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Pre-Columbian soil management, settlement, and land use in Amazonia: Insights using micro-regional predictive modelling in Gurupá, Brazil.

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PRE-COLUMBIAN SOIL MANAGEMENT, SETTLEMENT, AND LAND USE IN AMAZONIA: INSIGHTS USING MICRO-REGIONAL PREDICTIVE MODELLING IN GURUPÁ, BRAZIL

By

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ABSTRACT

PRE-COLUMBIAN SOIL MANAGEMENT, SETTLEMENT, AND LAND USE IN AMAZONIA: INSIGHTS USING MICRO-REGIONAL PREDICTIVE MODELLING IN GURUPÁ, BRAZIL

Lauren Zacks

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The results of a micro-regional predictive model of terra preta sites in the municipality of Gurupá are presented here. A Maximum Entropy approach was selected and modified to fit a presence-background model, rather than a presence-absence model typical of binary classifications. 13 known terra preta sites were used as input samples for the relative suitability model, with explanatory variables in the respective categories of topography, hydrology, soil type and vegetation index. A 30m spatial resolution DEM served as the basis for the former two categories, while additional TauDEM analysis was performed for the hydrology category. A Sentinel-2A mosaicked quarterly composite image of January 2021 served as the basis for derived data in the vegetation index category, NDVI and NDWI. Results of the model show the single most important predictor is the Gleysol soil type variable, with downslope at rivers being moderately contributive when riverine sites are used as test samples by the model. Notably, in addition to indicating presences in riverine fluvial contexts, this model displays strong presence signals at interfluves. When 2 out of 3 test samples used are interfluvial sites, slope, rather than downslope at rivers, is

a major predictor of terra preta presence. In contrast to a basin-wide predictive model of terra preta sites (McMichael et al. 2014), elevation is a consistently absent variable when it comes to predictive power for this model. This is unsurprising, as Gurupá is generally low-lying with negligible increases in elevation towards its southeastern borders. This paper suggests that a basin-wide predictive model is unable to capture fine-scale environmental correlations with terra preta sites at the micro-regional scale. This research is a contribution to the growing body of work that includes the analysis of remote sensing data in the identification of terra preta sites in this region of Amazonia (Choi, Wright, and Lima 2020).

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CHAPTER 1

INTRODUCTION

This thesis investigates the distribution patterns of terra preta within the Eastern Amazon, focusing specifically on the municipality of Gurupá, which lies along the lower course of the Amazon River. The primary objective is to establish which environmental predictors can effectively indicate the presence of these pre-Columbian anthropogenic soils, renowned for their rich nutrient content and historical significance. To address this research problem, the study employs Geographic Information Systems (GIS) and maximum entropy predictive modeling to analyze and predict terra preta site locations across this broader municipal area, enhancing future sampling efforts and understanding of the variables that signal high probabilities of site presence.

There are debates within Amazonian archaeological research about the topographical predictors of terra preta amongst the Amazonian Dark Earths (Glaser and Birk 2012; McMichael et al. 2014; Glaser 2006; Edelstein and Tonjes 2012; Rhodes 2012). Terra Preta, a subset of the category "Amazonian Dark Earth," is a type of fertile soil found in the Amazon rainforest region. It is characterized by its dark color and high nutrient content, which makes it exceptionally fertile for agriculture. First, most terra preta sites have been sampled in floodplain-upland environments (Petersen, Neves, and Heckenberger 2001). “Floodplain” and “upland” have been adopted as translations for *várzea* and *terra firme* in Amazonian archaeology. The former specifically refer to seasonally inundated forested areas, whereas the latter refers to valleys surrounded by non-flooded forests (Pupim, and Sawakuchi et al. 2019). The *várzea*, or floodplain areas, exhibit dynamic hydrological changes: during the wet or monsoon seasons, these areas are transformed into expansive waterlogged landscapes, akin to temporary wetlands, which recede in the dry season to expose rich, fertile mudflats frequently cultivated. In stark contrast, the *igapó*—the permanently flooded forest areas found further upstream—maintain a consistent aquatic environment year-round, characterized by darker, acidic waters that inundate the forest floor. This consistent flooding supports a distinct type of vegetation less variable than the seasonally changing *várzea*. These terms describe terrain types, rather than soil types. *Terra firme* soils can therefore not be accurately translated as meaning "upland soils", but rather acidic, sand, and clay-rich soils which formed on ancient river terraces (Meggers 1971).

The vast majority of Eastern Amazonian soils are formed on *terra firme* and are distinct from lower Montaña soils present in the Upper Amazon, the former being most often found in association with riverine terraces (Salomon and Schwartz 1999). Terra firme make up 98% of the Amazon basin, while the adjacent *várzea* are rare by comparison (Meggers 1971).

Establishing whether this coupled topography is actually the best environmental predictor for the presence of terra preta sites is the aim of this study.

Terra preta soils are unique with respect to their provenience in the Amazon more generally (Lehmann et al. 2009), and more specifically their prevalence along tributaries of the Amazon River. Confoundingly, terra preta sites are known be formed of the dominant soil types of the Amazonas (e.g. Oxisols, Latosols). These latter soil types are typically barren, whereas terra preta are exceedingly fertile in comparison. Additionally, terra preta do not seem to exhibit a direct association with either *terra firme* or *varzeá*.

In the early 2000's, this understanding has shifted toward a coupled topography; only in immediate association with the seasonally inundated *várzea* could *terra firme* yield soils fertile enough to support human habitation and land use. Scholars in favor of this argument have suggested that maize and beans cultivated in association with habitation sites could have acted as nitrogen fixers (Petersen, Neves, and Heckenberger 2001).

The goal of my study is to include a more diverse set of samples, rather than formulating a judgment on the theoretical considerations of these debates. In addition to the fact that *terra firme* would only be able to support soils fertile enough to for human habitation and land use in combination with the presence of *várzea*, a predictive model consisting of variables including, but not limited to, elevation, slope, aspect, and relief extracted from a DEM would indicate whether these are also statistically significant in identifying where terra preta sites might be found. In order to achieve this, I here conduct a micro-regional analysis with GIS and maximum entropy predictive modelling. First, I create a predictive model of terra preta sites in Gurupá to assist future sampling efforts in the region. Secondly, I specifically identify and describe the relationships between environmental variables as they signal a high probability of site presence. Lastly, I identify high probability presence locations away from floodplains and in interfluvial areas. This work poses several critical questions that guide the investigation:

How can we accurately locate terra preta sites in Gurupá using environmental variables?

Which of these variables are most relevant in predicting the presence of terra preta?

Can the findings from Gurupá be extrapolated to predict terra preta sites in other regions of the Amazon with a high degree of accuracy?

These questions aim to move beyond the confines of regional studies, contributing to a more generalizable understanding of terra preta distribution across the Amazon. Specifically, they aim to expand the scope of research on terra preta beyond just local or regional considerations, implying that by addressing these specific questions about predicting terra preta sites in Gurupá, the findings could contribute to broader, more generalized knowledge about terra preta distribution across the Amazon. This broader understanding could enhance future predictive modeling efforts and offer insights that apply beyond the immediate study area, potentially guiding archaeological exploration and conservation strategies across diverse Amazonian landscapes.

Indeed, the primary goal is to use a spatially explicit predictive model, specifically Maximum Entropy (MaxEnt), to identify potential locations of terra preta sites within the specified study area. By applying this model and incorporating a range of environmental variables, the research aims to predict where terra preta sites are most likely to be found, enhancing the efficiency of archaeological explorations, and potentially uncovering new sites across varied landscapes within the Amazon Basin.

At the same time, addressing these questions is crucial for refining future predictive models in Amazonia, cautioning against overgeneralizations at the basin-wide or regional levels, which could misinterpret the nuanced dynamics of terra preta site distributions.

The Maxent approach used here is a relative suitability model. This means that it should not be interpreted as a presence-absence model (Guillera-Arroita, Gurutzeta et al. 2014). Rather, it is a presence-background model which relies on the scaling of probability from 0-1.

This work adopts a landscape ethnoarchaeological perspective, investigating whether terra preta sites cluster around floodplains and, if not, identifying which environmental variables indicate their presence near interfluves. It consists of two parts: A ‘‘desk’’ ethnoarchaeology (Carrer 2013), which is focused on a remote sensing analysis of current landscape change in the sample area of Gurupá. Additionally, a ‘‘field’’ ethnoarchaeology which places the observed human activity in context of its underlying cultural reasons and subsequently identifying a link to human settlement strategies (Carrer 2013). The successful incorporation of these considerations will then yield an ethnoarchaeological predictive model.

In this work, the region of interest is the Amazon basin in a broad sense, and more locally, the Lower Xingu River Basin. Using known terra preta sites in the Lower Xingu region collected by the *Origins, Culture and Environment* (OCA) Project, co-directed by Dr. Anna Browne Ribeiro with Dr. Helena Pinto Lima between 2014-2015 (sole director since 2015), I will build a model to predict hitherto unknown areas where terra preta sites might be found. The results of this study will inform future archaeological fieldwork and aid the financial aspect of the decision-making process. Predictive models, more generally, show great promise in terms of their potential to resolve global- and disciplinary problems. This predictive model of terra preta sites aims to further our understanding of the complex relationships between people, soils, and forests. What follows is a description of terra preta as a unique soil type, as well as its characteristics in context of most commonly found soil types throughout Amazonia.

CHAPTER 2

BACKGROUND

2.1 Prevalent Amazonian soil types

Amazonia is generally characterized by a variety of soil types associated with its rainforest ecosystem. Common soil types include Spodosols, Inceptisols, Histosols, Ultisols, and Oxisols.

Spodosols are found in areas with sandy parent material and high rainfall. They are characterized by a distinctive leaching and accumulation pattern, with a bleached or grayish upper layer and an underlying layer enriched with organic matter and iron and aluminum compounds.

Inceptisols are relatively young and moderately developed soils. They have a wide range of textures, from sandy to clayey. Inceptisols are characterized by limited soil profile development and often have a mix of mineral and organic materials.

Histosols, also known as peat or organic soils, occur in waterlogged areas where the accumulation of organic matter is greater than decomposition. These soils are typically found in wetlands, swamps, and floodplain areas and are characterized by high organic content.

Ultisols are moderately weathered soils with a clayey texture. They are commonly found in areas with older landscapes and moderate to high rainfall. Ultisols are typically acidic, have a reddish or yellowish color, and can be nutrient-deficient.

Oxisols, also known as lateritic soils or Latosols, are common in the Amazonian rainforest. These soils are typically reddish in color, highly weathered, and low in fertility. Oxisols have a clay-rich composition and are well-drained due to their sandy or gravelly textures. Oxisols are dominant soil types in the Amazonian lowlands, are highly acidic, nutrient poor, and are only suitable for long-term agriculture by adding natural fertilizers (Soentgen, Hilbert et al. 2017).

2.2 Defining terra preta as a unique soil type

Terra Preta, a subset of "Amazonian Dark Earths," is a type of fertile soil found in the Amazon rainforest region. It is characterized by its dark color and high nutrient content, which makes it exceptionally fertile for agriculture. Terra preta soils were created by indigenous cultures in the Amazon up to thousands of years ago. These cultures developed a sophisticated system of organic waste management and soil enhancement techniques. They would mix charcoal, bone fragments, pottery shards, kitchen waste, and other organic materials into the soil, creating a unique and highly productive agricultural substrate.

The precise composition of terra preta varies, but it typically consists of a mixture of charcoal, plant residues, remnants of animal bones, and other organic matter. The high charcoal content in terra preta helps to retain moisture and improves soil structure (Novotny et al. 2006). The fertility of terra preta soils is due to several factors. The charcoal acts as a sponge, holding onto nutrients and preventing leaching. The porous structure also enhances water retention and drainage, reducing erosion and improving soil fertility. Additionally, the organic matter in terra preta provides a steady supply of nutrients (Chia, Munroe, Joseph et al. 2010).

Terra preta have been found to be extremely productive, supporting a wide range of crops and plant species. They can sustain agricultural activities for extended periods without the need for synthetic fertilizers (Costa, Kern, et al. 2004). The discovery of terra preta has sparked interest in sustainable soil management practices and carbon sequestration techniques, as they have the potential to mitigate climate change and improve agricultural productivity (Lepodise, Lewis, Constable et al. 2022). Scientists and researchers continue to study terra preta soils to understand their composition, formation processes, and the potential for replicating their beneficial properties in other regions (Lepodise, Lewis, Constable et al. 2022).

Terra preta has been formed in the humid tropical environment of the Amazon rainforest since before the arrival of European colonists in the 16th century (Soentgen et al. 2017). The specific conditions that contribute to the formation of terra preta include a combination of natural processes and human activities. The process begins with the natural weathering of parent materials, such as clay-rich sediments and volcanic ash, over long periods. These weathered materials, along with organic matter derived from the abundant vegetation in the rainforest, may have provided the initial ingredients for terra preta formation.

Human activities play a crucial role in enhancing and intensifying the development of terra preta. Indigenous cultures in the Amazon practiced a form of agriculture known as slash-and-char or slash-and-burn farming. Glaser (2006) considers the possibility that pre-Columbian peoples may have created terra preta soils by chance, or intentionally, and introduces the concept of “Terra Preta nova” (ibid.) to explain this phenomenon. In the case of accidental terra preta formation, clearing forested areas may have resulted in charred biomass, primarily charcoal, which would then be mixed into the soil along with other organic waste materials such as food scraps, animal bones, and pottery sherds. The charcoal would then have served as a stable carbon sink, retaining nutrients, and enhancing the soil's fertility. The organic waste materials contribute organic matter, nutrients, and beneficial microorganisms to the soil, further enriching it.

While black earths have been proposed to exist in other areas such as Africa (Fairhead and Leach, 2009), it is unknown how indigenous peoples were able to cultivate these soils in the Amazon - an environment in which highly acidic soils such as Oxisols - are a type of predominant soil. The knowledge of how to create terra preta “de novo” in other geographic contexts is lacking since this knowledge has only been transmitted in the form of oral traditions in the Amazon. While it has been revealed that black earth soils contain high amounts of pyrolized carbon, the modern replication of ADE in other contexts has failed (Kamman 2013). ADEs are a unique soil by virtue of them containing phosphate and other human-indicator compounds (Balée et al. 2023). While biochar can contribute to soil fertility, the formation of terra preta involves a more complex process that includes the intentional addition of organic matter, such as charcoal, along with other cultural practices (Balée et al. 2023). This is to say that the archaeological record for de novo terra preta formation is incomplete.

2.3 Indicators of human intervention

Terra preta soils are unique by virtue of their inclusion of pottery sherds (McMichael et al. 2017). These “ceramics” refer to pottery artifacts associated with the soil deposit. These ceramics are significant because they provide evidence of ancient human activity and settlement in the Amazon. The pottery sherds found within the terra preta soils offer insights into the technological and cultural practices of past societies. The ceramics associated with terra preta display various characteristics that reflect the knowledge and skills of the ancient inhabitants. These ceramics often exhibit well-developed craftsmanship, such as intricate designs, incisions, and decorative elements. They also show evidence of specific manufacturing techniques, including clay tempering, burnishing, and firing methods. The presence of ceramics in terra preta soils suggests that pottery-making was an important aspect of the cultural and economic activities of ancient Amazonian societies. The pottery vessels would have been used for cooking, food storage, and other domestic and ritual purposes.

Browne Ribeiro and colleagues (2016), for instance, discuss the spatial organization of precolonial settlements in the Gurupá region of the Amazon. The research findings indicate that precolonial settlements had a different spatial distribution compared to later periods. One terra preta site I discuss in this paper, Carrazedo, lies within the Lower Xingu region, Amazonia. This site has been the subject of extensive fieldwork and research. Browne Ribeiro and colleagues (2016), discuss results from pilot archaeological fieldwork at Carrazedo. The Carrazedo site, in particular, shows a higher frequency of precolonial terra preta sites compared to colonial-historical settlements. The size and density of anthropogenic features suggest a densely occupied settlement (2016). The distribution of precolonial settlements overlaps with colonial-historical and contemporary settlements, but the former occurred at a higher frequency and covered a wider range of ecological zones (2016). The habitation area associated with the Historical Village in Carrazedo measures approximately 6 hectares, while the terra preta site measures approximately 30 hectares. Pre-colonial ceramics were found almost exclusively at the excavation of a mound and were subdivided into two distinct technological styles (2016). The first being white slip and cut lobed rims, with occasional red paint (IN: Figure 7a–f; Browne Ribeiro et al. 2016). The second type consists of plastic decorative techniques which depict anthropomorphic or zoomorphic figures on wall and rim sherds of restricted vessels (2016). Both types have correlates with regions elsewhere, (e.g. Almeirim, Altamira, Guianas). Their (2016) findings position precolonial Gurupá as a true crossroads along riverine and overland trade routes.

Thusly, terra preta ceramics helps archaeologists understand the social, economic, and technological aspects of ancient Amazonian cultures. It provides valuable information about the daily lives, cultural practices, trade networks, and technological advancements of these societies.

In addition to ceramics, other archaeological artifacts, such as stone tools, shell ornaments, and animal bone fragments, are often found in association with terra preta sites. These diverse material remains contribute to our knowledge of the past human-environment interactions and the long history of human settlement in the Amazon rainforest.

2.4 Description of uniquely Amazonian landscape types

Amazonian *várzeas,* also known as Amazonian floodplains, refer to the specific floodplain areas found in the Amazon region, particularly in the Amazon Basin (Assis et al. 2014). These floodplains are influenced by the Amazon River and its numerous tributaries, which overflow during the wet season, resulting in extensive inundation of the surrounding land. Amazonian *várzeas* are characterized by their vast size, dynamic hydrological patterns, and rich biodiversity (ibid.). Key features of Amazonian *várzeas* include their size and extent, hydrological dynamics, ecological significance, flora, and fauna, as well as indigenous communities and livelihoods.

Amazonian *várzeas* are among the largest and most extensive floodplain systems in the world. They encompass millions of hectares of land and stretch across multiple countries, including Brazil, Peru, Colombia, Ecuador, and Bolivia. The hydrology of Amazonian *várzeas* is driven by the annual rainfall and the vast network of rivers and streams in the region. During the wet season, the rivers rise and spill over onto the floodplain, leading to extensive flooding. This flooding is crucial for nutrient replenishment and the maintenance of the floodplain ecosystem.

Indigenous communities have long inhabited the Amazonian *várzeas* and have developed unique cultural practices and adaptations to the floodplain environment (Peña-Venegas et al. 2015). They rely on fishing, agriculture, gathering, and hunting as essential components of their subsistence strategies. Traditional knowledge and sustainable resource management practices play a crucial role in their way of life. Amazonian *várzeas* are ecologically significant areas within the Amazon Basin, contributing to the overall biodiversity and functioning of the Amazon rainforest. They provide critical habitats, resources, and livelihoods for indigenous communities while playing a vital role in regional hydrology and nutrient cycling. Bush and colleagues (2007) problematize the fact that pre-Columbian occupation is known to occur frequently in *várzeas*, but less so in *terra firme* environments.

