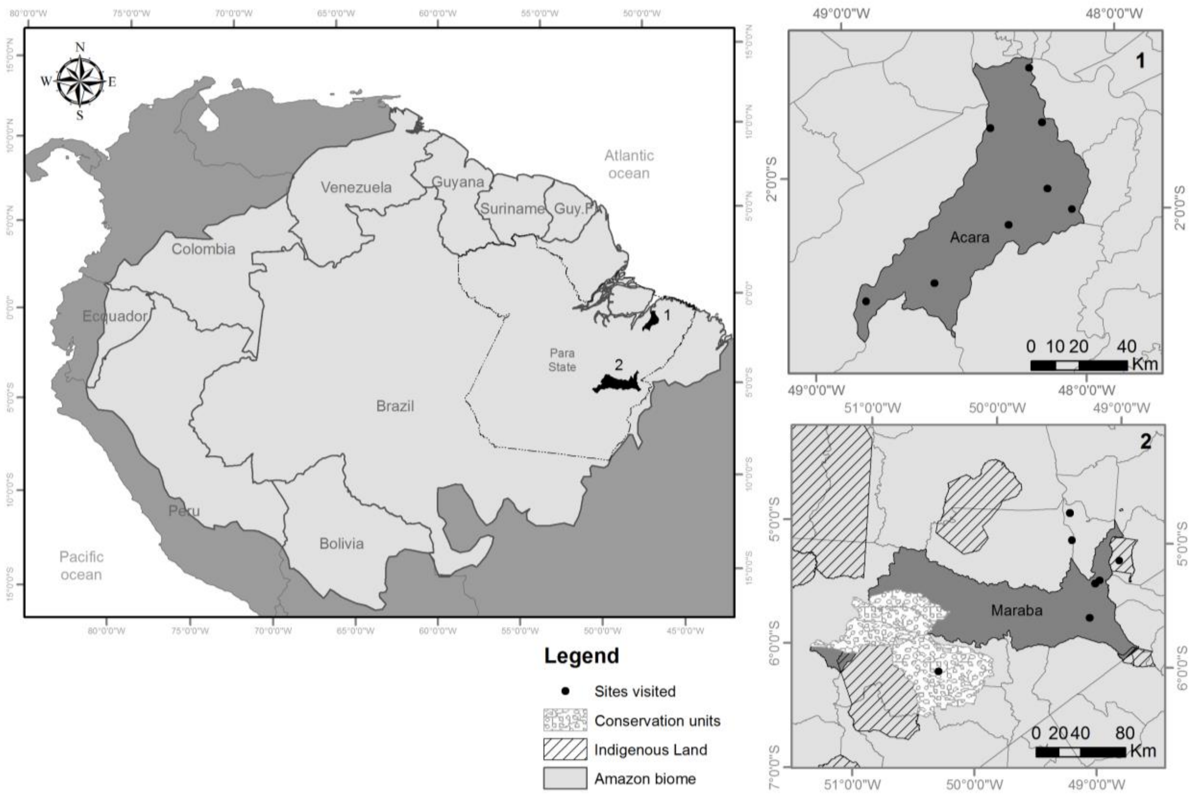

Figure 1. Location of the study areas and sites visited in two municipalities in State of Pará (Brazil): Acara (1) and Maraba (2) to access local communities and public managers' perception on problems and solutions for Amazon-nut planting and conservation.

3.2.2 Municipality's background

With a territorial extension of 4,343.8 km² and population, predominantly rural, of about 54,080 inhabitants (IBGE, 2016), Acara is located in State of Pará, at 66 km from Belem (capital). Economic activities commonly practiced are large and small scales agriculture, with palm oil (*Elaeis guineensis*), black pepper (*Piper nigrum*) and manioc (*Manihot esculenta*), cattle grazing, and forest products extraction, such as açaí (*Euterpea* *oleracea*), *amazon-nut* (*B. excelsa*), cupuaçu (*Theobroma grandiflorum*) and pupunha (*Bactris gasipaes*). Currently, forest loss is 2,385.1 km^2, e.i, 54.7 % of the municipality (PRODES, 2017). This value represents a threat to native ecosystems in the region, since there are no conservation units to protect forest areas from the agricultural frontier expansion. Therefore, the remaining forests patches are distributed in rural legal reserves, in collective lands of Quilombo people (slave descendants) and small proprieties. Among the last one, there are 12 agrarian settlements implemented projects (MDA, 2018). Even with a forest reduction, this municipality ranked at the third position in Amazon-nut extraction (900 tons) in State of Pará, when we conducted this study in 2015 (IBGE SIDRA, 2016).

Maraba is located in the southeast of State of Pará, with 15,128 km² of territorial extension and an estimated population of 271,594 inhabitants (IBGE, 2016). This county was one of the largest Amazon-nut producers from 1920s to 1980s, when governmental settlement projects encouraged farmers to migrate to the region for agriculture development, cattle grazing and wood exploitation labor, compromising the Amazon-nut extractivism (Kitamura & Müller, 1986). As a result of this process, there was a large Amazon-nut groves devastation and a significant nut production reduction from 17.732 tons in 1970 (Homma, 2014) to 21 tons in 2016 (IBGE SIDRA, 2016). As a strategy to protect part of the Amazon ecosystem from the accelerated forest loss, three reserves were created under federal management: Tapirapé biological reserve (992.7 km2), National forest of Tapirapé-Aquiri (1965 km2) and National forest of Itacaiunas (1367 km2), which preserve a rich density of regional fauna and flora (ICMBIO, 2009). Furthermore, there are large indigenous lands next to the municipality, such as Mae Maria (624.9 km2) and Xikrin do Rio Catete reserves (4,391.5 km2) for instance. An alternative to reduce land concentration into large landholdings was the creation of agrarian settlement projects outside protected areas (Schneider & Peres, 2015). At present, there are 81 implemented projects in Maraba under Brazilian Federal Agrarian Agency - INCRA jurisdiction (MDA, 2018). However, studies have shown that settlements have contributed to increasing deforestation rates (Schneider & Peres, 2015). Currently, there are 8,675.4 km^2 of deforested areas, e.i., 57.2 % of the municipality area (PRODES, 2017). The main economic activities are livestock, mining (iron, gold, copper and manganese), and agricultural production (cereals, vegetables, oilseeds, fruticulture).

3.2.3 Recruitment of the participants

As primary stakeholders, we visited a set of nine local communities that has been collecting Amazon-nut for domestic consumption and/or sale. They were chosen according to geographical and socioeconomic information officially made available by public institutions, based on production type, Amazon-nut occurrence and localization in protected and no protected area. In addition, we selected communities with an established social representation, such as associations, since focus groups are often conducted with existing groups (Morgan, 1996). Therefore, we chose indigenous people, quilombos people and agrarian settlers to represent perception of local communities.

As secondary stakeholders, we recruited public managers and local researchers involved with species. Four public institutions were officially contacted considering their stronger interaction with public administration in the rural environment. Those interested in the research agenda, organized meetings and invited technicians who have been working closely with the Amazon-nut to participate in the discussion with us. As far as the researchers, we contacted some individually and others in groups. In 2016, some of them were gathered for a workshop in Amapa State and were invited to participate in a focus group with us. These researchers were member of the MAPCast project "Mapping of Amazon-nut groves and socio-environmental and economic characterization of Amazon-nut production systems in the Amazon" from 2013 to 2018 (https://www.embrapa.br/en/projetos).

Our research team was composed by five people, who were previously prepared to assist in the proposed activities. The team consisted of a moderator, a facilitator, two assistants and a student. The author of this thesis had the moderator role, which means to coordinate and explore the most varied topics on the theme, while the facilitator was a local people who brought participants to collaborate with the research. Sometimes, the moderator was assisted in fieldwork by experienced professors.

3.2.4 Ethical approval and consent

All participants in the research were asked for their consent and availability to participate, as well as, if they agree to have their audio and image recorded, according to Brazilian's law n° 13.123/2015 (Art. 9). Their consents were fixed by signatures. In indigenous lands, access was authorized by leaders of the ethnic groups Akrâtikateje and Kyikatejê from Mae Maria indigenous reserve and by National Indian Foundation (FUNAI - Regional coordination). This research is also registered in the National System of Management of Genetic patrimony and Traditional knowledge associated (MMA, n°A3906D8).

3.2.5 Data collection

To explore stakeholder`s perceptions, we used multiple methods for qualitative and quantitative analysis, combining social and natural science approaches. *Focus group* was the main qualitative method employed for the three stakeholder groups - communities, managers and researchers. This method has been used as a more flexible research tool than questionnaire in social science, for providing detailed information on the participant`s views and producing interactions with moderator (Bernard, 2006). Moreover, groups discussion encourages reflections, allows people to change their opinion after interactive discussion and generates collectively constructed arguments (Morgan & Krueger, 1998). Hence, in the last years, focus group has been more popular in environmental studies (Bakhtiari et al., 2014; Kraaijvanger et al., 2016).

Focus group can be conducted in a short time, from one to three hours, with a small group selected from a broader population and following an interview guide (Newing et al., 2011). Therefore, it was the most appropriated method to collect data from Amazonian communities, due to logistic difficulties usually encountered to conduct research. When gathering a group of people was not possible, *individual interviews* were an alternative, following the same open semi-structured questions used in focus groups. The combination of focus groups and individual interviews have been recommended, because interviews offer information individually, details on respondent's life and facilitates evaluation on the opinion debated in group (Gondim, 2003). The disadvantage is that there is no opportunity for the participant's ideas to be confronted and thus no reflection on his/her own opinion (Morgan, 1996).

The focus group with researchers's findings were also adopted to formulate a *questionnaire* sent by email to scientists who have been developing or developed some kind of research on *B. excelsa* (see Appendix B). This survey was a strategy to increase sample size of researchers' group, since it is difficult to bring together scientists who have been working in several Amazon locations. The questionnaire is a method of structured interview that can quickly be answered and each informant is exposed to the same stimulus (Bernard, 2006). We elaborated five multiple choice questions and four open-questions to give the partakers the opportunity to write comments. Thus, we obtained 19 responses, which were incorporated in our database.

Overall, we conducted thirteen focus groups (174 people), individual interviews (10) and questionnaires (19), generating information from 203 participants engaged to discuss Amazon-nut planting and conservation (Table 1). Although expressive, we know that the number of cases surveyed was not enough to achieve a theoretical saturation on the current species situation, due to the Amazon biome continental scale, with diverse landscapes and people interacting with this species. However, our sampling strategies focused on information diversity gathered in two municipalities, seeking at understand and comparing the perception of these distinct groups.

3.2.6 Conducting focus groups

Focus groups discussion generally took place in the communitarian center for communities and in public facilities for public manager and researchers. There were no inclusion criteria such as age or gender, all members of the group interested in the theme could participate. Language was regulated by a moderator, a native person of the Amazon region and able to recognize local ways of expressing concepts on the theme. For indigenous groups, discussions were in Portuguese, since it is one of the spoken languages by both Akrãtikatêjê and Kykatejê people. The following set of open-questions was prepared to help the moderator introduce the theme, identify the current scenario, and discuss problems and solutions on the subject:

Where could Amazon-nut tree be found?