Amazonian *terra firme* are the upland or non-flooded areas of the Amazon rainforest. It is characterized by relatively higher elevation, well-drained soils, and a lack of regular flooding (Bobrowiec et al. 2014; Lieshout, Kirkby and Siepel 2016). *Terra* *firme* areas are not subject to prolonged inundation, unlike the *várzea* (seasonally flooded) and *igapó* (permanently flooded) regions of the Amazon. Due to their relatively stable and less inundated nature, *terra firme* forests have been more accessible to contemporary human settlement and agricultural activities compared to floodplain regions.

While floodplain environments have historically been more commonly associated with past human settlement due to sampling bias, it is thought that communities and traditional populations in the Amazon have historically inhabited *terra firme* areas, practicing subsistence agriculture, hunting, and gathering. Palaeoecological analyses in the central and western Amazon revealed that human impacts on *terra firme* settings were not confined to waterways, but that proximity to permanent open-water bodies might be an indicator of continuous habitation (Bush et al. 2007).

Terra firme forests are also vulnerable to deforestation and other human activities, including commercial logging, agriculture, and infrastructure development. The conversion of *terra firme* forests for agriculture, particularly for soybean cultivation and cattle ranching, has been a major driver of deforestation in the Amazon region.

It is, however, becoming more apparent that the Amazonian rainforest may not have been untouched and free from human land use in the past (Piperno, McMichael, and Bush 2017). In fact, it has been argued that indigenous communities have radically altered and transformed the Amazon, and that *terra firme* forests are particularly resilient (Piperno, McMichael, and Bush 2017). The conversion of *terra firme* forests for modern agriculture has revealed the pre-existence of relationships between climate change and cultural resilience in late pre-Columbian Amazonia (Souza, Robinson, et al. 2019).

Carson and colleagues (2014) have proposed that pre-Columbian land use did not require extensive rainforest clearance to support dense zones of habitation.

The Amazon region encompasses a vast area with various *várzeas*, or floodplain areas, each with its own distinct characteristics:

Várzea de Solimões: The Solimões River, the upper stretch of the Amazon River, creates extensive várzea areas. These floodplains are subject to annual flooding and play a vital role in the region's hydrology (Pöhlker et al. 2019). The várzea de Solimões supports diverse ecosystems and is characterized by rich biodiversity and abundant aquatic resources.

Várzea de Purus (Théry and Maurence 1997)*:* The Purus River, a major tributary of the Amazon River, forms extensive várzeas within the Brazilian state of Amazonas. The várzea de Purus is known for its flooded forests and is home to various plant and animal species. Indigenous communities in this area rely on fishing, hunting, and subsistence agriculture for their livelihoods.

Várzea de Juruá (Théry and Maurence 1997): The Juruá River, another major tributary of the Amazon River, creates várzeas that are renowned for their biological diversity. This region features flooded forests, lakes, and channels, providing habitats for numerous species of fish, birds, and mammals. Indigenous communities in the várzea de Juruá engage in fishing, agriculture, and gathering activities.

Várzea de Marajó (Daly and Mitchell 2000): Marajó Island, located at the mouth of the Amazon River, is known for its extensive várzeas. The várzea de Marajó is characterized by a mosaic of flooded forests, savannahs, and wetlands. It supports unique ecosystems and is home to wildlife such as capybaras, marsh deer, and various bird species. Indigenous communities in this region practice traditional agriculture, including the cultivation of manioc.

Várzea de Mamirauá: The Mamirauá Sustainable Development Reserve, located in the Brazilian state of Amazonas, encompasses a large várzea area. This flooded forest region is recognized for its exceptional biodiversity and is home to various endangered species such as the Amazon River dolphin and the black caiman (Koziell and Inoue 2002). Indigenous communities living in the várzea de Mamirauá engage in fishing, agriculture, and sustainable resource management.

These are just a few examples of the diverse *várzea* areas in the Amazon region. Each *várzea* has its own ecological characteristics, cultural practices, and significance for local communities. In *várzeas*, indigenous communities historically and currently cultivate a variety of crops suited to the seasonal flooding and nutrient-rich characteristics of the floodplain soils. The specific crops grown can vary depending on local cultural practices and preferences, but some common crops cultivated in *várzeas* include Manioc, also known as cassava, a staple crop in many *várzea* regions. It is well-suited to the floodplain conditions as it can tolerate temporary flooding. Manioc roots are processed into flour, used to make various traditional dishes and bread, and can be stored for extended periods.

Maize is another important crop grown in *várzeas* (Müller et al. 2022; Gasché 2008). It is a versatile grain that provides food for humans as well as feed for livestock. Indigenous communities often cultivate different varieties of maize adapted to local conditions. Beans are commonly cultivated alongside maize in *várzeas*. They provide an additional source of protein and nutrients in the diet. Indigenous communities grow various types of beans, including black beans, red beans, and others.

In some *várzea* regions, particularly those with extended periods of flooding, rice cultivation is practiced. Rice is adapted to wet conditions and thrives in the flooded areas during the wet season. Indigenous communities in *várzeas* also cultivate fruit trees such as mango, papaya, banana, and citrus fruits. These trees provide a source of fresh fruit, as well as potential income through trade or sale.

Additionally, in *várzeas*, communities often engage in fishing and gathering of wild edible plants as important components of their food systems (Knoop et al. 2020). The seasonal flooding in *várzeas* not only supports crop cultivation but also contributes to the natural biodiversity and availability of aquatic resources that are utilized for sustenance.

It is important to note that the specific crops cultivated in *várzeas* can vary depending on the cultural practices, preferences, and adaptations of indigenous communities in different regions. Local knowledge and traditional practices play a significant role in determining the crops grown in *várzea* environments.

Várzea and *terra firme* differ in terms of their topography, hydrology, soil characteristics, and vegetation composition (Haugaasen, and Peres 2005). *Várzea* refers to the seasonally flooded areas found along rivers and their floodplains. These areas experience regular inundation during the rainy season when rivers overflow their banks. In contrast, *terra firme* refers to upland areas that are not subject to regular flooding. *Terra firme* areas remain above water level throughout the year.

Várzea areas are characterized by nutrient-rich alluvial soils. The annual flooding deposits sediment and organic matter, resulting in fertile soils that support lush vegetation. *Terra firme*, on the other hand, has well-drained soils that are often less fertile compared to *várzea*. The soils in *terra firme* areas are typically weathered and can vary in composition.

Várzea areas support distinctive vegetation adapted to the seasonal flooding. During the dry season, *várzea* forests may appear as relatively open grasslands or savannas. However, during the wet season, these areas become inundated, and the vegetation consists of various types of aquatic plants and trees that can tolerate flooding. *Terra firme*, being non-flooded, hosts the dense and diverse canopy of the Amazon rainforest, with tall trees, understory vegetation, and a wide range of plant species.

Due to the seasonal flooding and fertile soils, *várzea* areas have historically attracted human settlement and agricultural activities. Indigenous communities and traditional populations have practiced agriculture, fishing, and hunting in *várzea* environments. *Terra firme*, with its higher and more stable ground, has also supported human settlements, but it is less prone to flooding and is more suitable for long-term agriculture and infrastructure development. It is important to note that *várzea* and *terra firme* are not mutually exclusive but rather exist as part of a continuum of ecosystems within the Amazon rainforest. The transition between these zones can be gradual, with areas that experience both seasonal flooding and non-flooded conditions.

2.5 On Interfluves

Interfluvial zones in the Amazon are areas located between two or more rivers or their tributaries. These zones have distinct characteristics that set them apart from other parts of the Amazon rainforest. Interfluvial zones have specific ecological conditions that differ from both *várzea* (seasonally flooded) and *igapó* (permanently flooded) areas (Haugaasen and Peres 2006). They are typically characterized by well-drained soils and are not subject to regular inundation. The interfluvial areas receive less water compared to *várzea* and *igapó*, leading to different vegetation composition and ecological dynamics. Interfluvial zones in the Amazon rainforest are recognized as hotspots of biodiversity. They support a wide range of plant and animal species, many of which are adapted to the drier and more stable conditions found in these areas. The interfluvial forests often have a diverse canopy with tall trees and a rich understory vegetation.

Interfluvial zones are known to harbor species that are endemic to these specific habitats. The isolation provided by the river systems and the unique ecological conditions contribute to the evolution of distinct plant and animal species found only in interfluvial areas. These endemic species have specialized adaptations that allow them to thrive in the specific interfluvial environment. Interfluves have been home to indigenous communities and traditional populations for centuries. The interfluvial forests have provided these communities with resources for sustenance, including food, medicine, and construction materials. Indigenous cultures have developed a deep knowledge of the interfluvial ecosystems and have implemented sustainable practices to manage these environments.

2.6 Study area

The study area we are working with is small compared to the vastness of the Amazon basin. Gurupá is a small municipality located just southwest of the mouth of the Amazon River. It is important that I define whether this study area is a region or a locality. In the present, one might refer to it as a locality since there are different drivers of landscape change here than, say, in Belém (e.g., forest conservation versus forest clearing). However, one might also consider it a region because of its *regional* climate (e.g., precipitation patterns). It has been shown previously that there are a multitude of ways to conceive of a landscape (Zunega-Lawrence and Low 2003). In this case, it is prudent to consider the study area as a transition zone; its unique ecological characteristics make it a difficult landscape to pin down and classify.

To specify what kinds of data to feed to this predictive model, it must be presumed that some kinds of variables affect the decision-making process as to where human agents might settle; these variables are things we likely take for granted in everyday life. For example, distance to water, distance to the nearest school or even the grocery store are all spatially contextualized phenomena that we consider when deciding to relocate. Similarly, distance to forest, soil drainability, or soil fertility might be analogous with respect to an archaeological context. Colleagues have also debated the influence of highly complex socio-cultural phenomena during the decision-making process (for the topic of encroachment and its role in place-making see Harvey 1996; Basso 1988).

Harvey calls into question whether place-making as it is described by Basso, occurs independently from encroaching outside economic structures (1988). It is thus important to acknowledge the pressures that exist around regions and localities, as opposed to analyzing them separately. Harvey, for instance, argues that there exists a dialectic between space and place, and that places depend on space to get made (ibid.). Outside pressures like environmental constraints, which are of relevance to our analysis, would thus be coming from 'space' and affecting 'place'. In a similar vein, Eckstein

(2019) considers the case-study of toxic environments as a form of maintenance of social stratification. Specifically, marginalized communities are deliberately placed in harm's way due to their being seen as "disposable" by local (or regional) governments (ibid.). One might go even further to say that, in this case, marginalized communities are discouraged from using their agency in the process of place-making. The following is a more in-depth explanation on my predictive model in conjunction with defining human agency and settlement patterns.

Situated in the Amazon region, Gurupá is a municipality located in the state of Pará, Brazil. The archaeological record of the municipality of Gurupá, which straddles the Xingu-Amazon confluence, presents substantial evidence for landscape modification and intensive habitation from c.a. A.D. 500 to A.D. 1550. The region was also the first inland site of European colonization in the Amazon Basin. Settled c.a. A.D. 1600, Gurupá is particularly well situated to highlight transitions or distinctions between indigenous and European forms of habitation and land use, as well as technological, environmental, demographic, and sociopolitical change (Browne Ribeiro, Lima, et al. 2016). Carrazedo, Jocojó, and Gurupá-Miri are sites located at three traditional communities that occupy prehistoric terra preta sites, practice similar agro-extractive resource management and govern traditionally defined territories.

In addition to the rivers and floodplains, Gurupá is also home to various wetlands and lakes. These water bodies are important for supporting aquatic ecosystems, providing habitats for fish, birds, amphibians, and other aquatic species. The wetlands and lakes in Gurupá contribute to the overall biodiversity and serve as important breeding and feeding grounds for many species. Gurupá is in a region characterized by numerous river islands.

These islands are formed by the branching and shifting of the rivers over time. They exhibit diverse vegetation and are often inhabited by local communities.

Gurupá is located in the Amazon region of Brazil, which is known for its extensive network of rivers.

1. Amazon River: The Amazon River is the largest river in the world by volume and is of great significance to the region. It flows through Gurupá, providing a vital waterway for transportation, fishing, and trade. The Amazon River is a lifeline for many communities in Gurupá and supports a diverse ecosystem.

2. The Gurupi River is a tributary of the Amazon River and runs through the municipality of Gurupá. It is an important watercourse in the region, contributing to the drainage of the area and serving as a transportation route. The Gurupi River has its headwaters in the Tocantins state of Brazil and eventually joins the Amazon River near Gurupá.

3. Jari River: The Jari River is another significant river that borders Gurupá. It forms part of the boundary between the states of Pará and Amapá. It originates in the Serra do Tumucumaque mountains in the Guiana Shield and forms the border between Brazil and the country of Guyana. The Jari River passes through Gurupá before joining the Amazon River.

4. Xingu River: While not directly flowing through Gurupá, the Xingu River is a significant tributary of the Amazon River located to the west of Gurupá. The Xingu River is known for its rich biodiversity and its connection to Indigenous cultures in the region.

2.7 Maximum Entropy approach for suitability analysis

Maximum Entropy (MaxEnt) modeling is a statistical modeling approach that has gained popularity in various fields, including archaeological research (Sales et al. 2022; McMichael, Palace, and Golightly 2014; Cruz et al. 2020; De Souza et al. 2018). Maximum entropy modeling is a machine learning technique used for predicting species distribution based on environmental variables. While it is commonly used in ecological studies, it can also be applied to archaeological research to understand past human behaviors and land-use patterns.

In archaeological research, MaxEnt modeling can be used to predict the distribution of archaeological sites or artifacts across a landscape (Bush et al. 2015; McMichael et al. 2014). It involves analyzing the relationships between known archaeological sites and environmental variables such as topography, vegetation, climate, soil types, and proximity to water sources. In this case, I have selected topographical variables such as elevation, slope, aspect, hydrological variables flow direction, catchment area, and average river slope, as well as edaphic conditions derived from FAO world soil maps. Additionally, I used derived NDVI and NDWI indices from a mosaicked, annual composite of the region from the Sentinel-2a satellite, to also be included in the model. These variables were chosen because they collectively represent the crucial environmental factors that affect the distribution of terra preta soils, such as topography, which influences soil formation and erosion; hydrology, which affects soil moisture and nutrient transport; soil type, which determines the base fertility and physical properties of the soil; and vegetation indices, which are proxies for plant health and biomass productivity. The interplay of these variables is essential for modeling terra preta site likelihood as they encapsulate the conditions under which these anthropogenically altered soils are most likely to be found. More detail on data source and processing are provided in the methods. By examining these relationships, MaxEnt modeling can generate a probabilistic map of potential site distributions.

The basic principle behind MaxEnt modeling is to find the distribution of maximum entropy (most uniform) that satisfies the observed constraints. In archaeological applications, the constraints are derived from known site locations, in the case of this study, Aycajó, Aldeinha, Cedro, Cemitério dos Antigos, Centro Antigo, Grota do Amado, Inajá, Piquiá do Jocojó, and others (Fig. 1). The model seeks to find the distribution of environmental variables that maximizes the entropy while remaining consistent with the observed data. In this context, the methodology around identifying possible terra preta sites involves using specific environmental variables to model where these archaeologically significant soils are likely to be found. By analyzing factors such as elevation, slope, soil type, and vegetation indices, the model aims to pinpoint areas with conditions similar to known terra preta sites, thereby guiding archaeological efforts towards unexplored regions that hold potential for discovering new sites.

This modeling approach can have several benefits, such as site prediction, as mentioned above. This approach can identify potential areas where archaeological sites are likely to be found. The integration of the environmental data I have acquired by generating elevation, shaded relief, slope, and aspect maps, MaxEnt provides a more comprehensive approach than relying solely on known site locations. Furthermore, analyzing the distribution of archaeological sites through MaxEnt can provide insights into past land-use patterns and settlement dynamics. It can help reconstruct ancient landscapes and understand how humans interacted with and modified their environments.

Additionally, MaxEnt modeling can assist in prioritizing areas for archaeological survey and excavation. By identifying areas with the highest predicted probabilities of site occurrence, it helps optimize limited resources and target efforts more effectively. Another benefit is environmental analysis. MaxEnt modeling allows for the investigation of relationships between archaeological sites and environmental variables. It can help identify environmental factors that influenced human settlement decisions, such as proximity to water sources or favorable soil conditions.

Figure 1. State of Pará and study area of Gurupá, with 13 known terra preta sites.

CHAPTER 3

METHODS

3.1 Data

Variable	**Source**	**Resolution**	**Literature**
elevation	*NASADEM Merged DEM Global 1 arc second V001*. Distributed by OpenTopography.	30m	Law et al. 2017.
slope	*Ibid.*	30m	Takata et al. 2007.
aspect	*Ibid.*	30m	Li et al. 2022.
D8slope	*Ibid.*	30m	Becker and Siegmüller 2021.
D8flowdirection	*Ibid.*	30m	Seibert and McGlynn 2007.
D8Area	*Ibid.*	30m	Welivitiya et al. 2021; Summerell et al. 2005; Zahedi et al. 2017.
FAO soil type	FAO & IIASA. 2023. Harmonized World Soil Database version 2.0. Rome and Laxenburg.	30 arc-second (1km)	Adem et al. 2020.
NDVI	Zanaga et al. 2022.	10m	Agapiou et al. 2013.
NDWI	Ibid.	10m	Krofcheck et al 2015.

Table 1. Variables used in the model, their sources, resolution, and previous uses in the literature.

The study focuses on Gurupá, located in Brazil's Amazon region (Figure 1.). Utilizing elevation, slope, and aspect data from NASADEM (30m resolution), soil types from FAO (1km), and NDVI/NDWI from Sentinel-2A imagery (quarterly, 10m), I aim to predict terra preta site locations. Data preprocessing involved cleaning and TauDEM analysis for hydrology. These data were chosen to reflect environmental factors relevant to terra preta distribution, capturing both physical terrain and vegetation health indicators. Initial data from thirteen terra preta sites, including proximity to rivers, surface presence of historic and pre-colonial ceramics, and signs of anthropogenic disturbances, set the groundwork for this analysis.

The study also leverages soil data from the Pre-LBA RADAMBrasil project (Negreiros, Alencar, and Schlesinger 2009) to address potential sampling biases and enhance the predictive model's accuracy. These data (ibid.) used a combination of soil pit information, aerial photography, and geologic maps from 1,153 soil pits distributed throughout the Amazon basin which were sampled by horizon and analyzed for texture and chemical composition. I examine whether interfluvial sites located further inland may have suffered a sampling bias relative to near-floodplain and upland sites (for interfluves as zones of dense habitation, see De Souza et al. 2018).

To understand the regional landscape ethnography of the Lower Xingu and a more localized one surrounding the municipality of Gurupá, I subsequently analyze these regions through the lens of cartography. It will be shown that the Gurupá municipality and its surrounding areas display a broad array of landscapes and corresponding complexity. Specifically, this complexity will be investigated through several maps. These maps were generated with the purpose of investigating whether they are potentially useful environmental variables and predictors of regions conducive to terra preta formations.

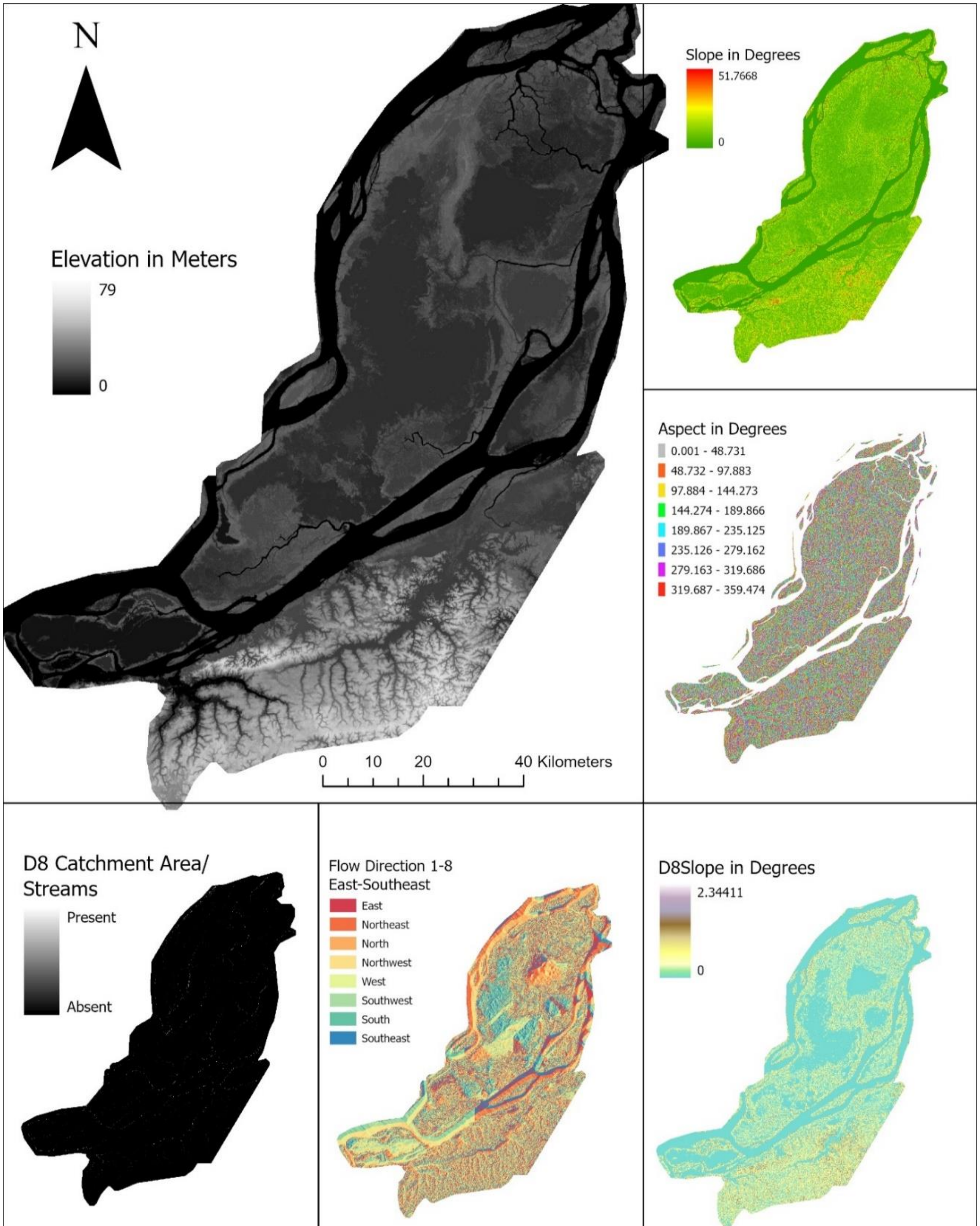


Figure 2. Topographic variables extracted from DEM in order of Bottom Left – Top: 1. D8 Catchment Area delineating likely areas of streams 2. Flow Direction showing how flow direction changes from East-Southeast on the northern Amazon, compared to West-Southwest on the southern half. 3.D8 Slope is higher in the southeast 4. Aspect/Direction of Slope 5. Slope showing very low slope overall, with slight increase near Carrazedo 6. Digital Elevation Model showing overall flat landscape, with slight increase toward southeastern border. (Source: s. Table 1)

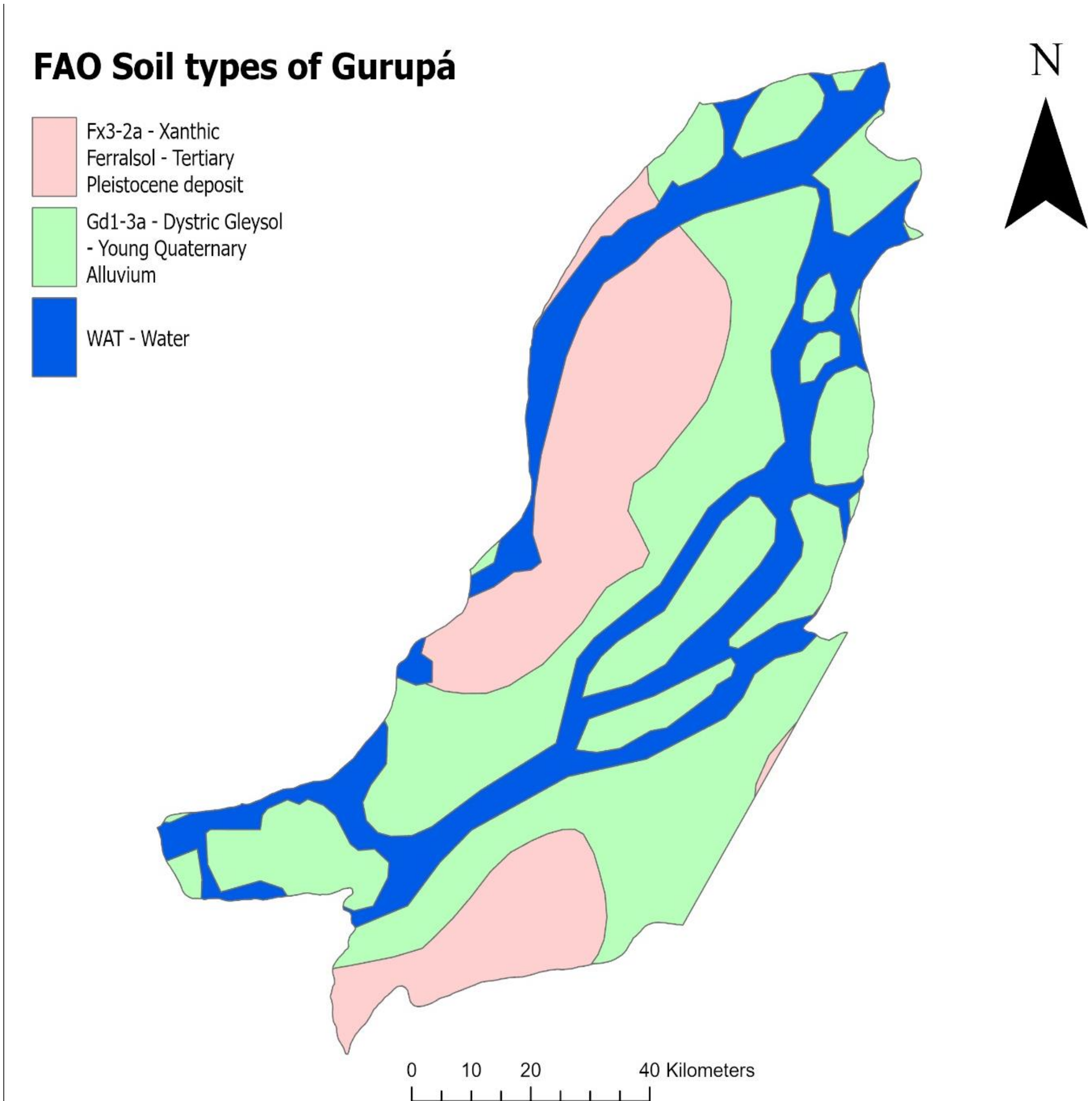


Figure 3. Gurupá and its dominant soil types. Dystric Gleysols are most common and found in association with Xanthic Ferralsols.

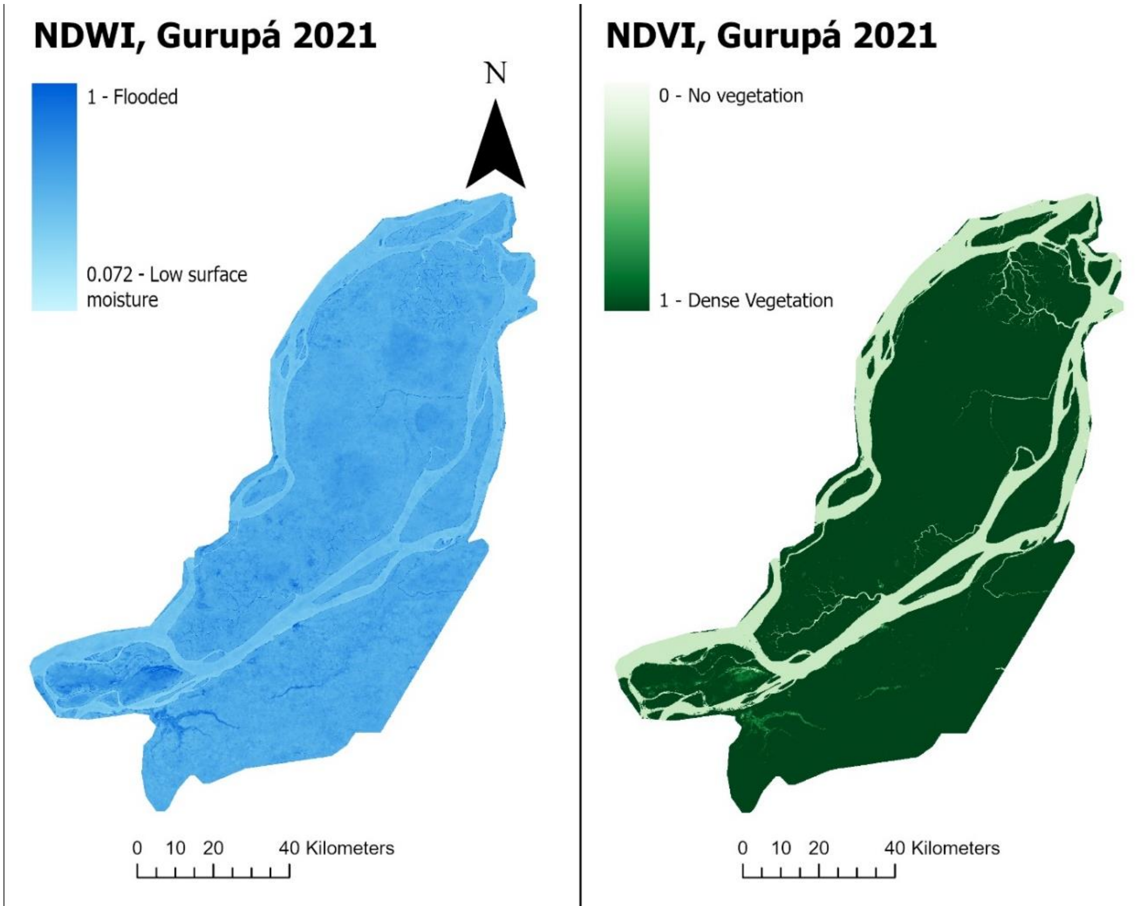


Figure 4. NDWI (left) and NDVI (right) maps of Gurupá show flooded areas concentrated in the south-southwestern borders and around streams. Except for flooded-, urban, and cultivated areas south of Carrazedo, Gurupá is densely vegetated.

I used an available DEM (Fig. 2) to generate a series of maps using ArcGIS to represent topographic variables elevation, slope, and aspect. This enabled to analyze individual landscape variables to observe landscape variation. The first, an elevation map, will show differences in elevation and consequentially, the way water flows across the landscape. These maps were generated with the purpose of investigating whether they are potentially useful environmental variables and predictors of regions conducive to terra preta formations. The shaded relief map (also named Hillshade map) was generated from NASADEM in global 1 arc second resolution [NASA JPL (2021)]. According to the USGS website shaded relief, or hillshading, is a technique where a lighting effect is added to a map based on elevation variations within the landscape. It provides a clearer picture of the topography by mimicking the sun's effects (illumination, shading and shadows) on hills and canyons. The third map (Fig. 2), a slope map, will give more detailed information that the illumination of elevation in our shaded relief map cannot provide. It will show the amount of how steep or flat the terrain in and around the Gurupá municipality is. In contrast to the elevation map (Fig. 2), a slope map will specifically show how elevation changes varies across the landscape in greater distances. These values are represented in percentages.

In addition to topography, I have made use of other variables in the domain of hydrology and vegetation for the region (all these derivative maps in Appendix). For hydrology, I have derived data such as D8 flow direction and contributing area with the TauDEM product made available on the OpenTopography website through David Tarboton of Utah State University and the parallel support of the US Army Corps of Engineers (2010-2015). An in-depth explanation of how to install and work with TauDEM data can be found on the Utah State University hydrology website (https://hydrology.usu.edu). For vegetation data, I have adduced the Sentinel-2 WorldCover Annual Cloudless Mosaic product made available through the Copernicus browser (https://dataspace.copernicus.eu/browser). I have selected the quarterly composite for January 2021, and downloaded pre-processed Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) imagery (Zanaga et al. 2021). NDVI is a standardized index that allows us to generate an image highlighting vegetation on Earth's surface. NDVI uses the visible and near-infrared light absorbed by vegetation to produce an indicator of photosynthetic activity that can be compared across various conditions and times. The NDVI is calculated based on the following equation:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

where:

NIR is the reflectance of the near-infrared band, and

Red is the reflectance of the red band. This index ranges from -1 to 1, with higher values indicating greater levels of live green vegetation.

NDWI is used to monitor changes in water content of leaves and is also applied in the delineation of open water features. Similar to NDVI, it is a normalized difference index, but it uses different bands of the electromagnetic spectrum. The NDWI is calculated using the following equation:

$$NDWI = \frac{Green - NIR}{Green + NIR}$$

where:

$Green$ is the reflectance of the green band, and

NIR is the reflectance of the near-infrared band.

The range of NDWI is also from -1 to 1, with positive values indicating higher moisture content and negative values indicating lesser moisture content.

Utilizing this pre-processed imagery is convenient because it saves the user the work of processing these images with the raw data available. Additionally, it significantly reduces the possibility of potential errors introduced by users who might not be familiar with processing raw imagery data, including the undoubtedly crucial step of removing noise introduced by cloud cover. This region of the Amazon is unsurprisingly extremely cloudy, so having a pre-processed cloudless mosaic available is supremely useful.

3.2 Data Processing

The elevation map (Fig. 2) is created from the Hillshade map and presents a good view of streams, channels, and flooded forest areas in the southwest. Of note is the generally low-elevation, floodplain type layout of the landscape.

Moving south, and away from the Amazon, elevation increases up to 77%.hse areas are intersected by the Igarape Ipixuna and Braço Camutá rivers. The Rio Pucuruí and surrounding floodplains are also visible toward the southwest.

The slope map (Fig. 2) emphasizes differences in incline on the landscape. The Slope tool measures the gradient from cell to cell within a digital elevation model. For each cell in the DEM, the slope function measures the rate of change to each neighboring cell, and outputs the maximum rate of change within that neighborhood into the target cell. The resulting slope raster characterizes the steepness of the terrain in the study area. Slope values are measured as percent (from 0% to 100%) or degrees (from 0° to 90°)" (Biddle 2020). For example, the elevation map above shows some high elevation towards the south-western part of the region. Looks can be deceiving; even though elevation increases upwards to 77%, the slope in these areas only increases to 11%. This means that relatively to the floodplains surrounding the Amazon River, the southwestern areas are indeed higher in elevation. They are not, however, high enough to display a large degree in slope. Of interest are the light-yellow areas along the Igarape Ipixuna and Braço Camutá rivers. The increase in slope here results from low-lying hillsides which surround the banks of channels of these two rivers. This aspect map (Fig. 2) is different from the others in that it shows us specifically which areas receive light and at which angles and sides. Certain vegetation thrives only in specific conditions, namely the angle at which the sun strikes the surface of the landscape.

The Pit Removal tool within ArcGIS Pro is the starting point for all hydrological derivative maps from the TauDEM processing service. A pit in a DEM is specifically defined as any cell(s) which has/have no downstream cells around it. If they are not removed, then they become sinks and isolate portions of hydrologic analysis. Pit filling increases elevation until a pit drains to a neighbor (Fig. 10). The comparison of the pit filled DEM to the original DEM is visualized in Fig. 11.

The requirement for calculating D8 Flow Direction takes this input, namely a corrected elevation grid, resulting in an output with each grid cell containing the D8 flow direction and slope. The former is similar to the aspect map I have already generated but models the direction water flow across terrain instead of the direction of slope across the landscape. As the name suggests, steepest descent from each grid cells is numbered 1-8 (Fig. 12)

The subsequent map is called D8 Contributing Area (also known as Flow Accumulation) and requires having completed the previous creation of D8 Flow

Direction. This function models the contributing area at different directions of flow. The process is visualized in Fig. 13.