Why are Amazon-nut trees diminishing in the landscape?

Why is Brazilian Amazon-nut fruit production decreasing in some places?

Which are the main problems that affect Amazon-nut occurrence?

How could we change this situation? What are the main solutions?

Table 1. Focus groups (G), individual interviews (I) and questionnaires (Q) carried out to gather stakeholder`s perceptions on problems and solutions for Amazon-nut planting and conservation at Acara and Marabá counties (State of Pará, Brazil). Researchers shared theirs perception on Amazon-nut situation in others states.

Counties	**Method**	**Participants**	**n° participants**	**stakeholder**
Acará	G	PA Araxiteua	9	communities
	G	PA Benedito A.Bandeira	10	communities
	G	PA Calmaria I	7	communities
	G	PA Nazaré	14	communities
	G	Com. Santa Rosa	12	communities
	G	Com.Rem.deQuil.Menino Jesus	7	Communities
	I	Agroextractivist woman	1	communities
	I	Agroextractivist man	1	communities
	G	SEMA	5	Managers
	I	EMATER	1	Managers
	I	Flora Nativa (ATER)	1	Managers
Marabá and surroundings	G	PA Agroextr. Massaranduba	6	communities
	G	TI Mãe Maria (Ald. Akrãtikatêjê)	22	communities
	G	TI Mãe Maria (Ald. Kykatejê)	60	communities
	I	Agroextractivist man	1	communities
	I	Agroextractivist man	1	communities
	G	INCRA	6	managers
	G	ICMBIO (Flona Carajás)	4	managers
	I	Floragri (ATER)	1	managers
	I	UEPA	2	researchers
	I	UNIFESPA	1	researchers
Amapá, Amazônas, Roraima, Pará	G	Embrapa Amapá, Embrapa Amaz. oriental, Embrapa Ama. Ocidental, Embrapa Roraima	12	researchers
Amapá, Amazônas, Roraima, Pará, Acre, Rondônia	Q	Embrapa Amapá, Embrapa Amaz. oriental, Embrapa Amaz. Ocidental, Embrapa Roraima, Embrapa Acre, Embrapa Rondônia	19	researchers
		Total	203	

To collect information and encourage all participants to respond, we used some participatory tools and techniques commonly adopted in social assessments (World Bank, 1998). Some techniques like ranking problems, seasonal calendar and future tree were adapted to the context of this work (Table 2). We always started with a short presentation to stimulate reflections, followed by hand dynamic in which participants were asked to summarize five main problems and solutions related to the Amazon-nut. On one paper sheet, they drew a red hand for the problems and a green hand for the solutions. For each finger, one problem was chosen with majority consent. Besides that, we used a future tree tool to register people's perspectives on future of the Amazon-nut, it was written in a canopy of tree.

We also employed others tools like the time line of local historical events; social mapping to describe the main infrastructures; and seasonal calendar to observe people's interaction with Amazon-nut to gather information from traditional communities. The generated information was important to understand in more depth the reality of participants' life. After the discussion, we visited the forest, measured and georeferenced some Amazon-nut trees using Global Positioning System (GPS), always with the community's people help. We used this moment to explain briefly geoinformation usefulness to science, mainly for species modelling distribution. Interesting conversations emerged in this second moment. The individual interviews took from 25 to 60 minutes, and each focus group from 80 to 130 minutes. Each conversation was digitally recorded for subsequent transcription.

3.2.7 Data analysis

Interviews digital audios were textually transcribed. On average, we spent eight hours to transcribe two hours of audio. In total, 275 pages of texts were generated. Then, we carried out quantitative and qualitative analyses for data obtained in these interviews and discussions, following the principles of systematic analyses proposed by Morgan & Krueger (1998). This process is complex, because it involves comparison of words, contexts, consistency of arguments, frequency, as well as intensity, extension and specificity of comments. Code strategy was adopted to facilitate this interpretative process using *RQDA* package of the R statistical environment (Chandra & Liang, 2014).

Table 2. Participatory tools and techniques used in the group discussions to gather stakeholder`s perceptions on Amazon-nut problems and potential solutions.

Tools	**Aims**	**Methods**	**Application**
Short presentation	To justify the research, the choice of the communities, municipality and species, and stimulate the discussion.	Introducing the theme, making key-questions and generating interest	
Ranking of problems (hand dynamic)	To quantify and order the five main problems and solutions related to Amazon-nut.	This technique helps the participant to discuss and summarize the main problems and solution, generating large amount of information.	
Future tree	To know people’s perspectives, concerns and wishes for the future of Amazon-nut.	This tool registers people’s future perspectives (positives or negatives). It was applied after we discussed the problems and solution.	
Time line	To know significant changes and historical events.	This tool is an exercise for people to look back in time and remember important events.	
Social mapping	To know the main infrastructures, distance of forest, rivers, or schools.	Drawing and describing the occupation of space in the community	
Seasonal calendar of Amazon-nut	To evaluate the power of observation and annual interaction of the people with the species.	Describing the phenological phases of the species.	

Codes are conceptual labels grouped together to form categories and subcategories that emerged in the discussion (Corbin & Strauss, 1990). Once the code is attached to some idea or phenomenon in the text, when the idea or phenomenon reappeared, the code is again attached (Morgan & Krueger, 1998). Coding allows greater data handling to provide insight on common and particular point of view. It has gained more authenticity through systematic protocols with computational support (Chandra & Shang, 2016).

Codes present in the conversation were identified through the transcript reread and words frequency analyzed per stakeholder group. First, we removed the moderator speeches from the transcriptions. Then, some connection words, such as punctuation, conjunctions, prepositions were removed with the support of *Text mining* packaged for the R environment (Feinerer, 2018). According to Bardin (2011) these are instrument words, which have no meaning. And finally, we organized the keywords by absolute frequency, since frequency is a measurement parameter of their importance.

Once codes were identified, they were assigned to twelve categories, which were defined in broader contexts, such as social, economic, political, environmental and cultural. These categories emerged from the discussions with stakeholders and are presented in results topic. Some codes were attributed to more than one category, since one code can be related to different contexts. According to Corbin & Strauss (1990) the precision is increased when comparison leads to sub-division of an original concept. Next, both codes and categories were introduced in the RQDA software to evaluate the frequency, connection and relationships between them. The impact of each code was calculated through their absolute frequency, i.e., the number of times a key-concept appears in the discussion, while complexity was proportional to the number of codes aggregated per category.

To verify the more relevant apprehensions to each stakeholder group, we analyzed the list of five main problem and solution ranked by them using *radial.plot* function of *plotrix* package for the *R* statistical environment (Lemon, 2006). Radial diagram is a way to represent qualitative data in a quantitative form, based on distance from the center, that is relative to a scale of comparison (Galbraith, 1994). Frequency of problems was used as a scale, ranging from 0 to 100 %. Finally, we discussed the most important contexts for each group, as well as, their solutions.

3.3 Results

3.3.1 Codes

Considering the sixteen most frequent words used by stakeholders, as well as their meaning, we found similarities and variations between groups (Figure 2). For all groups, the words “castanha” and “castanheira” were the most cited. The first one refers to both the tree and the fruit, and the second one only to the tree. Another word “castanhais” appeared most frequently in the researcher’s discourse and represents a form of distribution of Amazon-nut in groves. The word “production” and “sell” were frequently used by managers and communities related to large and small-farmers, fruit depreciation, lack of organization and market access difficulties. For researchers, the words “conservation” and “planting” were the most cited, often referring to lack of public policies and applied research projects. Another important word was “deforestation”, which was frequently mentioned by managers who have been acting in the environmental control and supervision municipalities’ actions. Still, communities and researchers pointed out the main deforestation causes, such as livestock, oil-palm, slash-and-burn agriculture, unavailable timber species and poverty. Using this procedure, we identified 36 codes linked to 12 categories of problems that affect Amazon-nut perceived by participants of this study (Table 3).

3.3.2 Broad and specifics categories

In the environmental context, stakeholders’ perceptions revealed that the problems affecting the Amazon-nut are associated with three categories: natural, biological and human factors. Among them, natural factor was the category with less complexity (2 codes) and human factor the one with greater complexity (8 codes). This results were expected, since the human has caused significant environmental alterations on Amazon biome (Nobre et al., 2016). In our study areas, wind and lightning were cited as natural factors associated to deforestation, which is a human factor:

“The wind blows it down very easily, today deforestation is widespread, so the winds get stronger”. PM

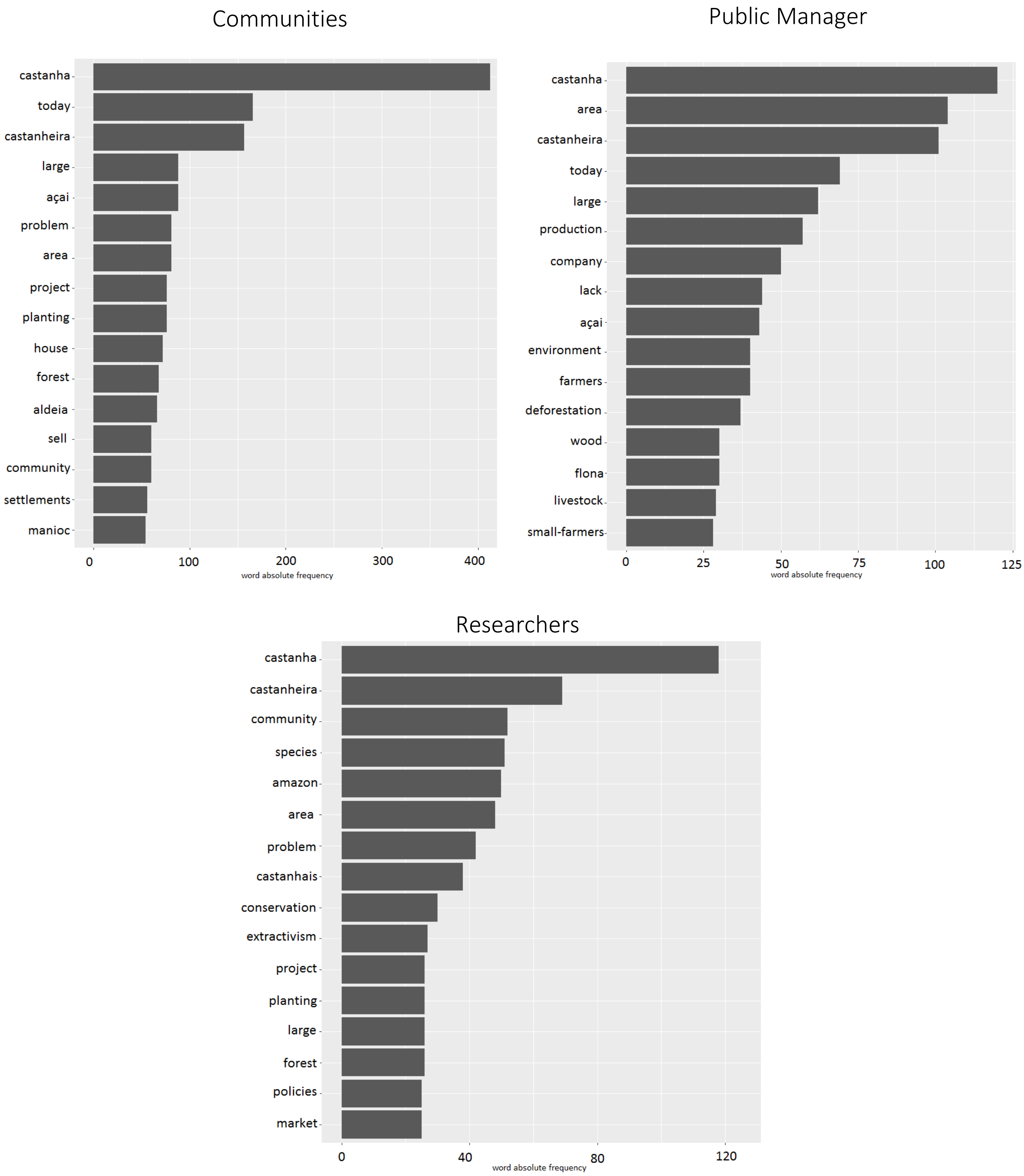

Figure 2. The most frequent words used by stakeholders in the focus groups, individual interviews and commentaries in the questionnaires about problems and solutions for Amazon-nut planting and conservation.