I have also created a simple stream network for the area (App. V), which is based on defining a threshold for the contributing area calculated before. The output is a stream

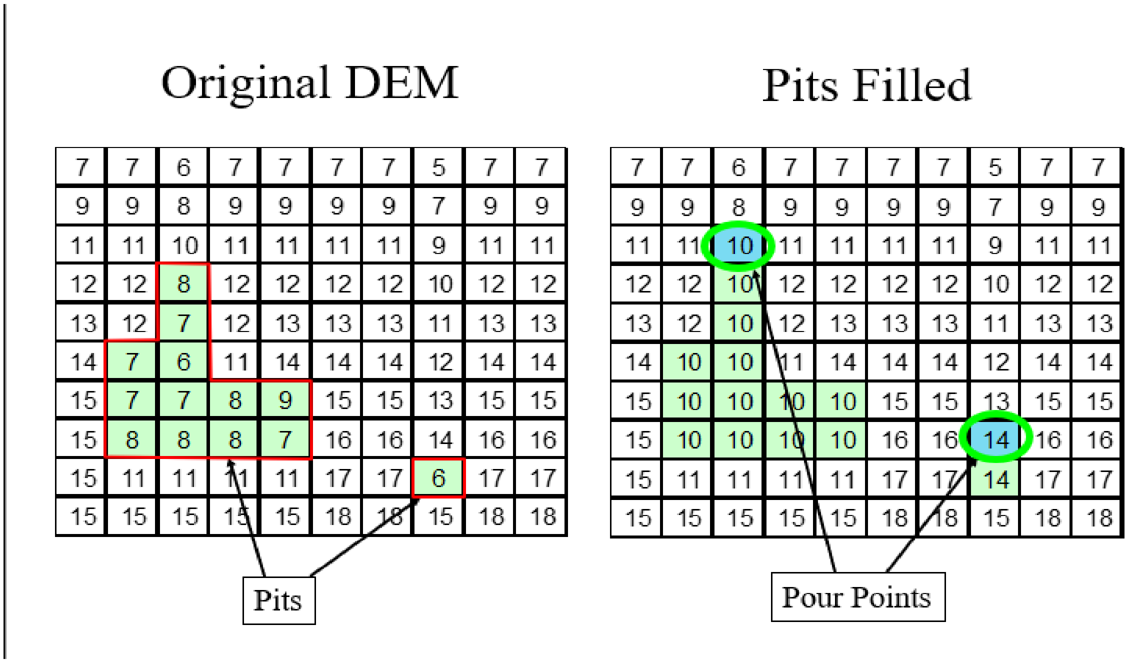


Figure 5. The process of Pit Filling. Elevations are filled to that of the pools pour point. [(IN Tarboton, D.G., (1997)]

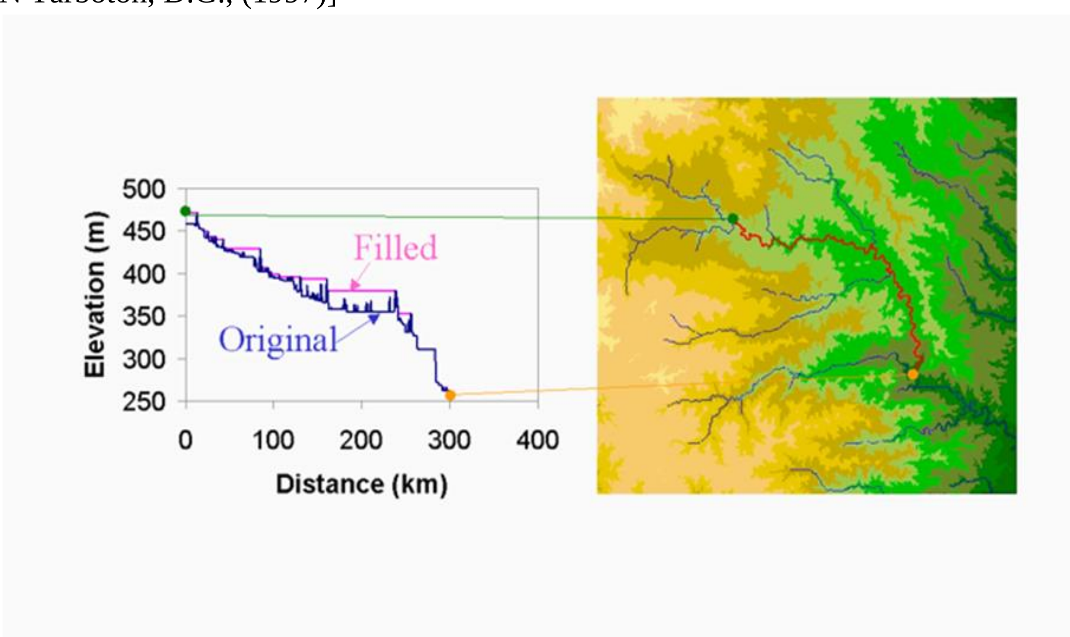


Figure 6. Effect of Pit Filling on Elevation. [(IN Tarboton 1997)]

raster grid, which displays values in between 0 and 1 for each pixel in the image. I have selected a threshold of c.a. 30,9 – 2,000,000 from the contributing area as the value 0 in the stream network, and 2000,000 – 119,349,808 as a threshold for the value 1 in the stream network. I have selected these thresholds in order to visualize smaller streams further inland and away from the major Amazon River.

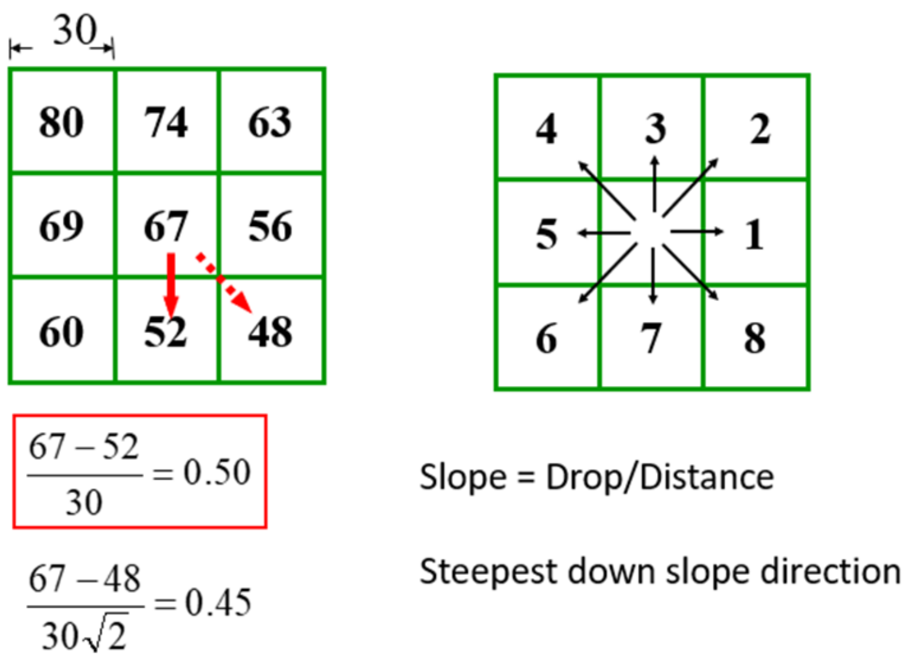


Figure 7. In the D8 Flow direction model, steepest descent from each grid cells is numbered 1-8. [(IN: Tarboton 1997)].

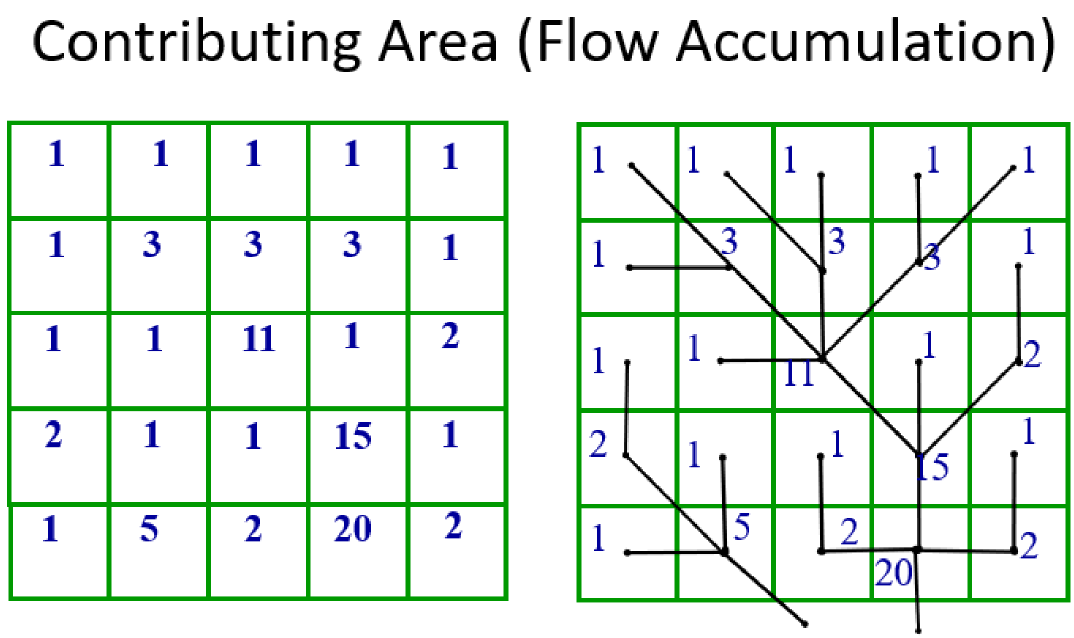


Figure 8. In the D8 Contributing Area or Flow Accumulation model, the area draining each grid cell includes the grid cell itself. [(IN: Tarboton 1997)]

I also utilized a TOPMODEL wetness index map (Topographic Wetness Index), which defines the ratio of slope to the specific catchment area / contributing area that I calculated before. This variable was not included in the MaxEnt model because it contained too many nodata values. I believe this index is useful to have on hand because it removes errors from dividing by 0 when slope is 0 by putting contributing area in the denominator.

If we are indeed assuming that site type (e.g. terra preta, historic site) is correlated with terrain type (e.g. flooded forest, terra firme, sandy), then there is the possibility of a relationship between slope direction, soil conditions, hydrological conditions, and possible resulting vegetation health. The question is: Is hydrology positively correlated with the presence/absence of terra preta sites? Is vegetation health correlated?

3.3 Model Description

First run

Input samples are all 13 confirmed points of terra preta presence. Environmental layers selected were those created for 4 categories: topography, hydrology, edaphic, and vegetation index.

The subcategories for topography were slope, elevation, and aspect.

For hydrology they were catchment area, flow direction (or paths) and their average downslope. Topographic wetness index was considered but excluded because of excessive nodata pixels.

For the edaphic category, layers selected were the world dominant and FAO soil maps (restricted to ROI). Since both layers are highly correlated, the world dominant soil type map was excluded from analysis, and the world FAO soil map was used instead.

Lastly, I used NDVI and NDWI maps from a mosaicked, annual (2021) Sentinel-2a composite image. These were included as layers for the vegetation category.

Two separate runs were conducted. First, a very simple run of all selected layers with one replicate. A random test percentage of 25% was selected instead of the more common 30% for ecological species distribution models, considering the latter often consist of up to hundreds of input samples because of more accessible data sources. In this case, the number of input samples were 13, and I decided a good compromise would be 25%. A regularization multiplier of 2 (as compared to, say, 0.5) was selected to minimize geographic bias. The importance of this study lies in its hypothesis that the probability of terra preta occurrence away from major rivers is high. Therefore, it is important not to limit the probability of presences, and instead assess the prediction power of the model across the entire area of interest, meaning any distance from major rivers is included. Setting this value =<1 runs the risk of overfitting. Maximum iterations of the optimization algorithm were set to 5000 instead of 500 to increase training. 5000 iterations vastly increase the probability of the sample locations for terra preta sites. Threshold rules were considered, especially a rule of maximum test sensitivity and specificity (MSS). It has been suggested that this is one of the most appropriate threshold rules for maximum entropy modeling (Liu, White, and Newell 2013).

3.4 Subsampling and Cross-validation

All parameters are the same, except the number of replicates and the replicated run type. 15 replicates were selected as a good size for average, minimum, maximum, median, and standard deviation statistics.

While the first run was just one cross validation of one replicate, this run subsamples 10 separate runs. This is a form of replication where presence points are repeatedly split into random training and testing subsets. Most importantly, each run consisted of a randomly selected seed.

The cross-validation run was done because it randomly splits occurrence data into equal-sized folds. The result is different models that leave out each of these folds in turn. It is advantageous to perform a cross-validation because compared to just defining a random test percentage (e.g., 25%) and training data split, it validates all of the data which is helpful when working with small datasets. Cross-validated ROC curves give unique information, namely the variability between models.

3.5 Model Metrics

I set the output format for all output data to logistic. The MaxEnt software (Phillips, Anderson et al. 2006) lets its users choose from 4 different output formats (raw, cumulative, logistic, cloglog). All of these formats show probabilities as output values between 0-1, but each with different scales. Different research questions require different scaling for better interpretation of the results. A raw output is better for comparing multiple distributions, whereas logistic and cloglog scaling are better for comparing the probabilities within one distribution because it better visualizes the relative differences between the output data. For example, a researcher wanting to investigate occurrences for different things (let’s say, geoglyphs and terra preta) and compare their distribution for the area of Gurupá, that researcher would be making best use of the raw output option.

In this research however, the question is how much of one area (i.e., Gurupá) is suitable and/or unsuitable for terra preta presence. This means only logistic or clogclog outputs would be viable choices. I tested logistic and cloglog outputs and chose the former because it better visualized the output data. By choosing the logistic option, a default prevalence value of 0.5 is set, which I or 'the user' can change in the settings panel. Any output with a higher value than 0.5 will be considered as a suitable site or terra preta presence.

This predictive model provides probability scores between 0 and 1 compared to binary classifications, but ROC curves and related metrics are used to evaluate their performance in the same way as one would with a binary classification. The key is to choose a threshold for converting probabilities into binary predictions.

1. Sensitivity or True Positive Rate is the proportion of actual positive cases that are correctly identified by the model. Since I am dealing with probability scores, I have set a threshold above which I consider a case as positive. Specifically, I set a threshold of 0.5, and so any predicted probability above 0.5 is classified as positive. So, sensitivity can be expressed as:

$$Sensitivity = \frac{Number\ of\ True\ Positives}{Number\ of\ True\ Positives + Number\ of\ False\ Negatives}$$

2. Specificity or True Negative Rate is the proportion of correctly classified negative cases by the model compared to the number of total negative cases. The true negative rate is calculated using the same formula:

$$Specificity = \frac{Number\ of\ True\ Negatives}{Number\ of\ True\ Negatives + Number\ of\ False\ Positives}$$

3. False positive rate is the proportion of incorrectly classified negative cases, i.e., False positives, by the model compared to the number of total negative cases:

$$False\ Positive\ Rate = \frac{Number\ of\ False\ positives}{Number\ of\ True\ Negatives + Number\ of\ False\ Positives}$$

False positive rate is also the complement of specificity and can be expressed as:

$$False\ Positive\ Rate = 1 - Specificity$$

4. The Receiver Operating Characteristic (ROC) curve is a plot of the true positive rate against the false positive rate for different threshold values. As you vary the threshold, you generate different points on the ROC curve, showing the trade-off between Sensitivity and 1- Specificity.

5. Area Under the Curve (AUC) is a measure of the model's ability to discriminate between positive and negative instances. It reflects the area under the curve for all possible threshold values. It ranges from 0 to 1, where a higher value indicates better discrimination. An AUC of 0.5 suggests a model that performs no better than random chance, while an AUC of 1.0 indicates a perfect model.

6. Commission or False Discovery Rate (FDR) is the rate of falsely identifying instances as positive. It is expressed as:

$$Commission\ (FDR) = \frac{Number\ of\ False\ Positives}{Number\ of\ True\ Positives + Number\ of\ False\ Positives}$$

7. Omission or False Omission Rate (FOR) is the rate of failing to identify positive instances. It is expressed as:

$$Omission\ (FOR) = \frac{Number\ of\ False\ Negatives}{Number\ of\ True\ Negatives + Number\ of\ False\ Negatives}$$

8. Response curves are a graphical representation that shows the relationship between the model's predicted probabilities and the actual outcomes. It provides insights into how the model's predictions vary across different probability thresholds. In the context of ROC curves, the response curve shows how sensitivity and specificity change as the decision threshold is adjusted.

9. Jackknife testing refers to a resampling method which is used for cross-validation of a predictive model. The model is first evaluated on all data points. Then a data point is dropped from the evaluation sample and the performance of the model is evaluated on all data points except the excluded one. This process is repeated for each data point, and the overall performance is averaged. Jackknife is a useful technique to estimate the performance of a model while maximizing the use of available data.

   In the context of this work, it is used to assess the stability and precision of the model's predictive ability.

With that being said, what follows are the results of the first run, or the cross validation of one replicate type. All forthcoming results presented were gathered with the MaxEnt software by Phillips, Dudík, and Schapire Version 3.4.1.

CHAPTER 4

RESULTS

Attribute	Description
Model Type	Maximum Entropy (MaxEnt)
Input samples	13 known terra preta sites
Variables included	8 (Topography, Hydrology, Edaphic, Vegetation Index)
Spatial Resolution	30m
Validation method	Test-train split (75% training, 25% testing)
AUC (Training)	0.806
AUC (Testing)	0.813
Variable Importance	1. FAO Soil Type (High) 2. Average Downslope (Moderate) 3. NDVI (Moderate) 4. Slope (Low) 5. Elevation (Negligible)

Table 1(c). Summary of Model Characteristics and Results of first run.

4.1 Comission and Commission

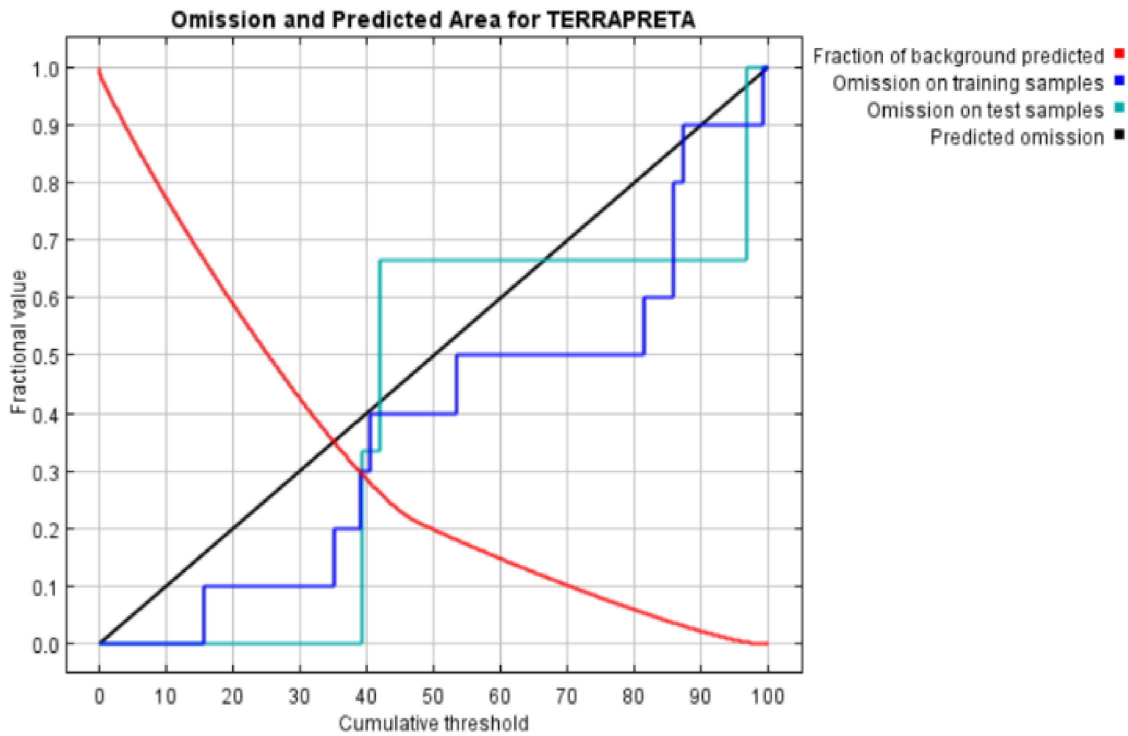


Table 1 (a) Omission rate and predicted area. Omission rate for training (in blue) and presence records (light green) are moderately close to predicted omission (in black).