Illegal logging was cited as a kind of land-use causing strong pressure on Amazon-nut in the past (1980 to 2010), while livestock, palm-oil and slash-and-burn agriculture were mentioned in the present. These land-uses have impacted habitat availability for *B. excelsa*, directly by logging and indirectly by reducing species interactions with other organisms, mainly when trees are isolate.

"F*ruit production is very little, exactly because it requires an interface forest, microorganism and especially pollinator". RE*

In the cultural context, we found that there were two categories of problems, those caused by tradition and those induced by public policies. Both presented even complexity, due to the number of problems listed in the study areas.

"Livestock began with the large-farmers, but the small-farmers wanted land too. They can't comeback, there were many people from Maranhão, from the northeast in general and started the agrarian settlements". C.

"They have more tradition with livestock than extractive practices". PM.

"Deforestation increased, because government only financed livestock project". C.

In the economic context, problems were split into two categories: large-scale producer and small-scale producer. The small-scale producer presented more complexity (5 codes). This result was expected, since we were not able to interview large producers. Nevertheless, their importance was cited by groups considered in this research. Market access difficulties and fruit depreciation were highlighted as causes of economic disinterest for extractivism and planting of Amazon-nut.

"Our biggest problem here is the market". C.

"We carry to sell in Belem, selling at R$0.70 [kilo]". C

"He can't pull out his nut from the community, so, he ends up selling to the middleman who goes there to get it". RE

"If it was appreciated nobody would take it down, because here, it will be a source of income". PM.

In social context, two categories emerged: income and education, and logistic and organization. Both categories describe problems faced by communities, which according to public managers and researchers make it difficult the species planting and conservation. For example, low education and weak technical knowledge are among the difficulties for community's organization.

"To strengthen the forest, you need to bring basic education…we cannot think that we will solve their problems, they have to find their own ways". RE

"One problem, for small-farmers is management, it is administration. How do you administrate what you have? It is not only coordinating an association but managing your propriety…you can finance a project, but you don't have capacity". C.

"The small-farmer does not know where to find seedlings, he doesn't know if this investment will work out". PM.

In the political context, there were three categories of problems expressed by stakeholders: the protected areas, non-protected areas, and problems related to training and technical assistance. In all three categories, absence and inefficiency of public power were highlighted. This can be noted through the codes prefixes and suffices related to: lack, failure and few. Among categories, "non-protected areas" had the greatest complexity (8 codes). The *failure of control* code was considered one central factor to Amazon-nut population reduction in the Amazon.

"Deforestations are taking place regularly and daily, even with specific legislation to protect the species". RE

"This place here should have a mapping…are they coming here see the situation? Are they verifying if people are taking down trees? Do they come here to check if people are conserving [the trees]?". C.

"We have a huge demand, really huge. The job for one or two enforcers is complicate. The time that he is controlling a place, many others are unattended". PM.

Table 3. Five broader categories (bold letter), 12 specific categories (underlined) and 36 codes used to evaluate the perception of different social actors on the factors that affect amazon-nut use and conservation in the Amazon region. Note that codes can belong to more than one category.

Environmental	**Cultural**	**Economic**	**Social**	**Political**
Natural factors -wind -lightning Biological factors -late-production -old-trees -problems-pollination -pest-diseases -wildlife-eat-fruits Human factors -climate-changes -deforestation -few-timber-species -fire -livestock -palm-oil -wood-coal -ore powder	Tradition -deforestation -fire -wood-coal -livestock Induction -deforestation -livestock -palm-oil -reduction-extractives-practices	Large-scale producer - legislation-failure -few-planting -fruit-depreciation -unprofitable Small-scale producer - market-access-difficulties - legislation-failure -few-planting -fruit-depreciation -poverty	Income and education -low-education -poverty -weak-environ-awareness - management-difficulties -few-technical-knowledge Logistic and organization -lack-organization -low-education - market-access-difficulties -harvest-difficulties	Protected areas - control-failures -few-applied-research -lack-rural-technical-assistance -lack-focus-species-conservation -lack-incentive-governmental No protected areas - lack-rural-technical-assistance - lack-urban-plan - lack-public-policies - control-failures - legislation- failures - lack-incentive-governmental - few-investment-governmental - few-planting Training and technical-assistance -few-investment-governmental -lack-incentive-governmental -few-applied-research -lack-public-policies -lack-rural-technical-assistance

3.3.3 Impact of codes-categories

Figure 3, we can observe the absolute frequency of key-concepts reported by 203 participants. Overall, deforestation was the most frequent problem visualized by them (59 times), followed by fruit depreciation (48), control-failure (41) and organization difficulties of the communities (36). Through colors, we observed the diversity of contexts that these problems are associated with. It can be reinforced by the top-five codes, since each one belongs to a different context. Therefore, our finding demonstrated a complex perspective of stakeholder’s narratives on the theme in the our study areas, where there are high vulnerability to this species.

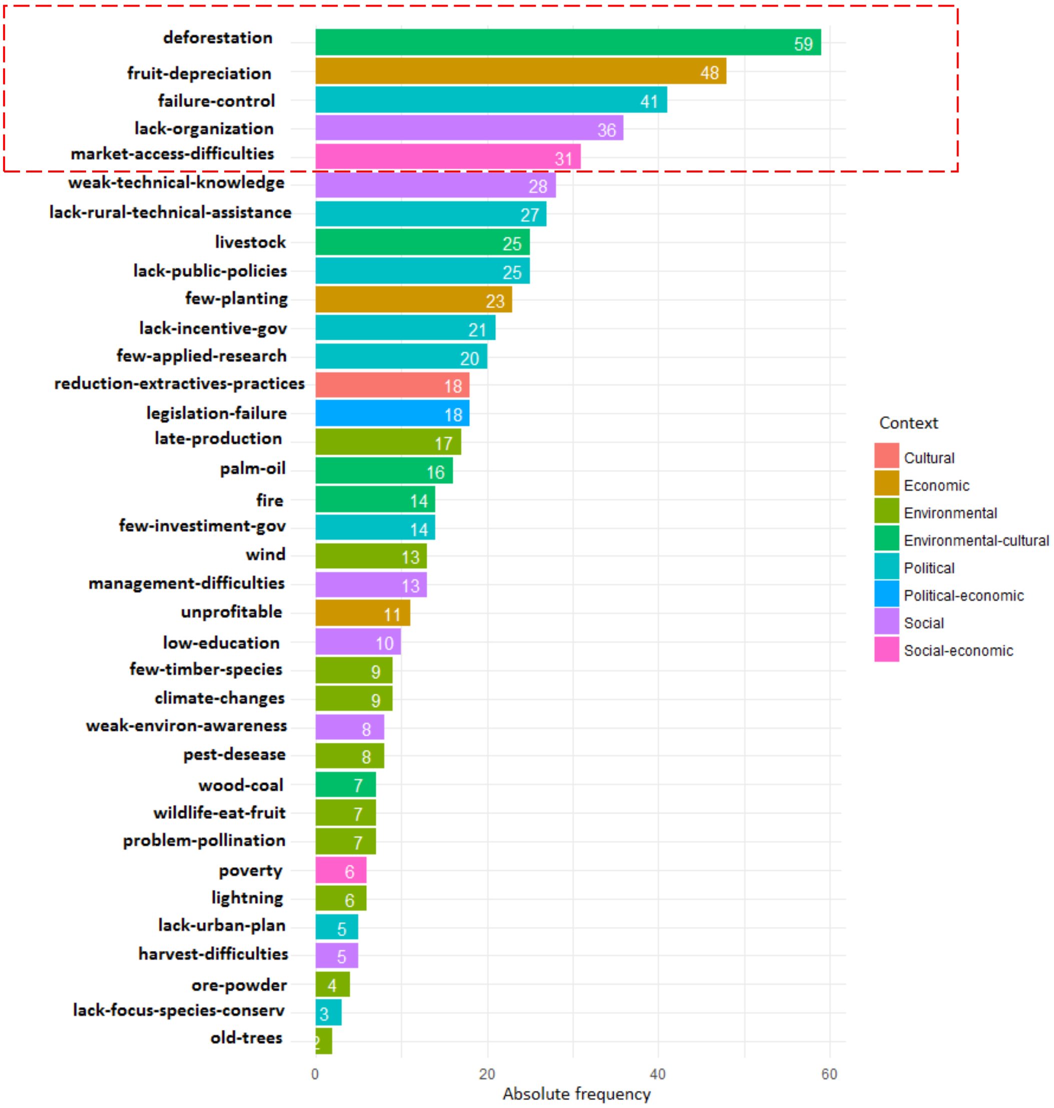

Figure 3. Code frequency perceived by traditional communities, public manager and researchers for factors that affect Amazon-nut. Each color corresponds to a category of context.

We also found particular point of views with lower frequencies (fig.3). It is predominantly composed by codes associated to environmental and social contexts. For instance, reduction in fruit productivity is caused by: pollination problems; wildlife eating the nuts in the few existing refuges; pests and diseases regulated by own forest; and those attributed to climate-changes. Despite the low frequency, these are environmental factors that can compromise the performance of the productive chain, therefore they need to be considered. As far as the social category, poverty and harvest difficulties were the least cited, although these factors challenge logistic and organization strategies. Figure 4 presents the flowchart of relationships between problems reported by participants and categorized by us.

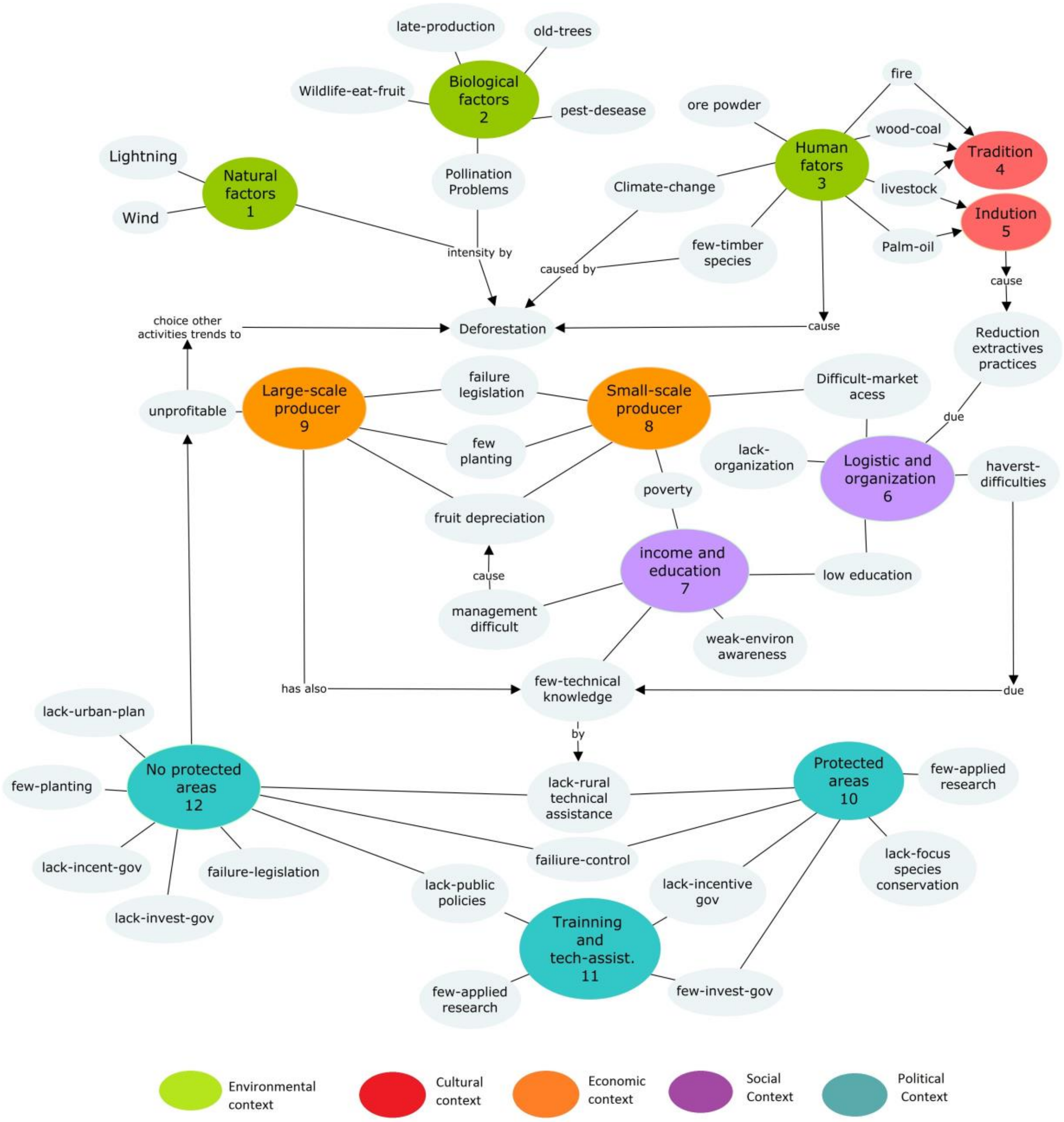

Figure 4. Relationships among codes (grey circles) and categories (colors circles) emerged from focus group, interviews individuals and questionnaires, representing the problems that affect Amazon-nut. Color circles were numbered to indicate the flow of direction for the reader following.

To analysing the conections and relationship among code and categories in Figure 4, we understood the reason of the deforestation have been the main threat mentioned. All categories converged to it, i.e, deforestation has only been happening, because there are other associated factors to it. To reduce species vulnerability and lost habitat caused by deforestation, it is required the recognition of the power public that this biggest problem has genesis in five other contexts (environmental, cultural, economic, social and political). People's perception was an important source of information to help us identify them.

3.3.4 Perception by group

Communities

People described feelings and memories with the Amazon-nut. One example is the personification attributed to one of these trees called Majesty, a name used to convey its grandeur and beauty. This tree measured 10.65 m of perimeter and was estimated to be 639 years, adopting an average annual increment of 0.53 cm*ano^{-1}(Salomão, 2009). It was found in an agroextractivist agrarian settlement in New Ipixuna of Para, next 100 km of Marabá city. In 2011, its owners were killed both for being activists in the forest protection. Five years later, in 2016, we observed degraded landscapes around this forest fragment (Fig5a-b). Similarly, in the Acará municipality the forest landscape was replaced by livestock and currently communities are vulnerable to the introduction of oil-palm planting by private and public incentives. Consequently, their properties become few diverse and with reduced extractive practices (Fig 5c-d). Analyzing a radial diagram of the five most important problems reported by these stakeholders, 12 % of traditional people highlighted that they have a weak technical knowledge to work with this species in both natural and planted forests (Fig 6a). This was attributed to the low governmental incentive and investment to provide technical assistance focused on forest management, planting and to insure the product trade.

"I believe that people are interested, but there are difficulties for lack of information ". C.

"Human resources need to believe that it will be profitable" [extrativismo and planting]. *C.*

"There is a lack of financing for Amazon-nut, if you are encouraged to trade, but no financing, you won't succeed".C

Public Managers

Technicians demonstrated interested on develop Amazon-nut use and conservation. As shown in the radial diagram (Fig. 6b), the lack of governmental incentive for planting (12 %), deforestation (12 %) and fruit depreciation (9 %) were the most mentioned negative drivers in this group. They confronted ideas on economic viability of Amazon-nut and concluded that for the small-farmers, it can be very profitable, but for a large-producer there are other activities economically more attractive. For them, if farmers are not obliged to restore, they will only do it, if there are government incentives.

> *"People have to be convinced to install an agroforest system…the difficulty is to break this paradigm of going from pasture to agroforest system… moving from consolidated areas to forested areas is a challenge". MA.*

In conserved areas, public managers highlighted their importance not only for the Amazon-nut conservation and sustainable use, but also stressed concerns about the creation of conservation units without focus on species conservation. According to them, many units were created to protect geopolitical interests, mainly in the 70th decade.

> *"Amazon-nut conservation was not a strategy for Conservation unit's implementation, but today it is a tool of conservation for us". PM*

Researchers

According to the researchers, extractivism is very important for conservation. They believe that forest people can live very well in the Amazon, when they are organized to access public policies and to negotiate a fair price in the market. In their opinion, organizational problems are much more impeditive than technical ones (Fig.6c). Therefore, logistic difficulties to market access were the biggest obstacle highlighted by them (18 %), followed by the lack of organization (13 %). Currently, the areas of forest are very distant to the main center. It has caused an increase in the transportation costs and a decrease Amazon-nut offer, which is a product almost 100% from extractivism. For them, public policies and government programs must be more based on scientific information.

"We have to guide extractivist people; they cannot continue doing the same since 1500 without the support of research". RE.

"We don't have a productive zoning for Amazon-nut… How is it possible to build policies based on lack of information?". RE.

Figure 5. Occurrence of Amazon-nut in the Amazon landscapes. a) Majesty Amazon-nut tree conserved in an agrarian settlement, next to Maraba, Pa. b) Degraded livestock around the forest fragment where the Majesty was found. c) Tree conserved by Menino Jesus Quilombo community in the Acara. d) Amazon-nut regeneration into palm-oil planting, in the Acara, Pa.

3.3.5 Potential solution

All reported solutions were exclusively focused on political context (Fig. 7). *Increase of planted area, technical assistance and reforestation taxes credit* were determined as the main solutions for Amazon-nut planting by three groups of stakeholders. They believe that without financial and technical support, it is impossible to develop a long-term sustainable land-use. They recognized that Brazilian government has been favorable to technical assistance (MDA, 2004), however, it must be more focused on agroforest system using species with high environmental and economic values. In addition, this assistance must be regular, numerically planned and the results shared to disseminate good experiences and give to communities more empowerment.

Another aspect was to ensure an *equitable price* in the market for Amazon-nut. Today, the fruit has a national and international value, but communities are very distant to markets and unaware of price policies. According to managers and communities, the government needs to encourage Amazon-nut oil and fruit productions and *guarantees the purchase*. The communities argued that the price currently offered is very low compared to the encountered harvest difficulties. To aggregate more value, managers and researchers consider indispensable to *strengthen* the local *micro-industry*, not only to encourage production, but also to explore and *popularie new technologies*. In addition, governmental support should take into account the low level of education and organization in most of the communities and invest in *consolidate rural schools.* The communities demanded investment in education, as well as a *territorial management plan* that value their culture.

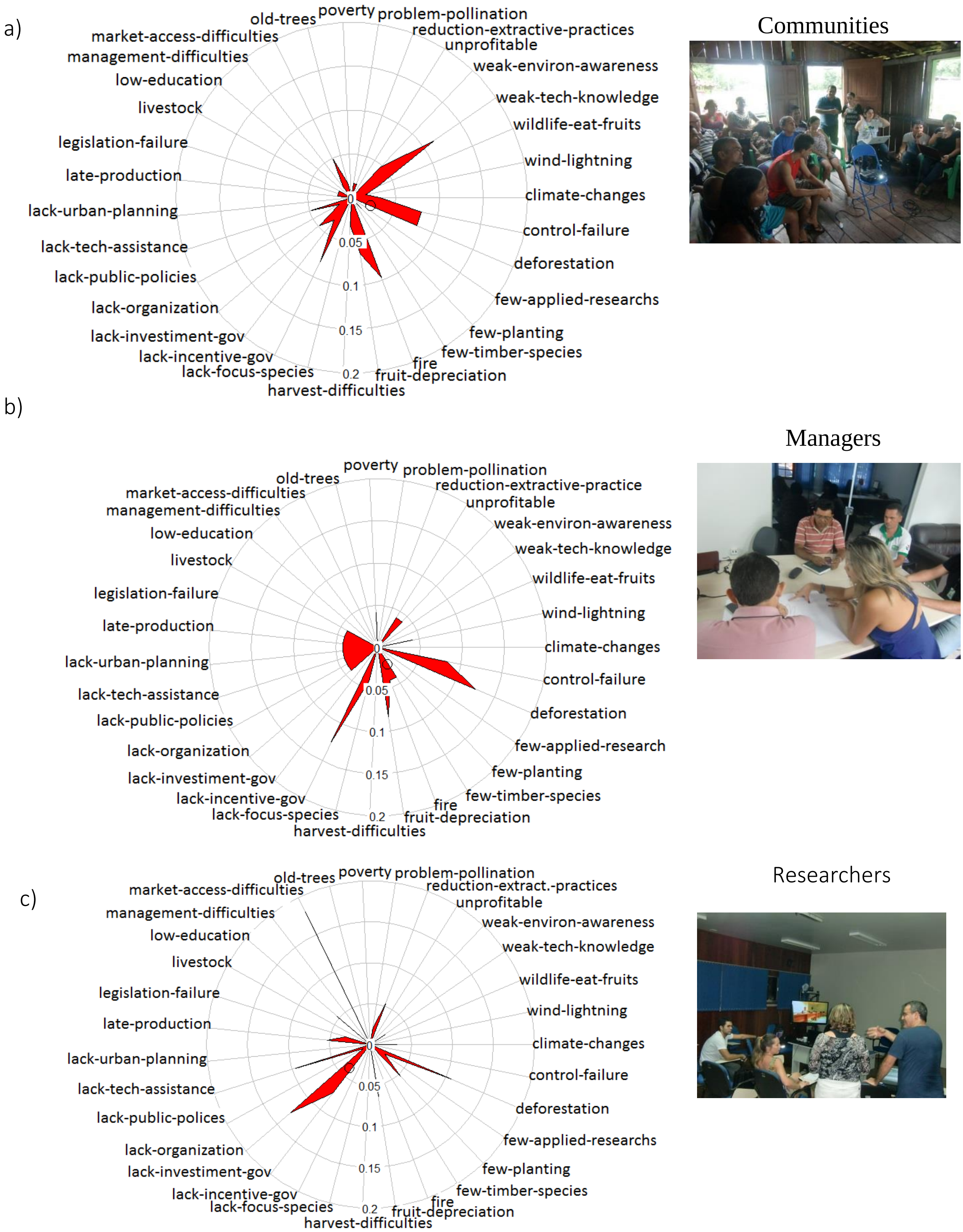

Figure 6. Radial diagram showing the relative frequency of five-main problems that affect the Amazon-nut conservation and sustainable use perceived by consulted stakeholders. a) Communities; b) Public Managers; and c) Researchers.