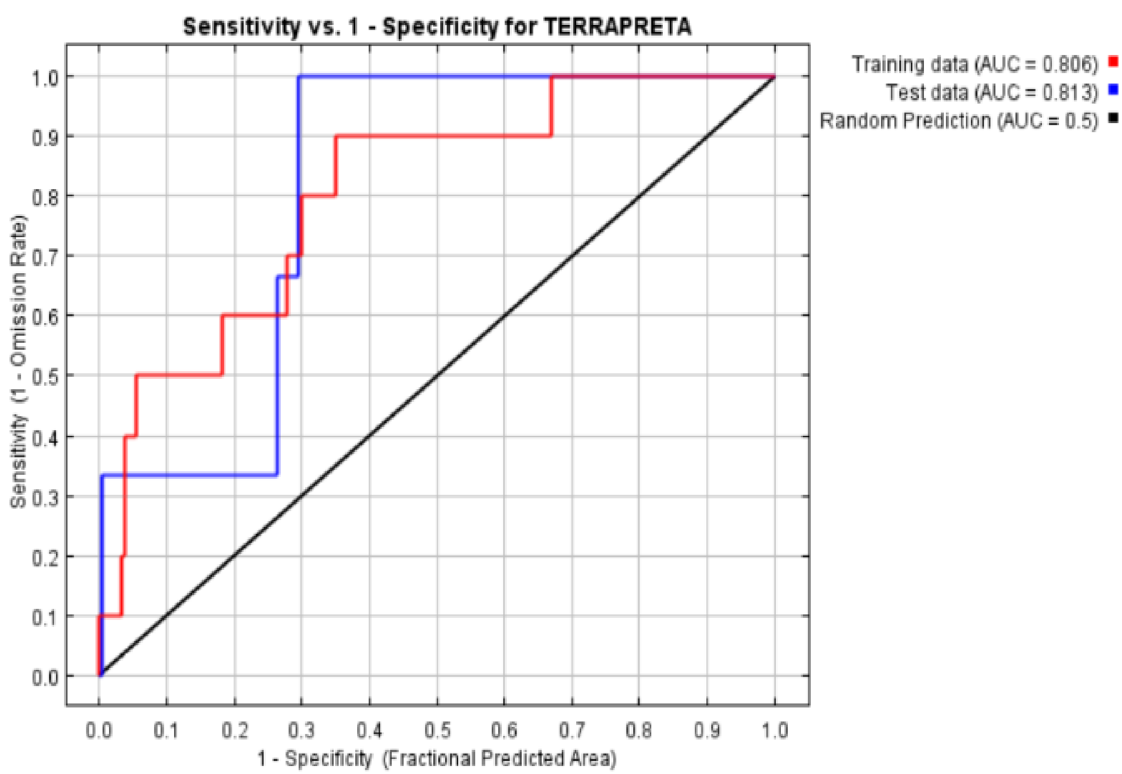


Table 1(b). ROC (receiver operating characteristic) curve for the omission rate and predicted area for terra preta.

For a cumulate threshold of 100, omission for training and test samples intersect with predicted omission at fractions 0.4 and 0.9-1 of background predicted. The ROC curve shows that the model resulted in a training AUC (area under curve) of 0.806 and test AUC of 0.813 for positives and negatives (i.e. presences and absences). Recall that training data represent 75% of the model, while test data represent 25% of the model. The training data here represents how well the model could fit to the data that was used to calculate (train) the model. Test AUC is about equal to training, which means that the model generalized fairly well to the test data. Test AUC is the crucial result here and shows the standard predictive performance of the model being 0.81.

4.2 Thresholds

Logistic threshold	Description	Fractional predicted area	Training omission rate	Test omission rate	P-value
0.237	Fixed cumulative value 1	0.964	0.000	0.000	8.948E-1
0.259	Fixed cumulative value 5	0.874	0.000	0.000	6.668E-1
0.277	Fixed cumulative value 10	0.772	0.000	0.000	4.603E-1
0.291	Minimum training presence	0.668	0.000	0.000	2.984E-1
0.347	10 percentile training presence	0.350	0.100	0.000	4.282E-2
0.369	Equal training sensitivity and specificity	0.299	0.300	0.000	2.662E-2
0.347	Maximum training sensitivity plus specificity	0.350	0.100	0.000	4.282E-2
0.371	Equal test sensitivity and specificity	0.295	0.300	0.333	2.1E-1
0.371	Maximum test sensitivity plus specificity	0.295	0.300	0.000	2.573E-2
0.230	Balance training omission, predicted area and threshold value	0.979	0.000	0.000	9.381E-1
0.281	Equate entropy of thresholded and original distributions	0.747	0.000	0.000	4.169E-1

Table 2. Threshold rules for the same model.

Actual threshold values (logistic) based on a certain criterion. Minimum training presence describes that with an increasing threshold, the amount of suitable area predicted as presence shrinks. This means omission rates and number of presences that are correctly predicted increases. For a (log) threshold of 0.29, 67% of the study area would be predicted present. As the threshold increases (e.g. 10 percentile training presence) the proportion of the study area predicted will decrease (e.g. 35%).

If a threshold were set as 0.371, to get a predicted area 30% of the region's size, the test omission rate is 0, meaning the model would have a success rate of 100%, which in turn is statistically significant indicated by a p-value of 2.573e-2 = 0.02573 < 0.5. The above curves used for the run are drawn independently of any threshold rule. However, it might be useful to run the same model with multiple replicates with the max test sensitivity plus specificity rule in the future.

4.3 Response curves

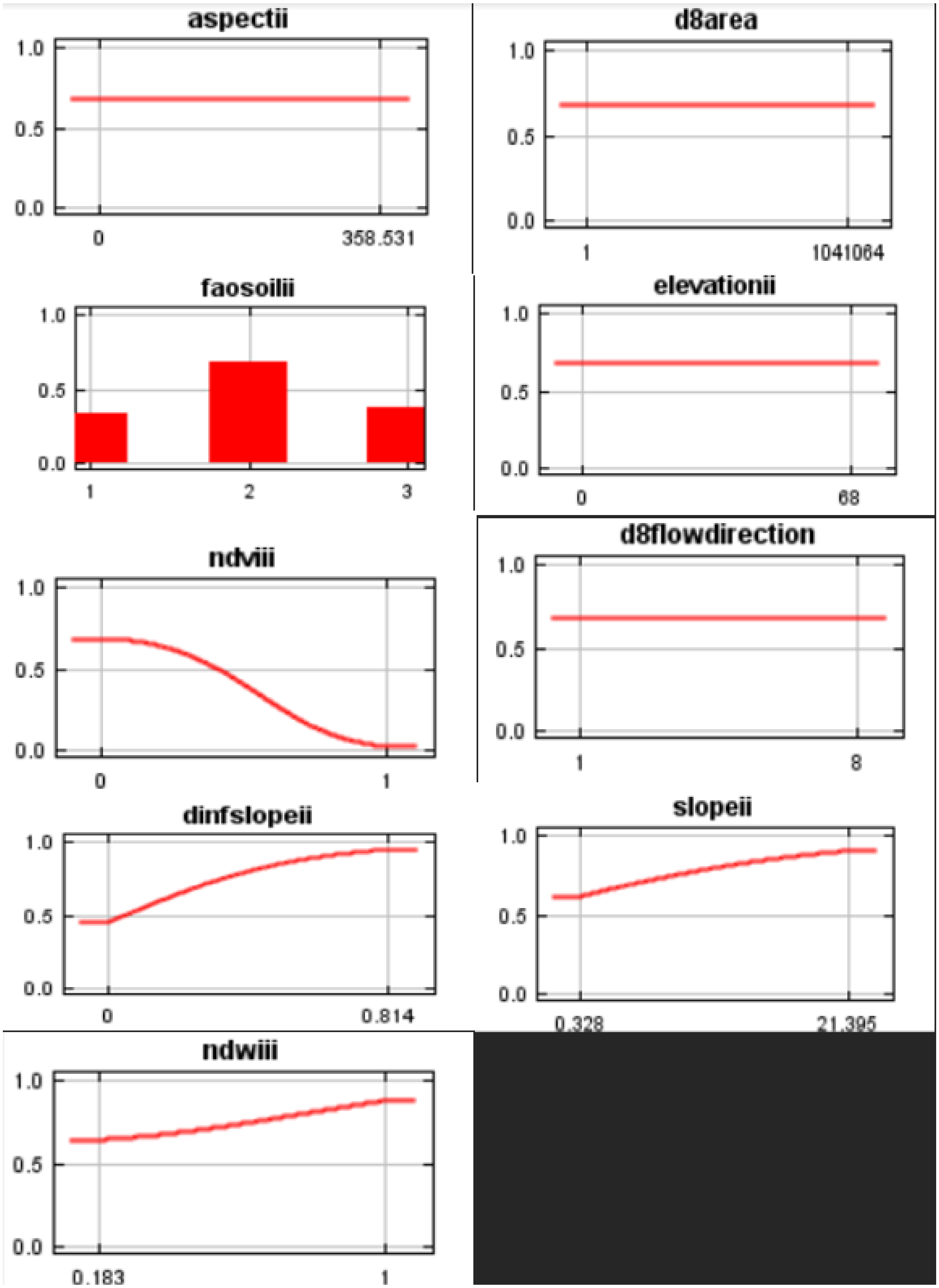


Table 3. Response curves for (a) Aspect (b) Catchment Area (c) FAO soil type (d) Elevation (e) NDVI (f) Flow Direction (g) Riverslope (h) NDWI (i) Slope

Favorable conditions for terra preta seem to exist when average downslope from streams is at 0.814, slope is at a value of 21.3, NDWI is at 1, and FAO soil type = 2 (Gleysol type). Aspect, catchment area, flow direction, and elevation are not contributing to the model. Each curve represents the contribution of a variable when all other variables are held constant at their average sample. Notice that the same variables that were flatlining before are doing so in these curves as well. This means that it is unlikely there is any correlation between any variables. Response curves are very smooth, indicating a good fit of the model.

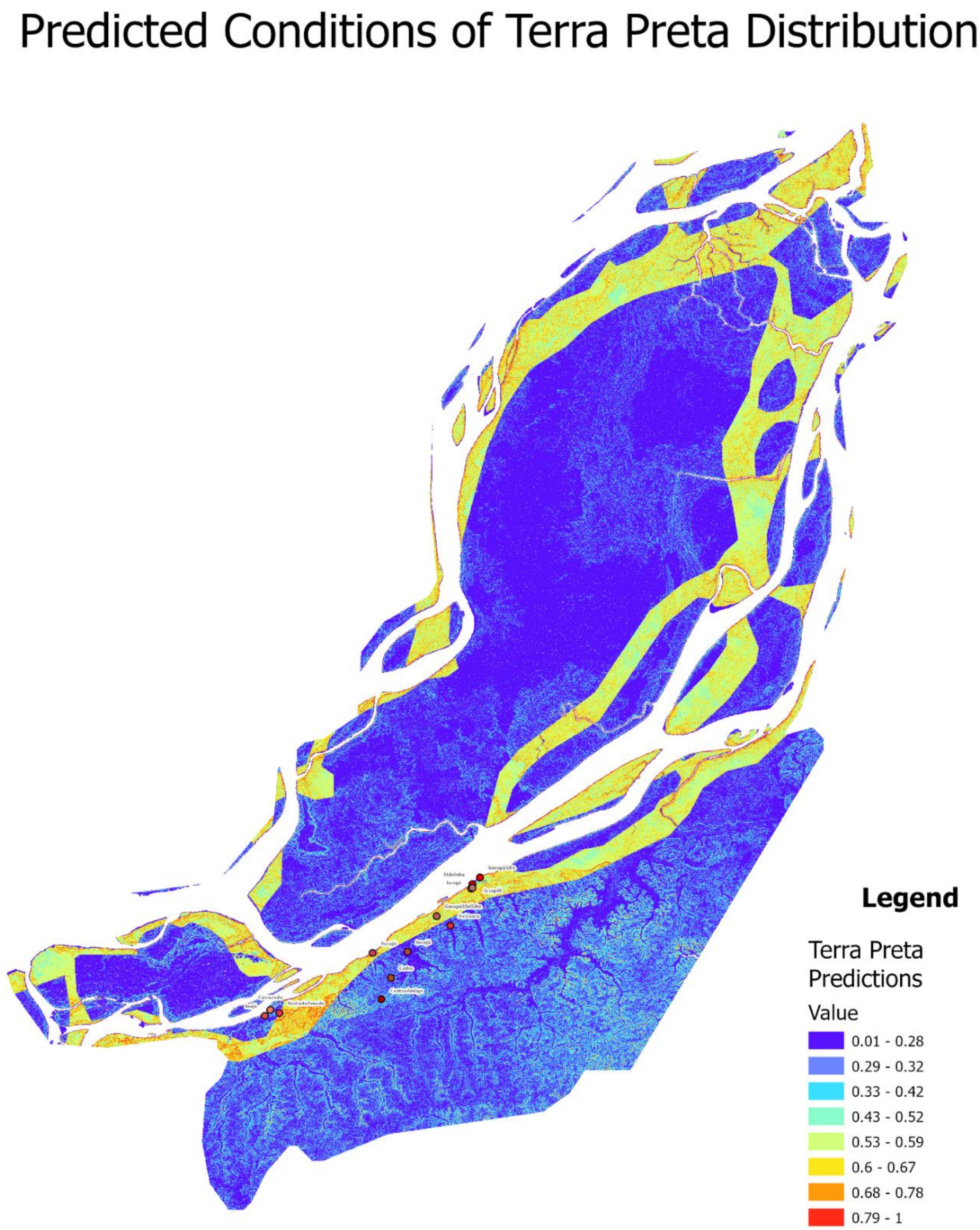


Figure 9. Map of areas predicted to be suitable for presence locations. Points represent locations of known terra preta sites. Zones of high interest are mainly located near streams and particularly around Carrazedo.

Variable	Percent contribution	Permutation importance
faosoilii	53.3	55.5
d8slope	34.3	0
ndviii	8.8	32.5
ndwiii	2.5	0
aspectii	0.5	1.5
d8flowdirection	0.4	2.6
slopeii	0.3	7.8
elevationii	0	0

Table 4. Variable importance with their relative contributions to Maxent model.

Table 4 gives estimates of relative contributions of the environmental variables to the Maxent model. To determine the first estimate, in each iteration of the training algorithm, the increase in regularized gain is added to the contribution of the corresponding variable, or subtracted from it if the change to the absolute value of lambda is negative. For the second estimate, for each environmental variable in turn, the values of that variable on training presence and background data are randomly permuted. The model is reevaluated on the permuted data, and the resulting drop in training AUC is shown in the table, normalized to percentages.

From this table, it is evident that slope and elevation contribute the least to the model. Flow direction and aspect similarly do not contribute much to the model. NDVI and NDWI have a moderate contribution, while FAO soil type and average downslope have the largest contribution to the model. The right-hand column measures a different kind of variable contribution to the model. The contribution for each variable is determined by randomly rearranging the values of that variable among the training points (both presence and background) and measuring the resulting decrease in training AUC. A large decrease indicates that the model depends heavily on that variable. Values are normalized to give percentages.

Interestingly, while slope does not appear to have a large overall contribution to the model, there is an 8% decrease in training AUC when it is rearranged among training points. This indicates that the model does rely on the slope variable more than it seems. For NDVI, this reliance of the model is even more apparent. The model relies on the NDVI variable almost 4x its contribution when it is permuted among training points. In contrast, the model does not rely significantly on NDWI and average downslope of watercourses, despite their larger contribution to the model.

The results of the jack knife tests are displayed in Table 5.

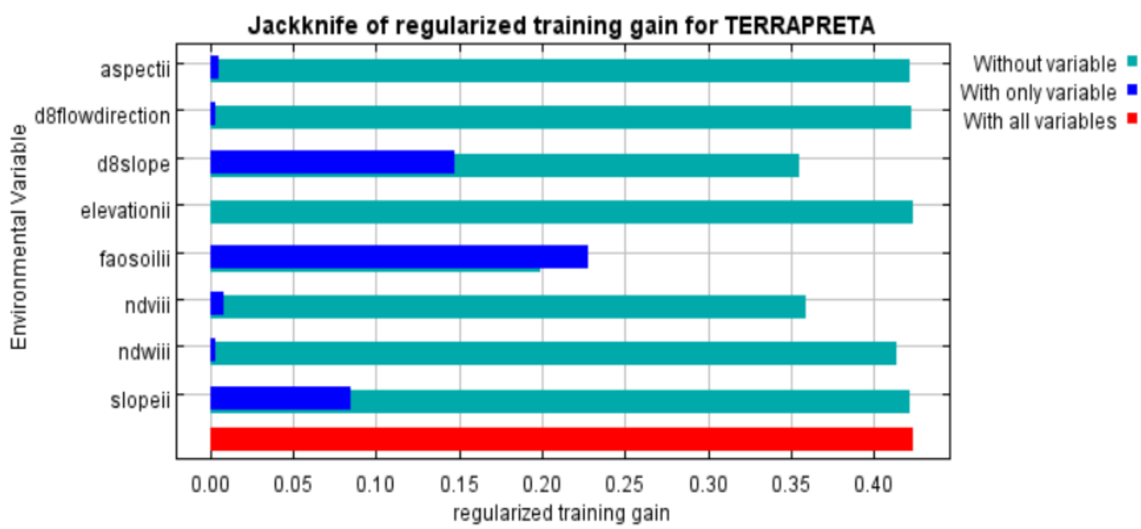


Table 5(a). Jackknife of regularized training gain.

All variables are excluded in turn, and a model is created with the remaining variables.

Aspect, flow direction, elevation, and NDWI display almost no gain, and therefore, when used in isolation, are not useful for estimating the distribution of terra preta sites. FAO soil type and average downslope at watercourses, by contrast, display a good fit to the training data.

Turning to the lighter blue bars shows that one variable, FAO soil type, contains a substantial amount of useful information that is not already contained in the other variables. Omitting this variable in turn did decrease the training gain considerably.

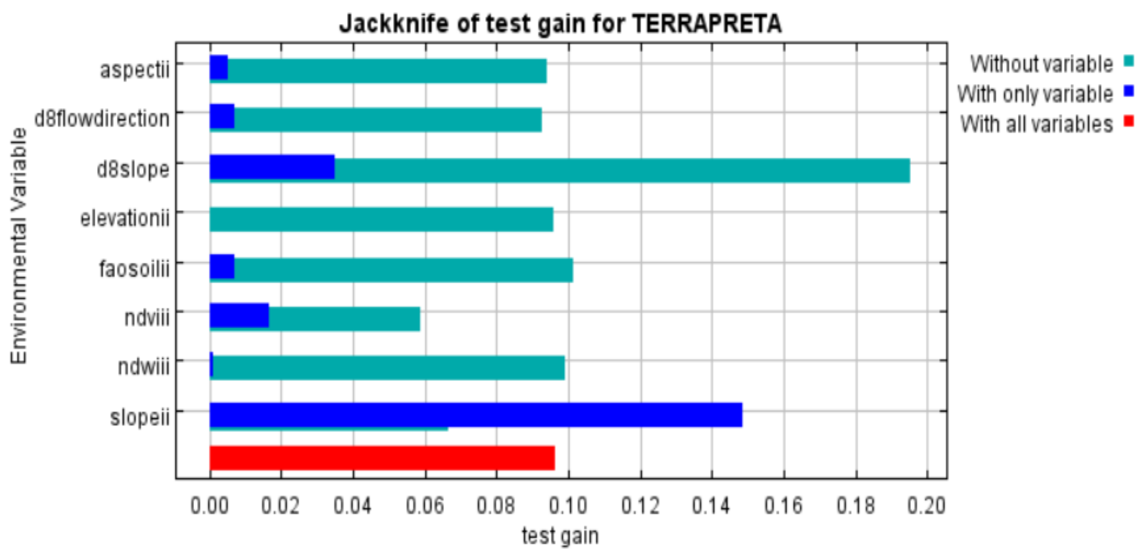


Table 5(b). Jackknife of test gain.