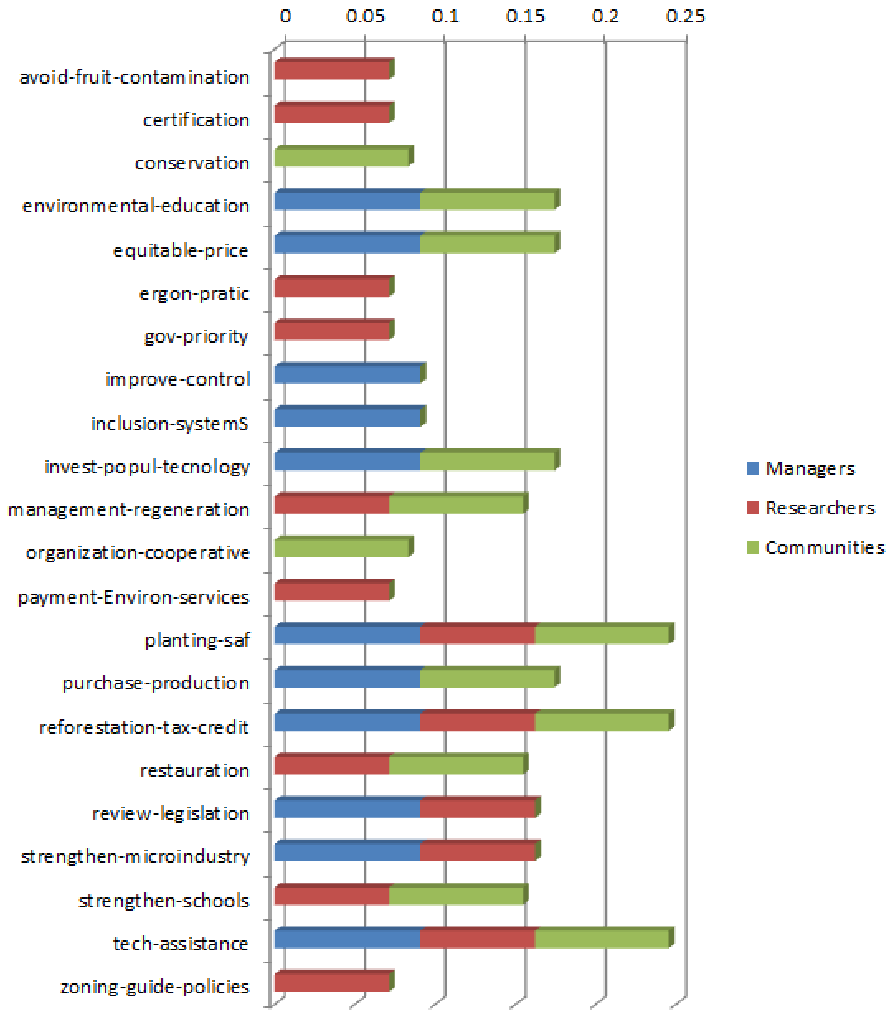

Figure 7. Frequency of the five-main solutions that affect the Amazon-nut conservation and sustainable use reported by consulted stakeholders.

Legislation review was another central solution cited for both managers and researchers. For them, there are failures in the current legislation (Decreto n° 5975, 2006), since this law ensures protection, but not long-term species conservation. First, when an individual is left isolated in the landscape, its ecological functions are collapsed, since this species has around 194 interactions with predators, dispersers, competitors, pollinators, floral visitors, pathogens and microorganisms (Santos-Silva et al., 2017). Second, in agricultural or livestock lands, the species becomes vulnerable to natural events, such as winds and lightning. In their opinion, the tree simply falls down, its population is reduced and all of this is not illegal. They also highlighted that clarity on the legislation about the planting and the use of planted timber is required. Another review would be in the Brazil's Forest Code (law n°12.727, 2012), because it reduced the environmental debts of large and small-farmers that deforested illegally before 2008 (Soares-Filho et al., 2014). Thereby, the legal reserves and permanent preservation areas passive to *restoration*, in which Amazon-nut could be introduced, are currently much smaller.

We also observed that some solutions were more important for this given group than others, such as improvement in the *measure of control* for managers, *payment for environmental services* for researchers and *organization* for communities. It could be explained by the context in which this group is currently in and the proximity to the subject.

3.4 Discussion

Several authors have pointed out that conservation means complexity, because most of the problems are complex and embedded in socioecological systems (Game et al, 2014; Sandbrook et al., 2013). Comparing the three stakeholders' groups presented here, we were able to identify 36 problems, distributed in specific and broader categories. Although categories are more abstract than codes, they are a grounding in the development of a theory (Corbin & Strauss, 1990). Our systematic analysis confirmed it. Indeed twelve specific categories emerged and were integrated in five broader categories according to their meaning. Impact evaluation and association of these categories were important to understand the causes and effects of problems which may threaten this species and require intervention.

In an environmental context, perception revealed that some natural, biological and human factors have impacted Amazon-nut. We observed that all of them are linked to deforestation that modifies landscapes and people's relationship with the land. The stakeholders and drivers which cause deforestation have been extensively discussed in the literature (Fearnside, 2006b; Rivero et al., 2009; Schneider & Peres, 2015), but few studies have been dedicated to quantify primary and secondary deforestation effects on species prevalence and productivity. Amazon-nut mortality caused by wind and lighting were not the most important problems cited, but both were mentioned by 100 % of communities and public managers. It demonstrated there is high species vulnerability when it is left isolated in the landscape. Similar vulnerability conditions were found in Peru (Zuidema, 2003). Another problem is seeds production decrease in open areas, such as pastures/agricultural lands or near roads. Reduction of pollinator agents is a biologic problem that can cause low productivity and it usually occurs where fragmented landscape, monoculture in large scale and indiscriminate use of agrochemicals predominate (Motta et al., 2015). As far as strictly human factor, a new problem emerged, the influence of *ore powder* on Amazon-nut trees along Carajás railway in Pará. The injury on Amazon-nut leaves is not scientifically acknowledged, however it was diagnosed by the visited traditional communities and requires further studies.

In cultural context, traditional and induced economic activities were pointed out as a source of impact on Amazon-nut. One of the main economic activities induced by public policies in the Amazon was disordered and livestock with low-level technics (Barbanti, 2015). From 2000 to 2006, it was identified as the main deforestation driver associated to logging (Rivero et al., 2009). In the same period, Amazon meat contribution in Brazilian exportations (Barreto, Pereira, & Arima, 2008) increased from 6 % (10 thousand tons) to 22 % (263.7 thousand tons). Currently, 40 billion are being destined by Brazilian government to develop agribusiness sector in SAFRA plan (MAPA, plan. 2018/2019). Despite incentives for good practices, concerns continue to raise because studies have shown that livestock intensification is not profitable in areas smaller than 150 hectares (Garcia et al., 2017).

In Maraba municipality, we observed many small-farmers raising cattle on very low productivity lands. In a focus group, a public manager related that these small-farmers have more tradition with livestock than extractivism practices, and they continuously request technical assistance linked to this economic activity. In the same group, another manager counter-argued saying that technical assistance is currently very active, but it only offers milk processing, improved grazing and milk derivative courses. He questioned to other colleagues on why small-farmers have not worked with forest essences too, such as Amazon-nut fruit processing, extraction of Amazon-nut oil, andiroba oil (*Carapa guianensis*) and copaiba oil (*Copaifera langsdorffii*). After a long discussion, they concluded that public policies are required to incentive the extensionist to exploit other economic alternatives. For communities, the bigger error was the credit incentive for cattle-raising, because according to them the bank only financed cattle projects, thus the intensification of deforestation. In their opinion, there is no incentive for non-timber forest products extractivism. For us, it demonstrated a distancing of communities from the implementation of Brazilian public policies for rural development. Although Brazil has created differentiated policies designed for small-farmers and traditional communities, such as national Policy on technical assistance and rural extension (PNATER), National Policy on Agroecology and Organic Production (PNAPO), National Program for Strengthening Family Agriculture (PRONAF), Food Acquisition Program (PAA) and National School Feeding Program (PNAE), the access to these policies is deficient, due to uncertainty in their application (Hespanhol, 2013).

In economic context, our results showed fruit depreciation as the second biggest reported problem. We found two main causes for it. One is illegal wood trade that still is more profitable than nut trade in the studied areas, because timber industry regularization process is incipient and favors purchase of illegal products. Indeed, Environmental Estate Secretaries (SEMAS) and Brazilian Institute of Environment and Renewable Natural Resources (IBAMA) have implemented various policies to combat environmental crimes (Castelo, 2015). However, trade of Amazon-nut timber is still recurrent, reducing opportunities of multiple uses of forest in the long run. The marginalization of small-producers and traditional communities from markets has been another difficulty, because forest areas are very distant from urban centers and they become vulnerable to intermediate buyers who offer an unfair price, below the minimum established by the national supply company (CONAB). To overcome this problem, in Acre State, the intermediate agents had to adapt to a new scenario, where there have been strengthening associations and cooperatives formed by extractivist and small-farmers. Consequently, the empowerment of these organizations opened new possibilities to aggregate more value to locally processed products, such as nuts in shell and dry, shelled, shelled without-skin, low-fat flour and amazon-nut oil (Bayma et al., 2014).

In State of Acre, this change was possible thanks to governmental support in three spheres (federal, state and municipal) and financial support for industry, conservation, infrastructure and technology from the Brazilian Development Bank (BNDES) and the Inter-American Development Bank (IDB). In State of Pará, we discussed with three agroextractivist groups interested in developing a more organized production though cooperatives: Quilombos, indigenous and agrarian settled people. For them, cooperatives could be an opportunity to have more autonomy, added value on forest products and improve community's life conditions. However, they have been facing some problems to develop it, such as little financial resource, lack of technical information to map Amazon-nut trees, productivity monitoring, lianas management, forest products processing, planting, transport and certification. They have a rich traditional knowledge and acknowledge the importance of the technical information to help them expand conservation strategies, valorize the culture and reduce the surrounding pressure.