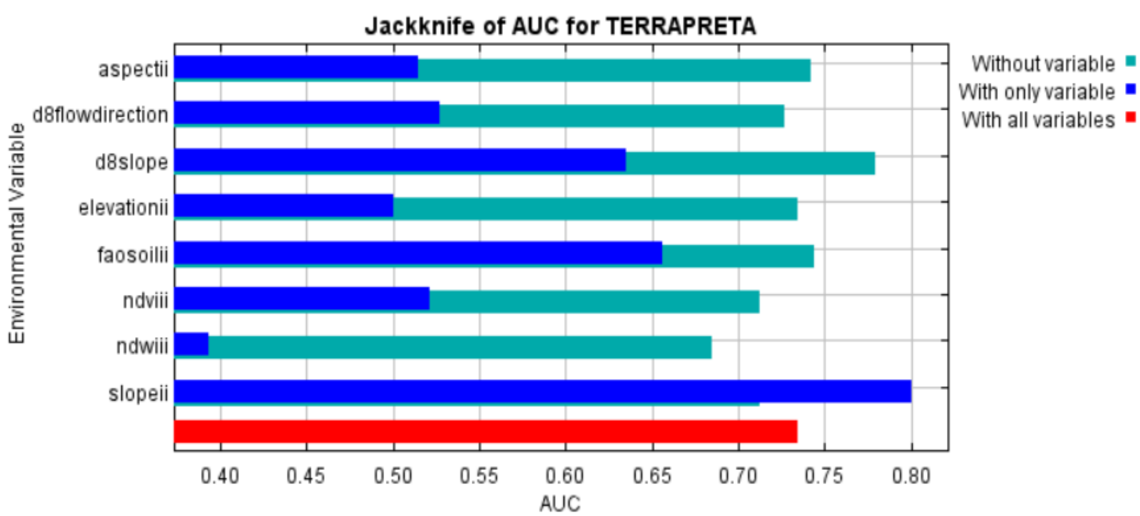


Table 6. Jackknife sampling for AUC.

While significantly smaller, there is also useful information contained in NDVI and average downslope at watercourses, which is apparent through a decrease in training gain when these variables are omitted.

In table 5(b) a model is created using each variable in isolation. The relative importance of the slope variable increases significantly, almost 5x that of average downslope at watercourses in the training gain plot. In addition, the light green bar for average downslope at waterways is twice as long as the red bar, meaning predictive performance of the model increases when this variable is not used. The opposite is true for slope and NDVI.

The AUC plot (Table 6) shows that slope is the most effective single variable for predicting the distribution of the occurrence data that was set aside for testing when predictive performance is measured using AUC. This is surprising, given the fact that it was hardly used when the model was built using all variables. Interestingly, slope now seems to have a slightly higher predictive performance over average downslope of watercourses. Like the test gain plot, the light green bar is larger than the red one, indicating here as well that predictive performance increases when the downslope at waterways variable is omitted.

4.4 Second Run

Sub-sampling and Cross-validation

To test the reliability of these results, the same variables were used for a second run (Tables 6a). Average, standard deviation, median, min and max results of 15 split-sample models were calculated (Table 7). In addition, a cross-validation with 13 folds was executed (Table 6b). Results of the second run confirm the observations

Attribute	Description
Model Type	Maximum Entropy (MaxEnt)
Input samples	13 known terra preta sites
Variables included	8 (Topography, Hydrology, Edaphic, Vegetation Index)
Spatial Resolution	30m
Validation method	15 Sub-sample split-validation
AUC (Average)	0.706
Variable Importance (Average across sub-samples)	1. FAO Soil Type (High) 2. Slope (High) 3. NDVI (Moderate) 4. Average Downslope (Low) 5. Elevation (Negligible)

Table 6(a). Summary of Model Characteristics and Results (Second Run with 15 Sub-Samples).

Attribute	Description
Model Type	Maximum Entropy (MaxEnt)
Input samples	13 known terra preta sites
Variables included	8 (Topography, Hydrology, Edaphic, Vegetation Index)
Spatial Resolution	30m
Validation method	13-fold Cross-validation
AUC (Average)	0.68
Variable Importance (Average across sub-samples)	1. FAO Soil Type (High) 2. NDVI (Moderate) 3. Slope (Moderate) 4. Average Downslope (Low) 5. Elevation (Negligible)

Table 6(b). Summary of Model Characteristics and Results (13-fold Cross-validation).

gleaned from the first model. 15 split-sample models show that slope, rather than average river slope, is the most consistent predictor of suitable conditions for terra preta presence. Results also confirm that elevation is a consistently absent variable when it comes to model contributions. Cross-validation of 13-fold samples shows results do not corroborate either those from the single replicate or the 15-split sample model. Instead, riverslope is a more important predictor than slope. An important distinction between the two types of model is that the split-sample uses 25% of presence records as testing (3/13) and the cross-validation only sets aside one presence record as a test sample. The results of one model from the 15 split samples is shown because it uses 2/3 test samples that are interfluves. This model shows that slope is a more consistent predictor of TP presence as compared to the above model which uses fluvial presence records as test samples and riverslope is a more important contributor to the model there. Cross-validation results show elevation as absent in list of important contributors to the model.

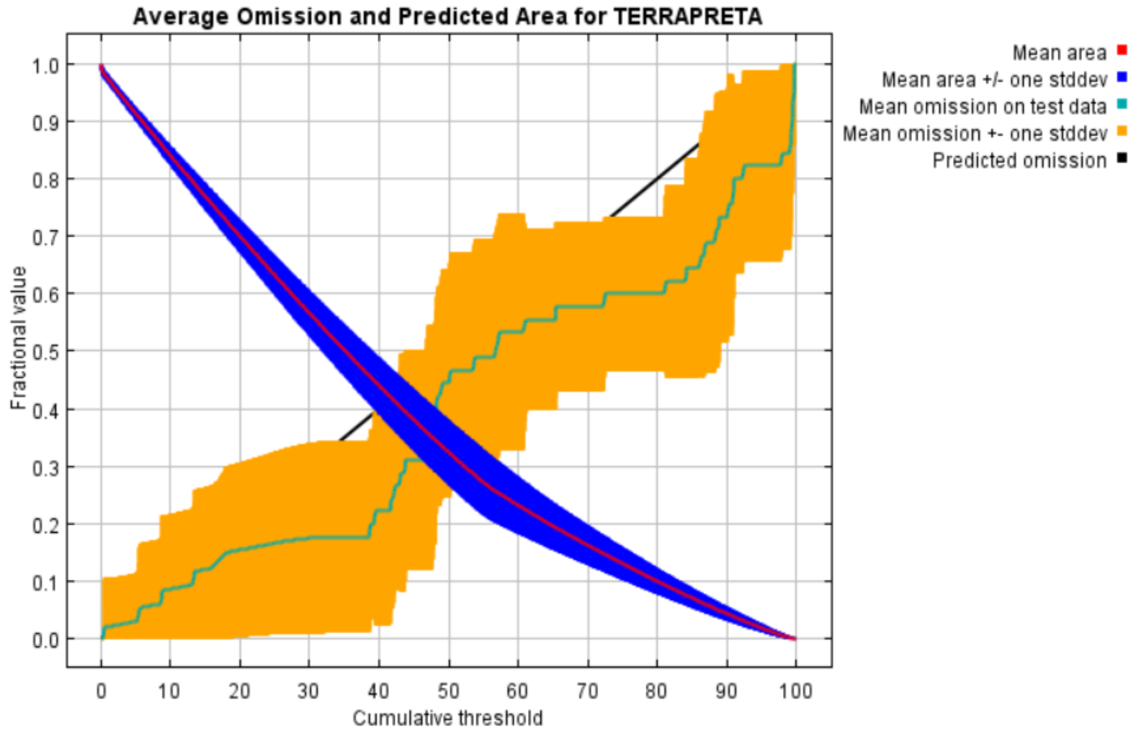


Table 7(a). Omission rate and predicted area. Omission rate for training (in blue) and presence records (light green) are moderately close to predicted omission (in black).

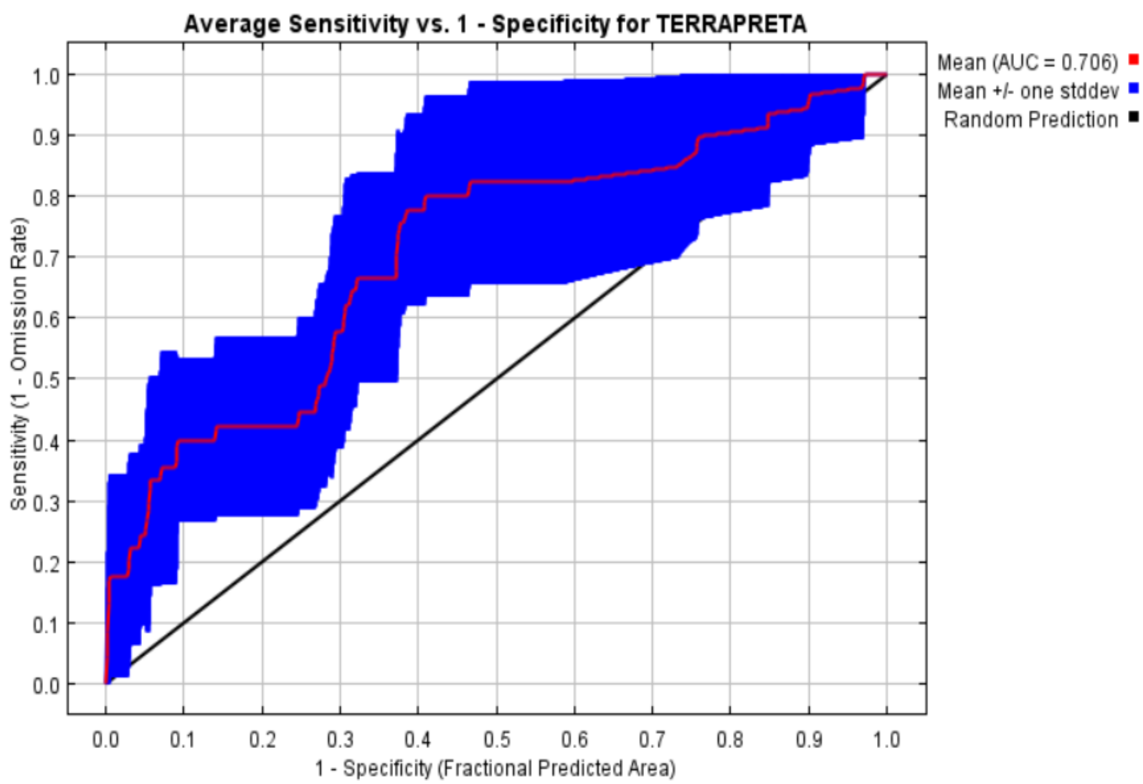


Table 7(b). ROC (receiver operating characteristic) with mean +/- 1 standard deviation (in blue) for the Omission rates and predicted area and mean AUC (in red) for 15 samples terra preta.

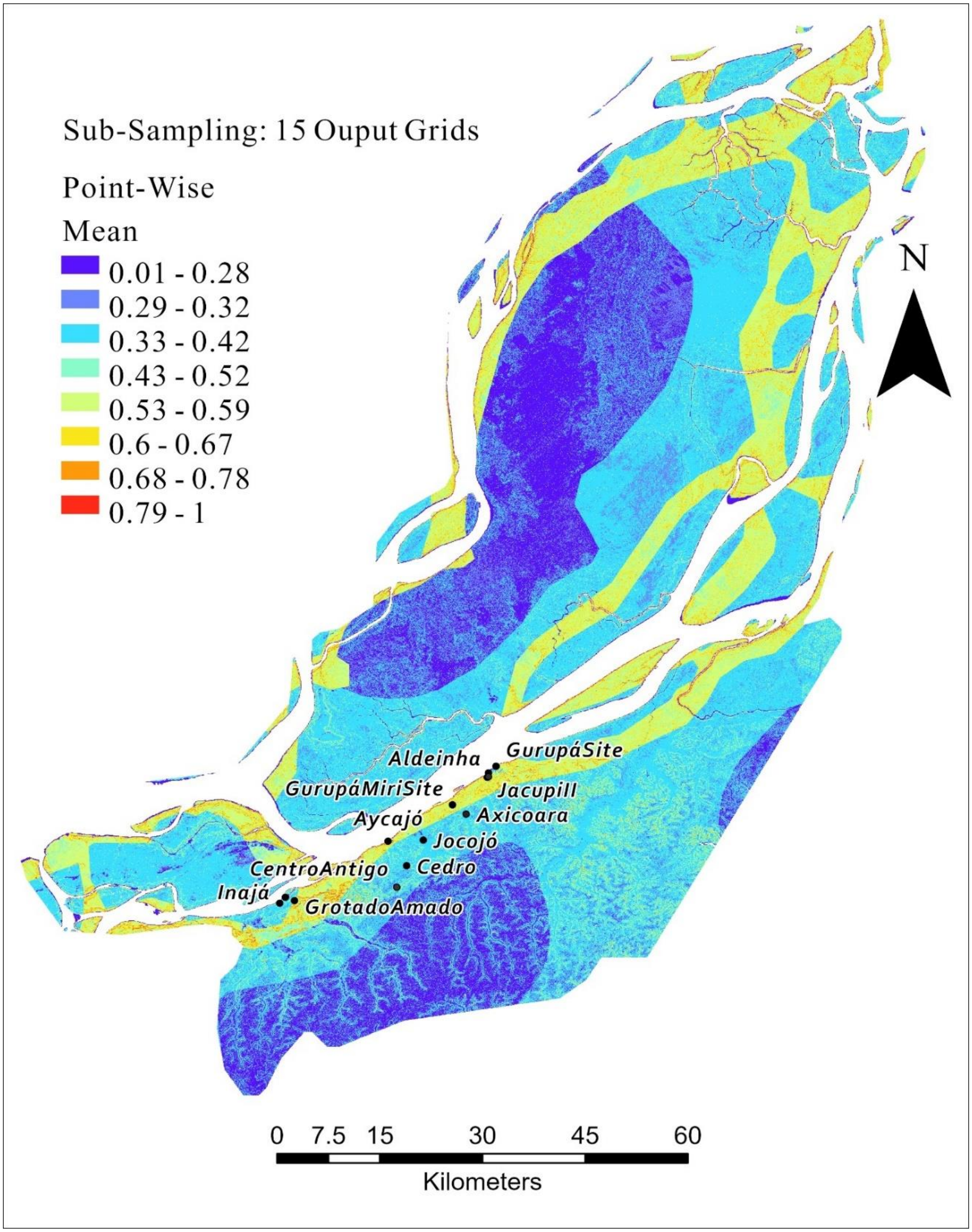


Figure 10. Point-Wise mean of 15 Sub-sample output grids.

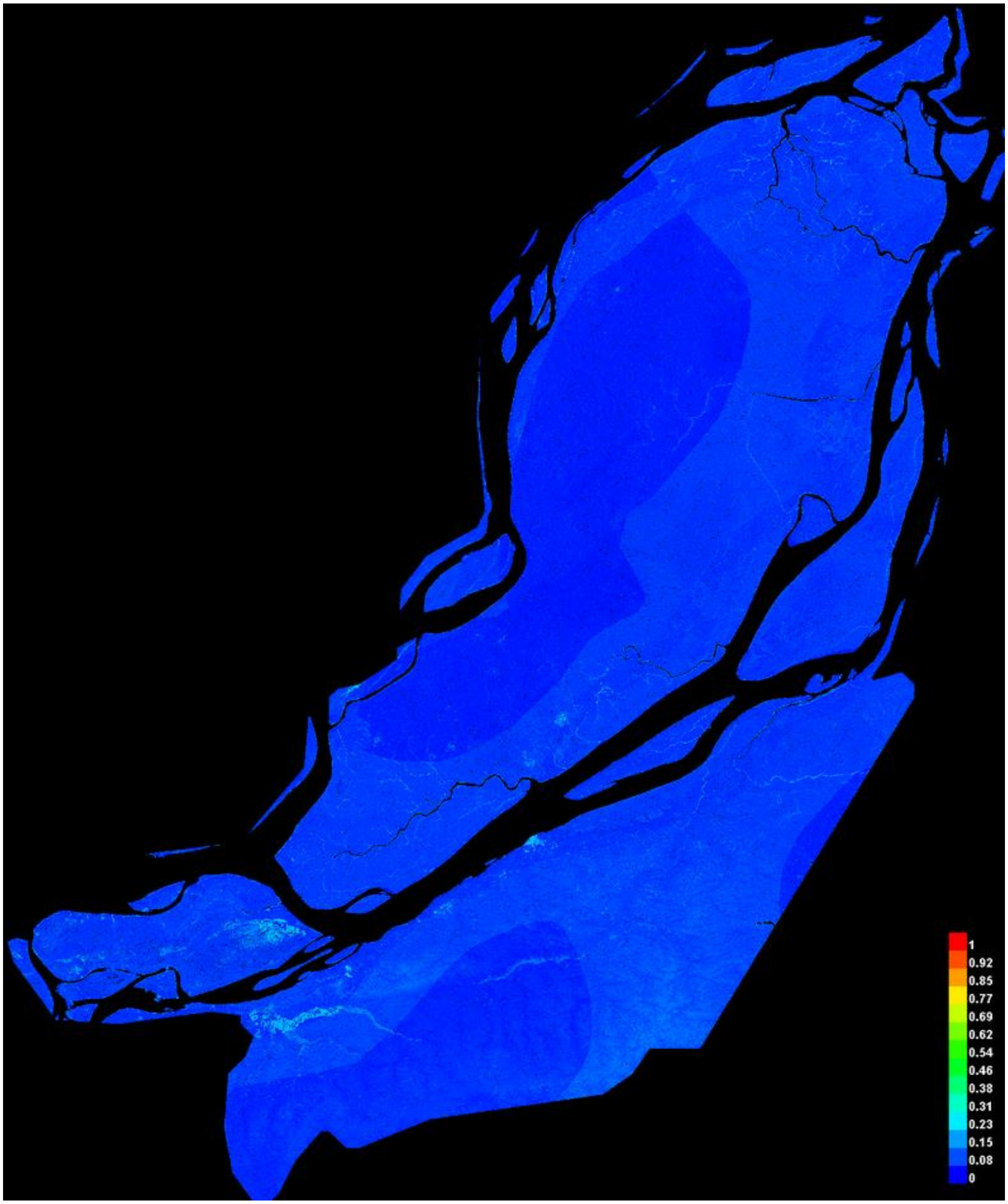


Figure 11. Standard deviation of 15 Sub-sample output grids.