In social context, every visited community and public institution demonstrated interest in working with Amazon-nut harvesting and planting. Yet, the lack of community organization was an obstacle recognized by all of them. Experiences in some countries, including Brazil, have showed that the collective management of forest resources is more effective by engaging people toward the sustainable use of resources (Arnold, 2001; Burke, 2012). Nevertheless, cooperatives require drastic social transformation that may tend to collapse, if economic opportunities exceed other principles such as democracy, participation, autonomy and self-sufficiency (Burke, 2012). Therefore, it is important to have a conservation planning that considers trade opportunities, strategies of management, environmental awareness and culture enhancement. Poverty and difficulties of access to basic necessities (education, health services, energy, safe drinking-water, non-nutritious food) often faced by communities should also be regarded.

Politically, the problems belong to three categories: protected areas, non-protected areas and training and technical assistance. It is the government's responsibility to create policies and programs to solve the obstacles to conservation and local development. One of the decisions made by the federal government was to decentralize environmental competences through the complementary law n° 140 (BRASIL, 2011). This certainly gave more autonomy to state institutions to work on deforestation control, still they have been facing challenges on the implementation of the law due to the lack of structure and financial restraints that involve operational limitations (Schmitt & Scardua, 2015). In visited protected areas, participants asked for more collaborative actions between communities and public institutions, because they reported difficulties to control the invasion of people seeking timber illegal extraction or capturing wild animals. This collaboration is also demanded in non-protected areas by communities who reported inefficiency in the complaint system, which is not completely anonymous. This practice leads to conflicts and discourages people to contribute with environmental control.

3.5 Conclusion

Amazon-nut conservation in Brazilian amazon should not be based solely on legal protection. Through stakeholder's perception, we found thirty-six problems that currently are affecting this species either directly or indirectly. In our studied areas, it was evident that current law has been a barrier to overexploitation of this species, since many trees were found isolated in landscapes dominated by agriculture and livestock. Nevertheless, Amazon-nut vulnerability has increased, because the surface of suitable habitats for this species is dropping.

Deforestation, as a result of other associated factors, was the main problem mentioned by the participants. Here, we discussed these factors combining qualitative and qualitative analysis. Categorization in specific and broader groups was an excellent method that helped us recognize and understand causes, effects and relationships between these problems.

The three stakeholder groups recognized the complexity of the problems threatening Amazon-nut trees in protected and non-protected areas. Rich discussions were obtained during focus group discussions. It allowed people to express their point of view, debate ideas and suggest collectively built solutions. After each meeting, we had a positive feedback and noted their involvement to change the current situation. Our findings suggest that people should be consulted, motivated and included in the decision process to improve governance and conservation in Amazonia.

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4. General conclusion

The combination of the species distribution modeling and environmental perception techniques was essential to achieve our interdisciplinary objectives. In this thesis, we found new ecological information and confirmed existing evidences, exploring several methodological aspects that could be replicated to other species with large distribution in the Amazon.

The research was developed in a large-scale of analysis (Pan-Amazon) and refined with local information about factors that cause Amazon-nut vulnerability (Case studies). This association of techniques presented various results; the most important of them was the increase in model quality when we used multivariate statistics associated to expert's knowledge. Our final model was developed based in results of different experiments to remove bias commonly present in the occurrences, predictor variables and model parameters. These fittings were fundamental to obtain a reliable model, which indicated that 32% of the Amazon biome is environmentally suitable to *B. excelsa* growth.

The best model indicated "soil coarse fragments > 2 mm and Clay" as being relevant variables to control Amazon-nut distribution, we recommended more investigation about the influences these soil physical parameters have on the species. We suggested our map to be used to quantify the real area occupied by this species, considering biotical and anthropogenic interactions. Also, it is possible to calculate the habitat percentage in and out of protected areas, but the shapefile of conservation units and indigenous land currently available has many topology and overlap errors. These databases need to be previously adjusted to give accurate results to the society. Moreover, through suitability habitat map it is possible to identify areas available for planting with a high potential of success.

The environmental perception through consulted local stakeholders revealed the complexity of problems that affect this species in the studied areas. 72% of these obstacles are in environmental and political context, in both protected and non-protected areas. Deforestation was the main threat mentioned, but the deep analysis in codes and categories allowed us to understand that it is a consequence of other associated factors. The communities request technical knowledge, managers affirm that people should be stimulated to manage and plant, and researchers stress that if the communities are organized, they can access public polices and negotiate a fair price.

We concluded that for effective Amazon-nut conservation, local people should be motivated to monitor and manage their natural forests or agroforests with the support of regular technical assistance, considering environmental, economic, political, social and cultural contexts.

APPENDIX A

General information data and elementary soil data analysis.

Table S1.1 B.excelsa's occurrence records obtained from researchers' databases, herbarium data, museums' geographical data, scientific publications and field survey data from 2015 to 2017.

Number of occurence	state/country	source
100	PA/Brasil	First authors 'field survey
24	PA/Brasil	Plano de manejo Flota Trombetas
74	PA/Brasil	GIBF-MAPCAST - Lucieta Martorano/ Embrapa
32	PA/Brasil	CRIA-MAPCAST- Lucieta Martorano/ Embrapa
5	PA/Brasil	Dário do Amaral e Diego de Sousa / Museu Goeldi/ IBAMA
2	PA/Brasil	REFLORA
22	PA/Brasil	LITERATURA
20	PA/Brasil	Maria Beatriz Ribeiro/INPA
2	PA/Brasil	Plano de manejo Flona Trairão
16	PA/Brasil	Herbário Embrapa
11	AC, AM, RR,RO,MT,PA	INPA-MAPCAST
39	PA, RR, RO, AM,	MAPCAST
34	AP/Brasil	Resex Rio Cajari - Marcelino Guedes/ Embrapa Amapá
205	AP/Brasil	Capoeira Marinho – Marcelino Guedes/Embrapa Amapá
15	AC, AM, MT,PA	Museu Goeldi - MapCast
105	AP/Brasil	Laranjal do Jari - Marcelino Guedes/Embrapa Amapá
641	AP/Brasil	Capoeira Marinho e Martins- Marcelino Guedes/Embrapa Amapá/Mapcast
540	PA/Brasil	Marcelino Guedes/Embrapa Amapa/Mapcast
29	PA/Brasil	Resex Lago Campana grande – Ricardo Scoles/UFOPA
8	PA/Brasil	Raquel dos Santos/USP
29	RO/Brasil	Lucia Wadt/Emabrapa/Mapcast
14	RR, AM,MT,PA,AM,AC	Katia da Silva/ Embrapa/Mapcast
1078	AM,PA, AP, AC, RO, RR, MT, Bolívia, Perú, Colombia, Venezuela, Guiana, Suriname	Evert Thomas/ CGIAR

Table S1.2. List of 102 environmental predictor variables assembled by categories for this study and predictors selected in each specifique group. Group1: PCA-derived synthetic predictors calculated using environmental data covering the entire geographic; Group2: All the variables recommended by experts; Group3: PCA calculated from a pre-selected variable set by experts.

Categories	Variable	Group1 (18 layers)	Group2 (29 layers)	Group3 (15 layers)
climate	BIO1 = Annual Mean Temperature		x	x
climate	BIO2 = Mean Diurnal Range (Mean of monthly (max temp - min temp))			
climate	BIO3 = Isothermality (BIO2/BIO7) (* 100)			
climate	BIO4 = Temperature Seasonality (standard deviation *100)			
climate	BIO5 = Max Temperature of Warmest Month			
climate	BIO6 = Min Temperature of Coldest Month			
climate	BIO7 = Temperature Annual Range (BIO5-BIO6)		x	
climate	BIO8 = Mean Temperature of Wettest Quarter			
climate	BIO9 = Mean Temperature of Driest Quarter	x	x	x
climate	BIO10 = Mean Temperature of Warmest Quarter			
climate	BIO11 = Mean Temperature of Coldest Quarter		x	x
climate	BIO12 = Annual Precipitation		x	
climate	BIO13 = Precipitation of Wettest Month			
climate	BIO14 = Precipitation of Driest Month		x	
climate	BIO15 = Precipitation Seasonality (Coefficient of Variation)			
climate	BIO16 = Precipitation of Wettest Quarter			
climate	BIO17 = Precipitation of Driest Quarter		x	
climate	BIO18 = Precipitation of Warmest Quarter			
climate	BIO19 = Precipitation of Coldest Quarter			
climate	PETa=Annual Potential evapotranspiration		x	x
climate	PET3= Evapotranspiration of Wettest Month			
climate	PET8=Evapotranspiration of Driest Month			
climate	PET9=Evapotranspiration of Warmest Month			
climate	PET7=Evapotranspiration of Coldest Month			
climate	PETweq=Evapotranspiration of Wettest Quarter			
climate	PETdrq=Evapotranspiration of Driest Quarter	x	x	
climate	PETwaq=Evapotranspiration of Warmest Quarter			
climate	PETcoq=Evapotranspiration of Coldest Quarter			
climate	ARa=Aridity Index			
climate	SWC3=Soil water content of Wettest Month			
climate	SWC8=Soil water content of Driest Month			
climate	SWC9=Soil water content of Warmest Month			
climate	SWC7=Soil water content of Coldest Month			
climate	SWCweq=Soil water content of Wettest Quarter			
climate	SWCdrq=Soil water content of Driest Quarter	x	x	
climate	SWCwaq=Soil water content of Warmest Quarter			
climate	SWCcoq=Soil water content of Coldest Quarter			
soil	Carb1= Organic Carbon in g. kg-1 (0)		x	
soil	Carb2= Organic Carbon in g. kg-1 (5cm)			
soil	Carb3= Organic Carbon in g. kg-1 (15cm)			
soil	Carb4= Organic Carbon in g. kg-1(30cm)			
soil	Carb5= Organic Carbon in g. kg-1(60cm)			
soil	Carb6= Organic Carbon in g. kg-1(100cm)			
soil	Carb7= Organic Carbon in g. kg-1(200cm)		x	
soil	Crfvol1=Coarse fragments volumetric >2mm in % (0)		x	x
soil	Crfvol2=Coarse fragments volumetric >2mm in % (5cm)			
soil	Crfvol3=Coarse fragments volumetric >2mm in % (15cm)			
soil	Crfvol4=Coarse fragments volumetric >2mm in % (30cm)			
soil	Crfvol5=Coarse fragments volumetric >2mm in % (60cm)			
soil	Crfvol6=Coarse fragments volumetric >2mm in % (100cm)			
soil	Crfvol7=Coarse fragments volumetric >2mm in % (200cm)		x	x
soil	CEC1=Cation Exchange Capacity in cmolc. kg-1 (0)		x	x
soil	CEC2=Cation Exchange Capacity in cmolc. kg-1 (5cm)			
soil	CEC3=Cation Exchange Capacity in cmolc. kg-1 (15cm)			
soil	CEC4=Cation Exchange Capacity in cmolc. kg-1 (30cm)			
soil	CEC5=Cation Exchange Capacity in cmolc. kg-1 (60cm)			
soil	CEC6=Cation Exchange Capacity in cmolc. kg-1 (100cm)			
soil	CEC7=Cation Exchange Capacity in cmolc. kg-1 (200cm)		x	
soil	dens1=Bulk density (fine earth) in kg / m3 (0)	x	x	
soil	dens2=Bulk density (fine earth) in kg / m3 (5cm)	x		
soil	dens3=Bulk density (fine earth) in kg / m3 (15cm)	x		
soil	dens4=Bulk density (fine earth) in kg / m3 (30cm)	x		
soil	dens5=Bulk density (fine earth) in kg / m3 (60cm)			
soil	dens6=Bulk density (fine earth) in kg / m3 (100cm)			
soil	dens7=Bulk density (fine earth) in kg / m3 (200cm)		x	
soil	ph1=Soil pH x 10 in H2O (0)	x	x	x
soil	ph2=Soil pH x 10 in H2O (5cm)	x		
soil	ph3=Soil pH x 10 in H2O (15cm)	x		
soil	ph4=Soil pH x 10 in H2O (30cm)	x		
soil	ph5=Soil pH x 10 in H2O (60cm)			
soil	ph6=Soil pH x 10 in H2O (100cm)			
soil	ph7=Soil pH x 10 in H2O (200cm)		x	
soil	sand1= sand mass fraction % (0)		x	x
soil	sand2= sand mass fraction % (5cm)			
soil	sand3= sand mass fraction % (15cm)			
soil	sand4= sand mass fraction % (30cm)			
soil	sand5= sand mass fraction % (60cm)			
soil	sand6= sand mass fraction % (100cm)			
soil	sand7= sand mass fraction % (200cm)		x	x
soil	clay1=clay mass fraction % (0)		x	x
soil	clay2=clay mass fraction % (5cm)			
soil	clay3=clay mass fraction % (15cm)			
soil	clay4=clay mass fraction % (30cm)			
soil	clay5=clay mass fraction % (60cm)			
soil	clay6=clay mass fraction % (100cm)			
soil	clay7=clay mass fraction % (200cm)		x	
soil	silt1=silt mass fraction %(0)	x	x	
soil	silt2=silt mass fraction %(5cm)	x		
soil	silt3=silt mass fraction %(15cm)	x		
soil	silt4=silt mass fraction %(30cm)	x		
soil	silt5=silt mass fraction %(60cm)			
soil	silt6=silt mass fraction %(100cm)			
soil	silt7=silt mass fraction %(200cm)		x	x
topografy	asp=Aspect	x		
topografy	elev=terrain elevation model		x	x
topografy	cti= Compound Topog. Index			
topografy	spi=Stream Power Index		x	x
topografy	slop=slope		x	x
geology	upslopesoil2=upland_hill-slope_soil_thickness			
geology	hvalbotton3=hill-slope_valley-bottom	x		
geology	upvallowland4=eyupland_valley-bottom_and_lowland_sedimentary_deposit_thickness			
geology	aversoilsed6=average_soil_and_sedimentary-deposit_thickness	x		

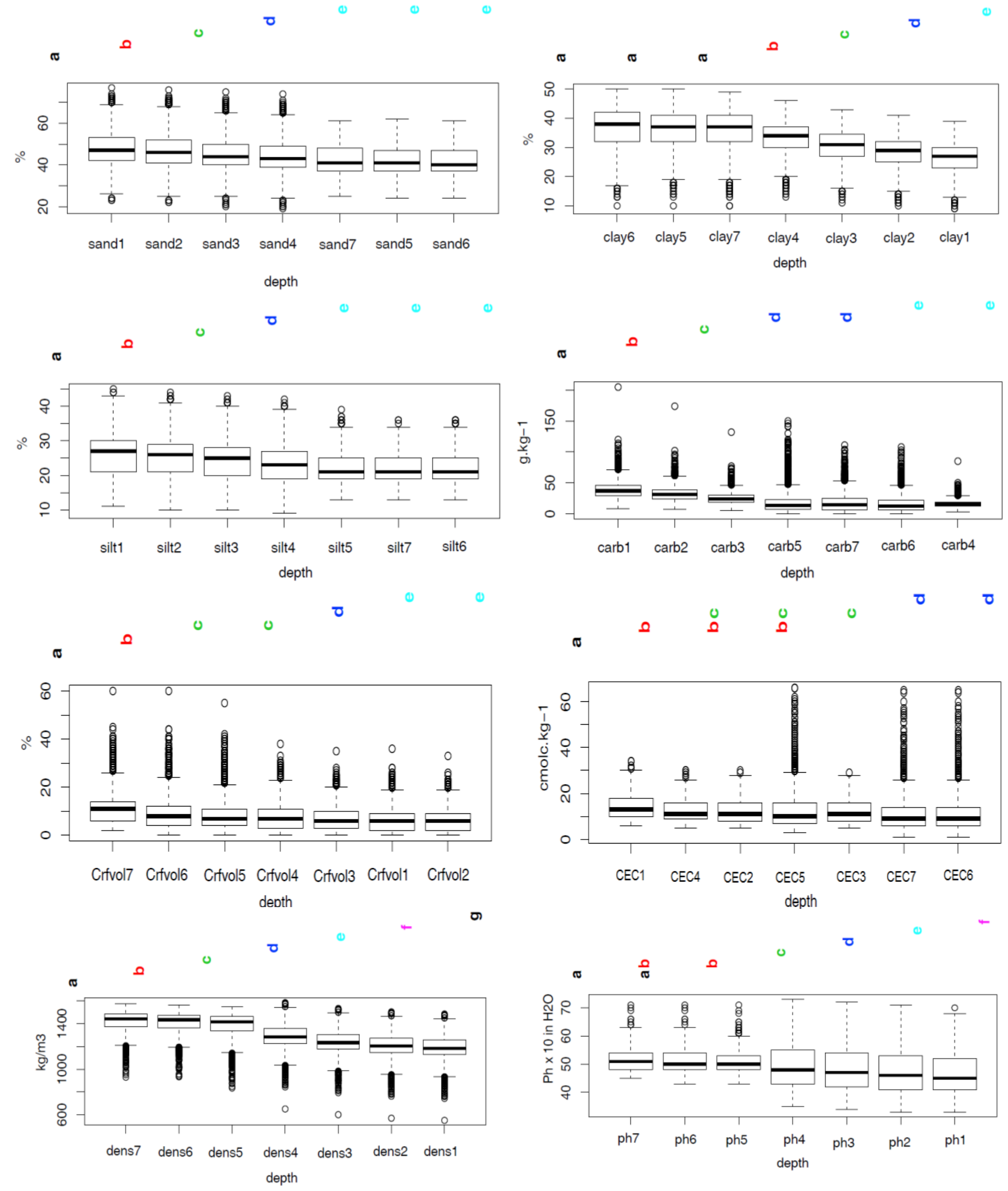

Figure S1.1 Boxplot graphics of soil variables submitted for pairwise mean comparisons in depths using *Tukey's test* (HSD) implemented on *multcompBoxplot* R function. Numbers from 1 to 7 indicate the depth (0cm, 5cm, 15cm, 30cm, 60cm, 100cm and 200cm). The used variables were sand mass fraction % (sand), silt mass fraction % (silt), clay mass fraction % (clay), Cation Exchange Capacity in cmolc. kg^{-1} (CEC), Organic Carbon in g. kg^{-1} (carb), Bulk density (fine earth) in kg / m^3 (dens), Soil pH x 10 in H2O (ph) and Coarse fragments volumetric in % (cfrvol). Differences between means in the depth that share a letter and color are not statistically significant ($P< 0.05$).

In the Amazon region, the soil proprieties with mean statistically significant in the following depth are: sand (1,2,3,4,7); clay (1,2,3,4,7); Silt (1,2,3,4,5); Carbon (1,2,3,5,6); Crfvol (1,3,5,6,7); CEC (1,3,4,7); dens (1,2,3,4,5,6,7) and PH (1,2,3,4,5,7). The relations between them were also analyzed in this study.

Summary of ordination data and similarity test between models

Table S2.1 Summary of PCA in the geographic space of the Amazon (**Group1**): Proportion of variance explained in the original data (1stPCA) and proportion of variance explained for only the most important variables in the principal axes (2stPCA). The accumulated variance with criteria (α_0 > 0.80) was adopted. Eigenvectors for the 2nd PCA close to 1 indicate a strong relation between axes and predictors.

		Principal components				
		PC1	PC2	PC3	PC4	PC5
1stPCA (%Variance accum.)	Climate	43.29	74.52	**87.11**	-	-
	Soil	38.98	62.21	74.31	**82.04**	-
	Geo	37.49	53.37	65.49	75.46	**81.84**
		PC1	PC2	PC3		
2ndPCA (%Variance accum.)	Climate	56.03	**92.40**	-	-	-
	Soil	47.46	68.37	**81.92**	-	-
	Geo	41.40	65.23	**85.22**	-	-
Predictors selected		Eigenvectors (loading*sdev)				
Climate	BIO9	0.93	0.27			
	PETdrq	0.81	-0.54			
	SWCdrq	0.33	0.93			
Soil	dens1	-0.51	-0.38	-0.72	-	-
	dens2	-0.51	-0.38	-0.72	-	-
	dens3	-0.51	-0.38	-0.72	-	-
	dens4	-0.51	-0.38	-0.72	-	-
	ph1	0.65	0.46	-0.51	-	-
	ph2	0.65	0.46	-0.51	-	-
	ph3	0.65	0.46	-0.51	-	-
	ph4	0.65	0.46	-0.51	-	-
	silt1	0.81	-0.48	0.12	-	-
	silt2	0.81	-0.48	0.12	-	-
	silt3	0.81	-0.48	0.13	-	-
	silt4	0.81	-0.48	0.13	-	-
Geophysical	asp	0.03	-0.04	1.00	-	-
	hvalbotton3	0.53	-0.77	-0.03	-	-
	aversoilsed6	-0.92	0.20	0.02	-	-

BIO9: Mean Temperature of Driest Quarter ; **PETdrq**: Evapotranspiration of Driest Quarter ; **SWCdrq**: Soil water content of Driest Quarter; **dens1:** Bulk density (fine earth) in kg / m3 (0cm); **dens2:** Bulk density (fine earth) in kg / m3 (5cm); **dens3:** Bulk density (fine earth) in kg / m3 (15cm); **dens4:** Bulk density (fine earth) in kg / m3 (30cm); **ph1:** Soil pH x 10 in H2O (0); **ph2:** Soil pH x 10 in H2O (5cm); **ph3**: Soil pH x 10 in H2O (15cm); **ph4:** Soil pH x 10 in H2O (30cm); **silt1:** silt mass fraction %(0); **silt2:** silt mass fraction %(5cm); **silt3**: silt mass fraction %(15cm); **silt4:** silt mass fraction % (30cm); **asp:** Aspect; **hvalbotton3:** hill-slope_valley-bottom;**aversoilsed6:** average_soil_and_sedimentary-deposit_thickness.

Table S2.2 Summary of PCA calculated to set of variables selected by the experts (**Group3**): Proportion of variance explained to the original data and the most important variables in the principal axes. The accumulated variance with criteria ($\alpha_0 > 0.80$) was adopted. Eigenvectors next to 1 indicate a strong relation between axes and predictors.