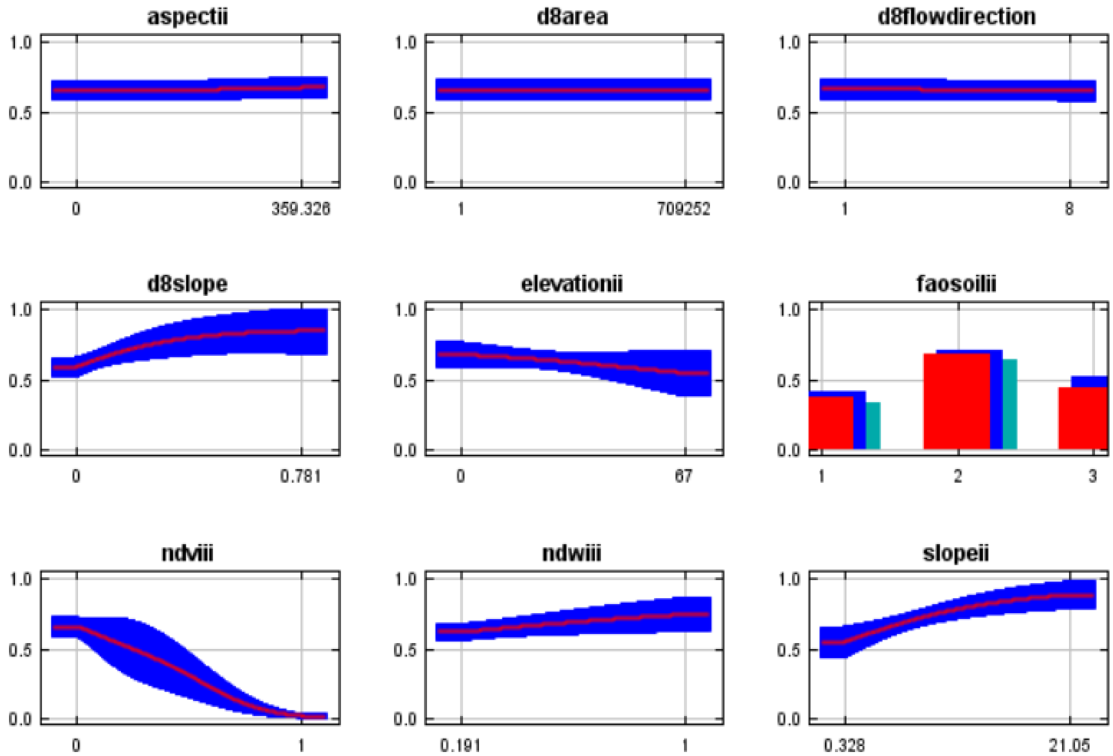


Table 8(a). Marginal Response curves of all variables.

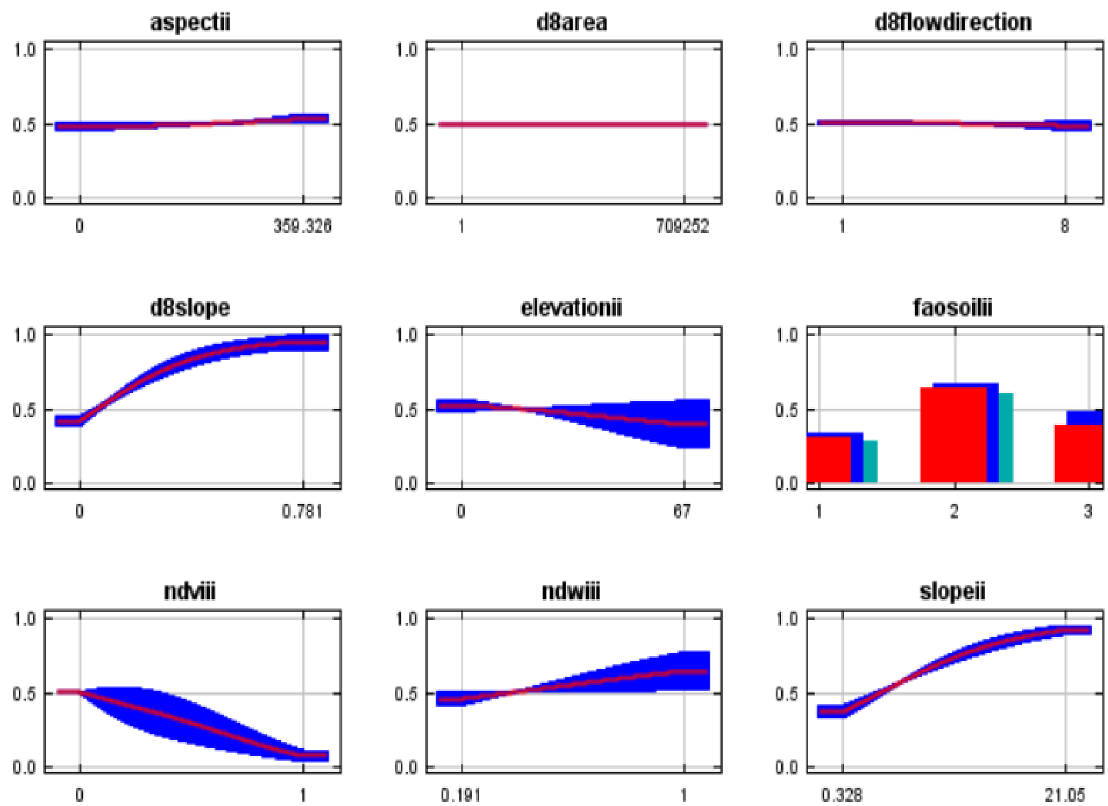


Table 8(b). Maxent model with only the corresponding variable.

Variable	Percent contribution	Permutation importance
faosoilii	36.9	25.2
slopeii	30	55.9
ndviii	18.5	0.8
flowdirectionii	9.4	11.6
dinfslopeii	3.3	5
elevationii	1	1.5
aspectii	0.9	0
ndwiii	0	0
d8area	0	0

Table 9. Relative contributions of environmental variables for second run.

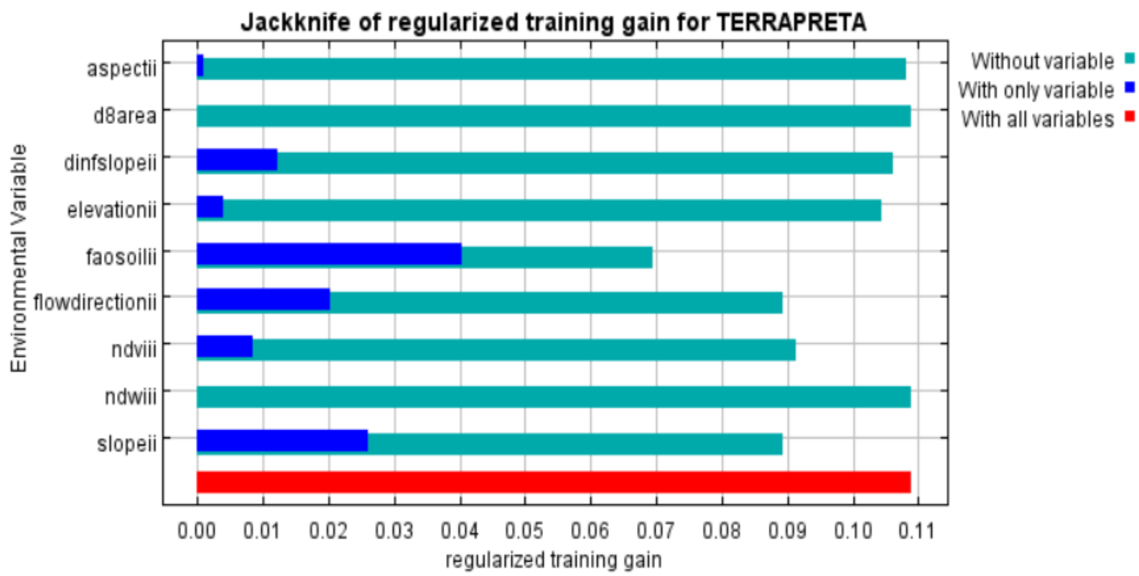


Table 10(a). Jackknife training gain of 15 Sub-sampling.

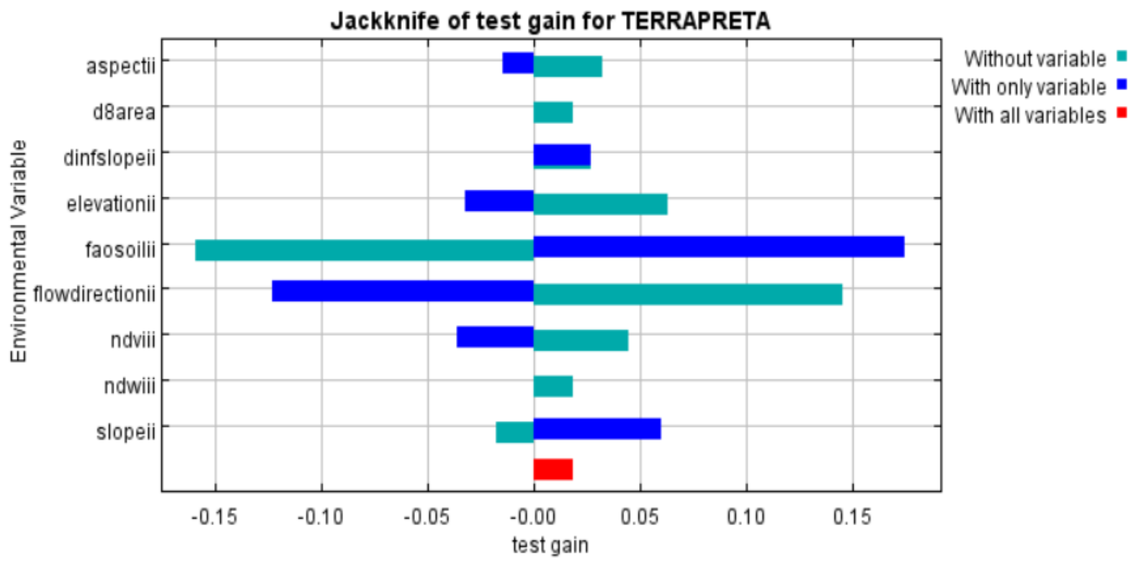


Table 10(b). Jackknife test gain of 15 Sub-sampling.

Lastly, we have the same jackknife test, using AUC on test data.

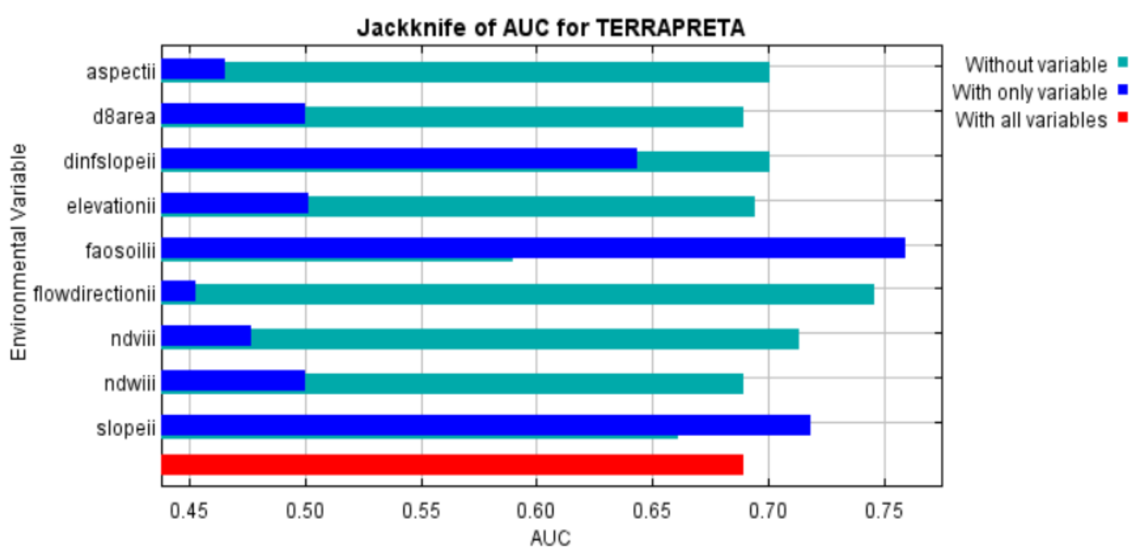


Table 11. Jackknife AUC for 15 split-samples.

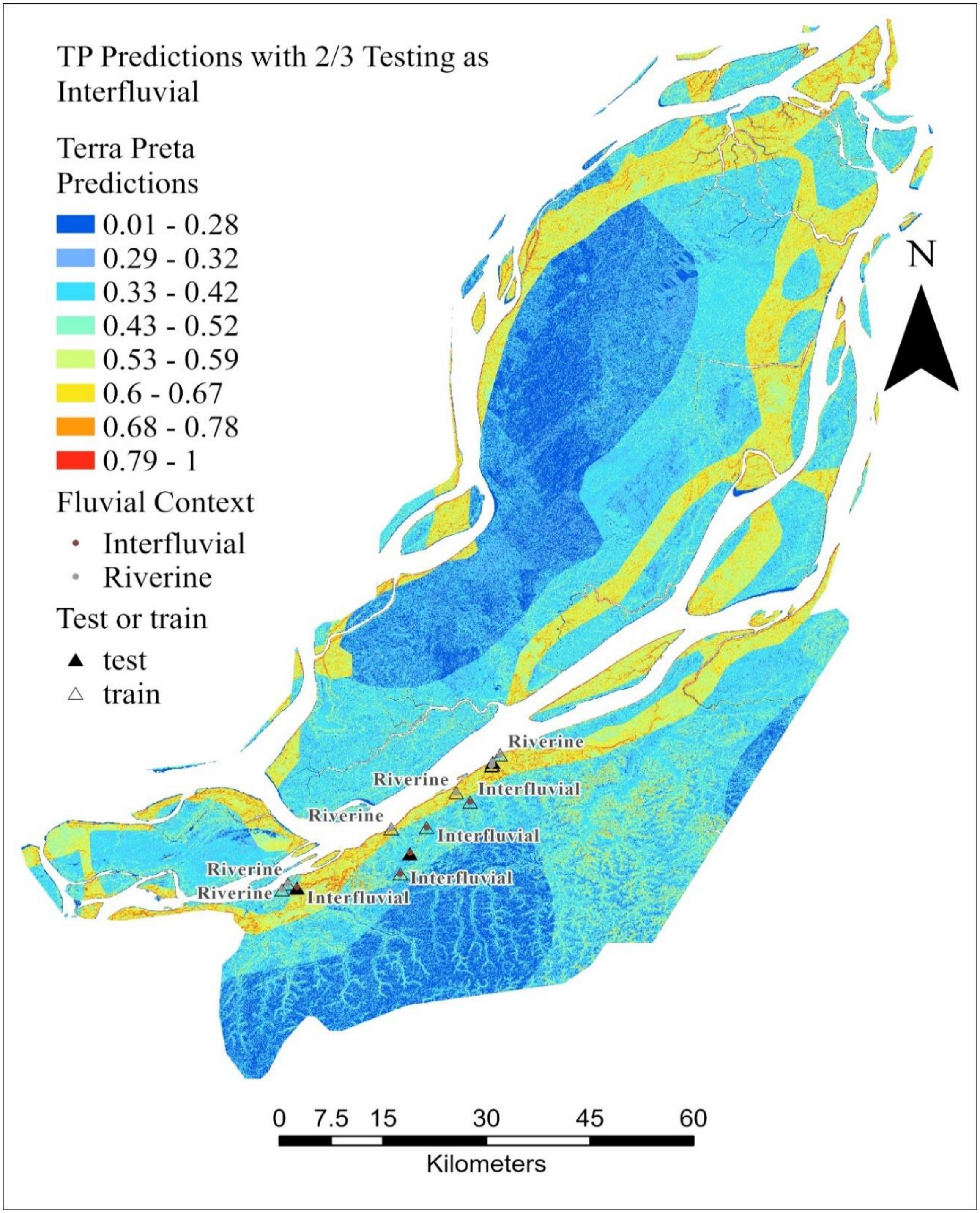


Figure 12. Example of one of the 15 subsamples where interfluvial sites made up 2 of 3 test samples.

Variable	Percent contribution	Permutation importance
faosoilii	54.7	39.3
slopeii	25	31.5
ndviii	11.3	23.8
d8flowdirection	4.7	3.4
aspectii	3.1	2
elevationii	1.2	0
d8slope	0	0
ndwiii	0	0
d8area	0	0

Table 12. Relative contributions of variables for the example sub-sample. Slope had the highest contribution and riverslope none. Compare this to the first run where test samples were largely riverine sites, and the highest contribution is riverslope.

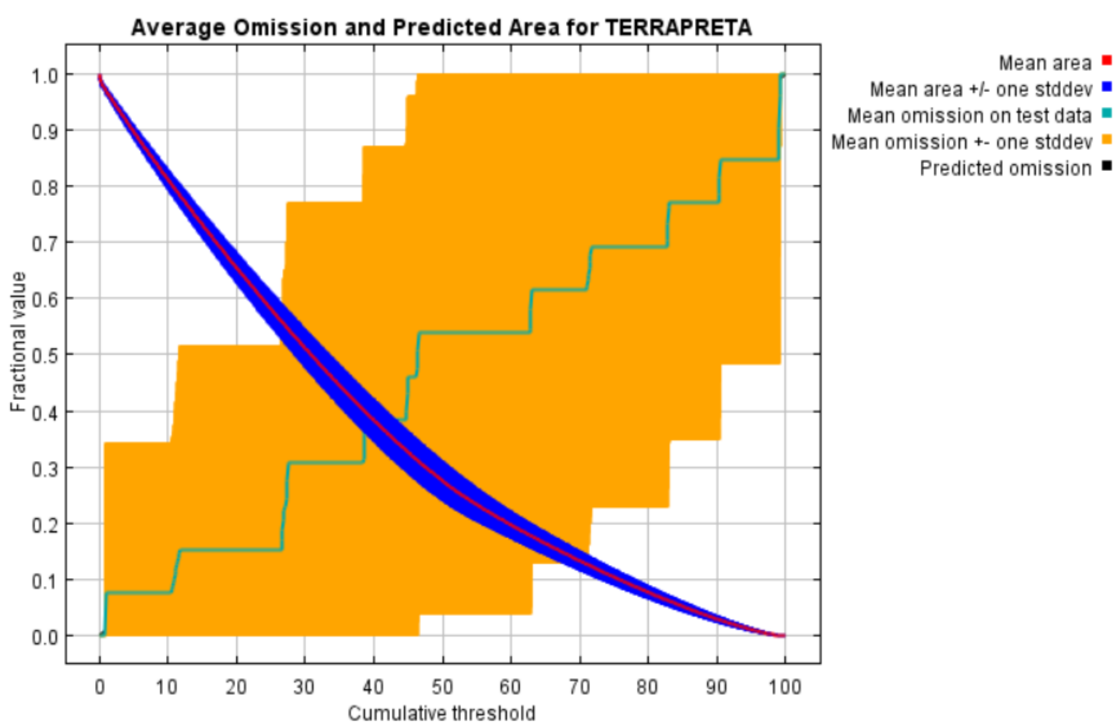


Table 13. Average Omission rate for 13-fold cross-validation.