		PC1	PC2	PC3	PC4	PC5
%Variance accum.	Climate	53.6	**86.8**	-	-	-
	Soil	38.2	62.4	72.8	79.3	**83.5**
	Geo	68.5	**90.0**	-	-	-
Predictors selected		Eigenvectors (loading*sdev)				
Climate	BIO1	0.84	-0.50	-	-	-
	BIO9	0.88	-0.40	-	-	-
	BIO11	0.85	-0.49	-	-	-
	PETa	0.35	-0.88	-	-	-
Soil	Crfvol1	0.78	0.02	0.32	0.43	0.12
	Crfvol7	0.76	0.04	0.29	0.42	0.11
	CEC1	0.76	-0.34	-0.05	-0.38	-0.07
	ph1	0.63	-0.21	0.47	-0.49	-0.06
	sand1	-0.33	0.81	0.32	-0.21	0.28
	sand7	-0.23	0.84	0.05	0.11	-0.31
	clay1	-0.13	-0.77	-0.21	0.02	-0.47
	clay7	-0.27	-0.85	-0.08	-0.01	0.34
	silt7	0.79	-0.03	0.05	-0.21	-0.05
Geophysical	elev	-0.86	0.35	-	-	-
	spi	0.72	0.69	-	-	-
	slop	-0.89	0.22	-	-	-

BIO1: Annual Mean Temperature; **BIO9:** Mean Temperature of Driest Quarter; **BIO11:** Mean Temperature of Coldest Quarter; **PETa:** Annual Potential evapotranspiration; **Crfvol1:** Coarse fragments volumetric >2mm in % (0); **Crfvol7:** Coarse fragments volumetric >2mm in % (200cm); **CEC1:** Cation Exchange Capacity in cmolc. kg-1 (0); **ph1:** Soil pH x 10 in H2O (0); **sand1:** sand mass fraction % (0);**sand7:** sand mass fraction % (200cm); **clay1:** clay mass fraction % (0); **silt1:** silt mass fraction %(0) **elev:** terrain elevation model;**spi:** Stream Power Index;**slop:** slope

Table S2.3 Pair-wise Schoener's D statistic measuring similarity between filtered models from group 3. The statistic ranges from 0 (no overlap) to 1 (the distributions are identical).

	Unfiltered	Filtered at 3km	Filtered at 5km	Filtered at 10km	Filtered at 15km	Filtered at 20km
Unfiltered	1					
Filtered at 3km	0.91	1				
Filtered at 5km	0.89	0.91	1			
Filtered at 10km	0.86	0.89	0.94	1		
Filtered at 15km	0.85	0.88	0.92	0.94	1	
Filtered at 20km	0.85	0.88	0.93	0.96	0.95	1

Table S2.4 Metric calculated for the 18 best models with lowest AICc (i.e. ΔAICc < 2).

	Preditors groups	**Presence data (Filtre at km)**	**Number of points**	**FC**	**RM**	**AUCTEST**	**OR10**	**ΔAICc**
Unfiltered models	1	Unfiltered	3252	LQHP	1	0.864	0.09	0.00
	2			LQP	1	0.865	0.10	0.00
	3			**T**	**2**	**0.889**	**0.10**	**0.00**
Filtered models	1	3	759	LQHPT	1	0.796	0.10	0.00
		5	673	T	1	0.78	0.11	0.00
		10	557	T	1	0.765	0.12	0.00
		15	495	T	1.5	0.747	0.12	0.00
		20	445	T	1.5	0.741	0.13	0.00
	2	3	759	LQHPT	1	0.857	0.17	0.00
		5	673	LQHPT	1.5	0.844	0.14	0.00
		10	557	LQHPT	1.5	0.822	0.13	0.00
		15	495	LQHPT	1.5	0.815	0.13	0.00
		20	445	LQHPT	2	0.809	0.11	0.00
	3	3	759	T	1	0.812	0.13	0.00
		5	673	LQHPT	1.5	0.806	0.11	0.00
		10	**557**	**LQHPT**	**1.5**	**0.785**	**0.11**	**0.00**
		15	495	LQHPT	2	0.775	0.13	0.00
		20	445	LQHPT	1.5	0.764	0.11	0.00

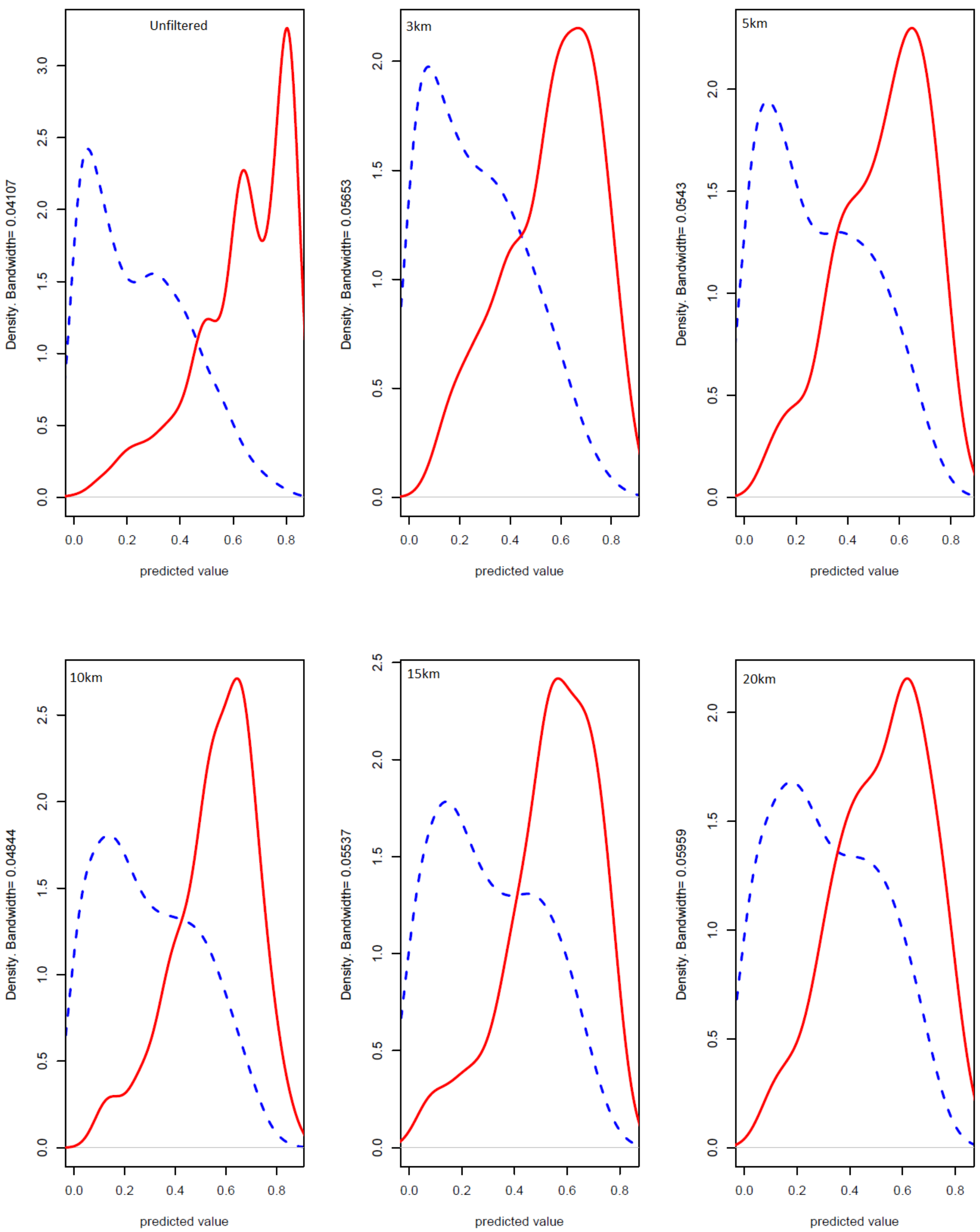

Figure S2.1 Density curves estimated in the best unfiltered and filtered models from group 3. The proportion of presence data are in red and absence data (background data) are represented by a blue dashed line.

APPENDIX B

Questionnaire answered by researchers

Title: The main problem and solution to Amazon-nut (*Bertholletia excelsa)* sustainable use and conservation.

1. Which are the five main problems that affect Amazon-nut use and conservation in the Amazon?
   - ☐ Low federal and state government budget destined to this productive chain.
   - ☐ Failures in the current legislation.
   - ☐ Low level of education of the local communities.
   - ☐ Organization difficulties (association and cooperatives).
   - ☐ Lack of logistic to the collect and transportation of the production.
   - ☐ Communities' ignorance of marketing policies.
   - ☐ Lack of technical and scientific assistance to the communities.
   - ☐ Deforestation and advancement of the agricultural frontier.
   - ☐ Fruit economic depreciation locally.
   - ☐ Climate changes.
   - ☐ Low species regeneration.
   - ☐ Pollination agents reduced.
   - ☐ Extractism practices reduced.
   - ☐ Others.

2. Please, use this space below to leave comments about your choice in the 1st question.

3. Please, rank the level of prevalence of problems associated to Amazon-nut in the different contexts (5= the most prevalence).

	1	2	3	4	5
Environmental					
Social					
Political					
Economic					
Cultural					

4. Why there is a small number of Amazon-nut plantations in the Amazon? Please, select the five main raisons for this.

- ☐ Little government incentive.
- ☐ Lack technology for seeds and seedlings
- ☐ Species has a very long biological cycle.
- ☐ There is no zoning for this species.
- ☐ Lack of Communities interest.
- ☐ Species chain is unprofitable.
- ☐ Activity requires more applied researchers.
- ☐ Few units of success.
- ☐ Technologies have been few communicated.
- ☐ Low-skilled extension workers in Amazon-nut.

5. Please, use this space below to leave comments about your choice in the 4th question.

6. In your opinion, has the current legislation that prohibit the cutting down and sale of Amazon-nut timber (Decreto Federal n° 5.975, de 30/11/2006) guaranteed protection and conservation of this species?

- ☐ Yes. It has certainly guaranteed both.
- ☐ Yes. It has only guaranteed protection.
- ☐ Yes. It has only guaranteed conservation.
- ☐ No. It has guaranteed neither.
- ☐ Other.

7. If you ticked options “no” or “others”. Please, leave your comments in the place below.

8. Which are the five main solutions for amazon-nut use and conservation?

- ☐ Strengthen basic education schools.
- ☐ Technical assistance and share knowledge.
- ☐ Become Amazon-nut chain a priority in the government agenda.
- ☐ Amazon- nut zoning for guide public policies and researches in the region.
- ☐ Develop ergonomic strategies to help Amazon-nut collect and transportation.
- ☐ Management of forest regeneration in anthropic areas.
- ☐ Strengthen small industries.
- ☐ Valuation of Amazon-nut ecosystem services.
- ☐ Develop good practices to avoid fruit contamination.
- ☐ Rural credit to reforestation practices.
- ☐ Changes in current legislation.
- ☐

Increase the inclusion of Amazon-nut in agroforest system.

9. Which are your perspectives to Amazon-nut future in Amazon Biome?