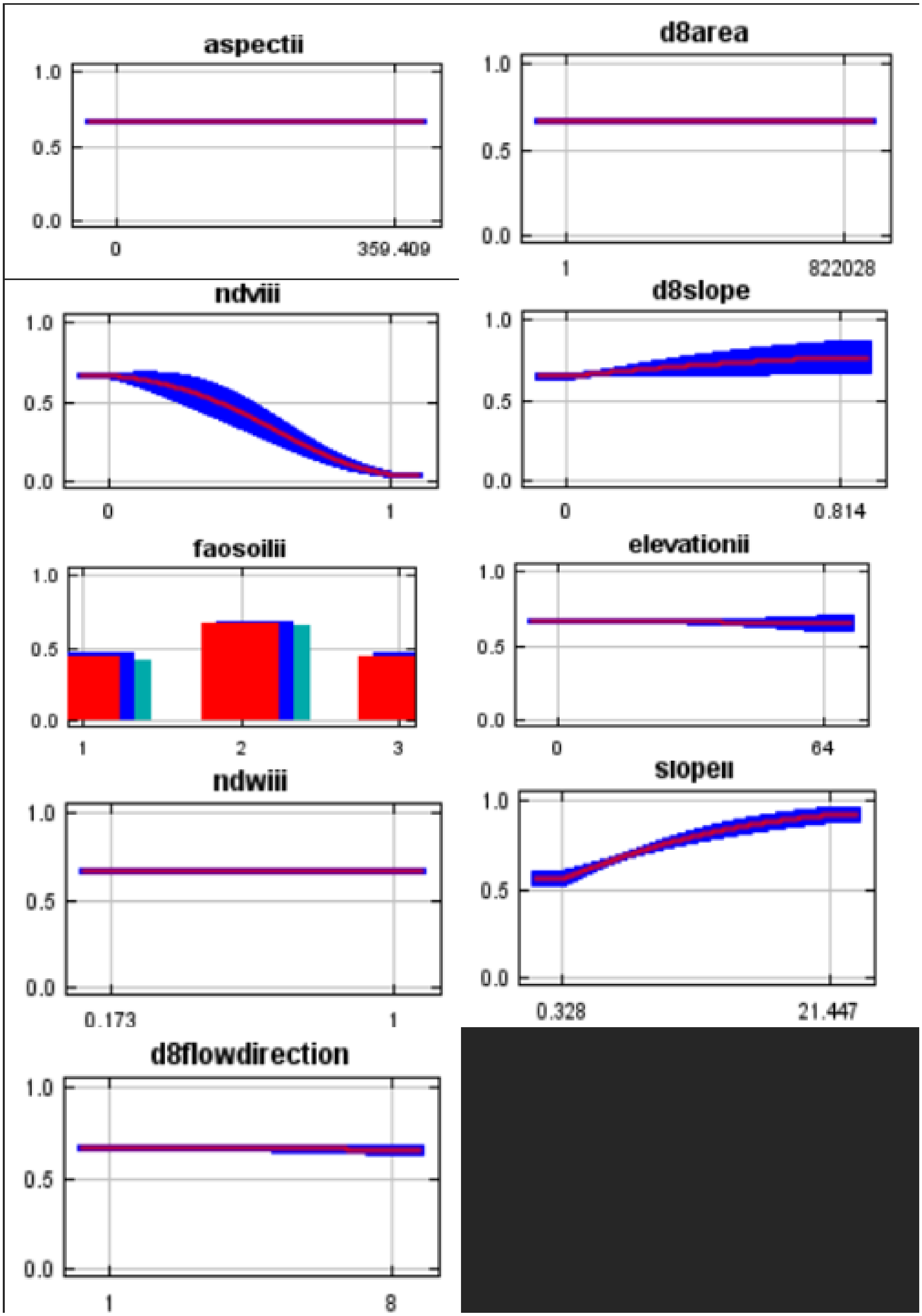


Table 14. Marginal Response curves for (a) Aspect (b) Catchment Area (c) FAO soil type (d) Elevation (e) NDVI (f) Riverslope (g) NDWI (h) Slope

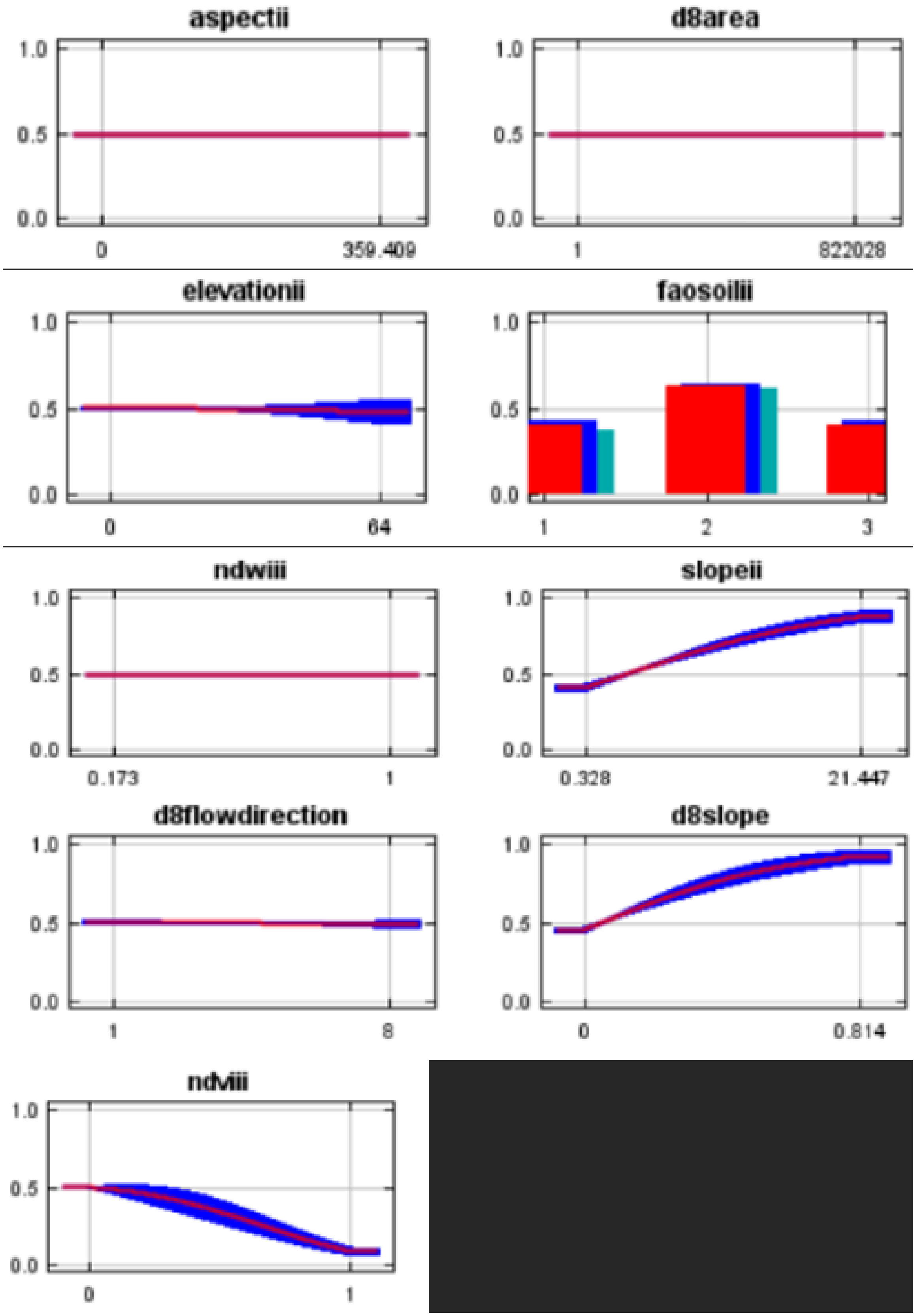


Table 15. Maxent model with only corresponding variable.

Variable	Percent contribution	Permutation importance
faosoilii	63.5	43.6
ndviii	17.6	4.2
slopeii	13.5	49.4
d8slope	4.2	1.2
d8flowdirection	0.9	1.3
elevationii	0.2	0.3
ndwiii	0	0
d8area	0	0
aspectii	0	0

Table 16. Variable contributions for 13-fold cross-validation.

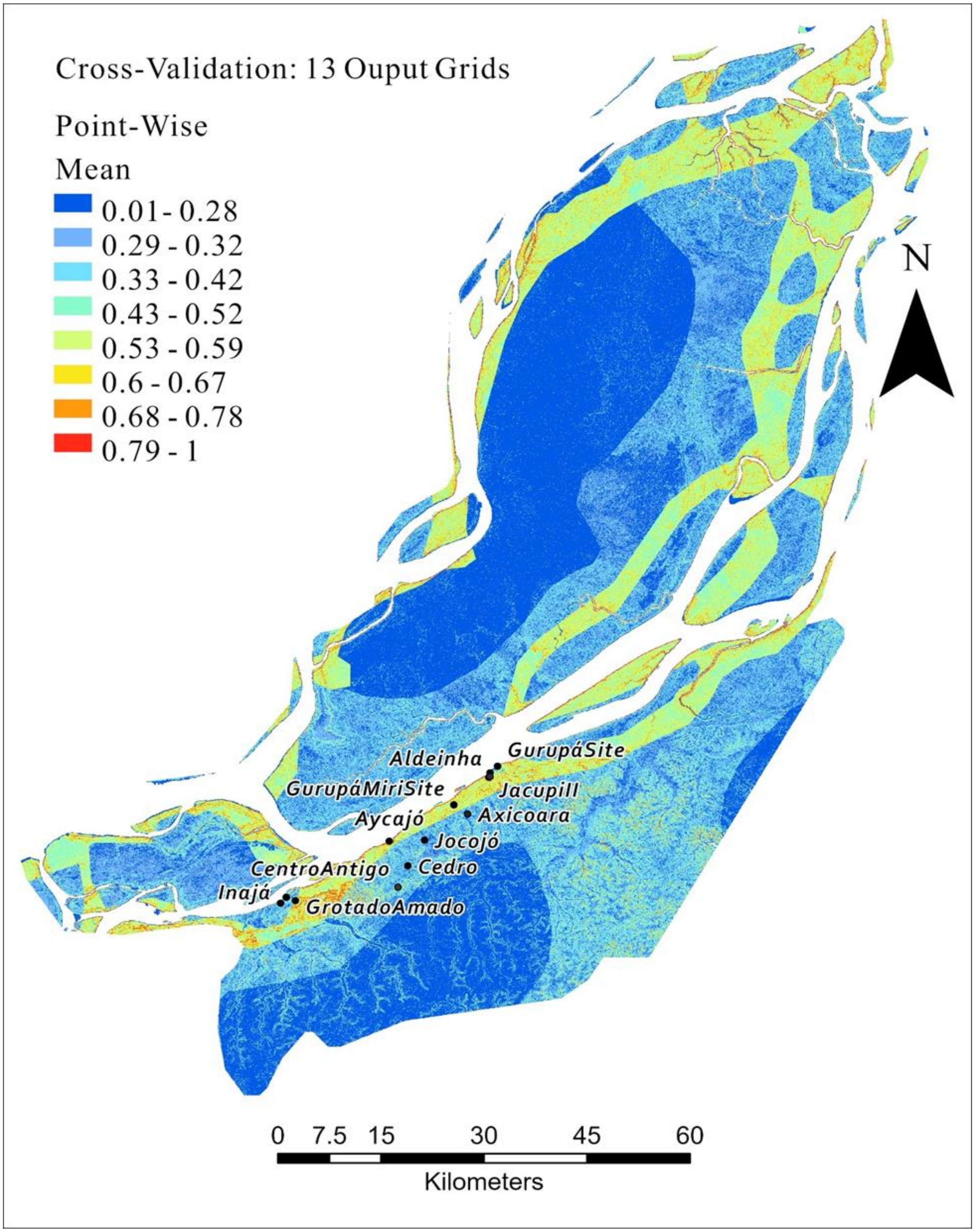


Figure 13. Point wise mean for 13-fold Cross-Validation.

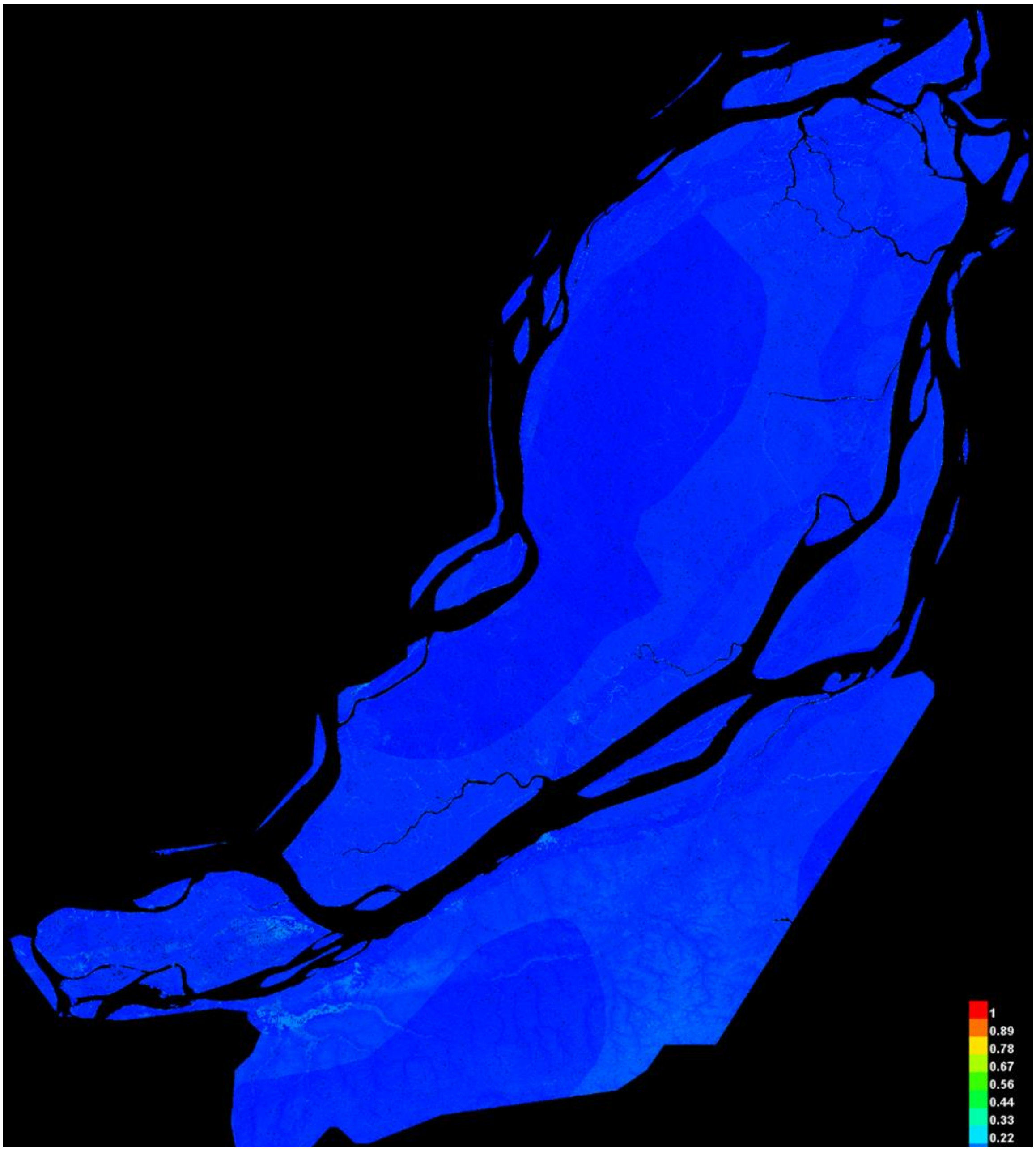


Figure 14. Standard deviation of 13-fold cross-validation

CHAPTER 5

DISCUSSION

The predictive modeling of terra preta sites in Gurupá using a Maximum Entropy approach reveals significant insights into the environmental predictors of these ancient soils. The main findings highlight the robustness of this model in identifying terra preta sites with a high degree of accuracy, emphasizing the critical role of soil type, specifically Gleysol, and topographical features, such as slope and elevation, in predicting site locations. These results challenge and refine our understanding of terra preta distribution, suggesting a nuanced interaction between soil properties and topographical characteristics that influence the presence of these anthropogenic soils. Comparing these findings to broader literature, this research contributes to the evolving narrative of pre-Columbian Amazonian land use, aligning with studies that underscore the complexity of human-environment interactions in the region. Unlike basin-wide models that might overlook micro-regional environmental variability, this study demonstrates the importance of localized environmental analysis for a more accurate prediction of terra preta sites. The study, however, is not without limitations. The reliance on current environmental data to model historical phenomena introduces uncertainties, given the potential changes in landscape and climate over centuries. Additionally, the study's scope, constrained by the availability of high-resolution environmental data and the complexity of modeling techniques, suggests areas for future research. Improvements could include integrating paleoenvironmental data to account for historical landscape changes and exploring alternative modeling algorithms to enhance predictive accuracy.

Observable from these plots is that FAO soil type and average downslope at waterways variables are helping the model to obtain a good fit to the training data. In comparison, the slope variable performs better, as evidenced through its better results on the 25% of samples set aside as testing data. In summary, one might assume that FAO soil type and average downslope at waterways variables are less useful when applied to other predictive models of terra preta. The latter variable being less transferable might be considered a function of fluvial erosion. There is evidence that, "Terras Caidas" (Bandeira et al. 2021), or areas of soil displacement erosion, are known to occur at the rims of major Amazonian tributaries. Another important consideration are the effects of seasonal rainfall on water levels, and the resulting variability of downslope at major rivers. Water levels are known to fluctuate as much as 10m or more during an average year at major confluences with the Amazon River. Additionally, the discharges of its three large tributaries, Tapajos, Madeira, and Xingu rivers cause strong backwater effects on the Amazon River. Seasonal rainfall affects their discharge rates, which in turn modify annual rise and fall of the lower Amazon River. It has been found that, as a result of this, mean river slope is greater during falling stages than during rising stages (Meade, Rayol et al. 1991).

What this paper aims to address, is the fact that sampling bias is likely to occur for terra preta presences in proximity to major waterways, and a comparative lack of targeted sampling efforts in interfluvial zones away from major waterways. The implication of average downslope at waterways not being a transferrable variable for other predictive models indicates that riverine environments are not always suitable conditions for terra preta presence, but that their presence depends more on average slope independently of the proximity to large rivers. Broadly, these results show some significant signal away from major rivers (i.e., interfluves) which very much corroborates a shift of thinking away from a floodplain-centric terra preta distribution model (e.g., “Cardiac Model”: Lathrap 1970) but towards a much more complex model of terra preta distribution which does not run the risk of over simplifying human settlement decisions to the nearest body of water.

5.1 First Run

The results of this study provide substantial insights into the environmental factors that influence the distribution of terra preta soils. The Receiver Operating Characteristic (ROC) curve and subsequent Area Under the Curve (AUC) analyses indicate a robust predictive model with high accuracy. A test AUC of 0.813, in close agreement with the training AUC of 0.806, demonstrates the model’s generalizability and its potential utility in the identification of new Terra Preta sites.

The intersection of omission for training and test samples with predicted omission suggests that the model has effectively balanced sensitivity and specificity across the range of thresholds. Particularly, at a logistic threshold of 0.371, achieving a 100% success rate in predicting terra preta presence within the test samples is both remarkable and statistically significant, given the p-value of 0.02573. This precision in predicting terra preta presence is crucial for practical applications such as targeted archaeological surveys.

The analysis of variable contribution and permutation importance provides nuanced insights into which environmental factors are most critical for the distribution of terra preta. Notably, FAO soil type and average downslope have emerged as the largest contributors to the model. The moderate contributions of NDVI and NDWI, along with their greater reliance indicated by permutation importance, suggest that vegetation indices are significant in understanding the ecological niche of terra preta. Conversely, slope, despite showing a lesser overall contribution, exhibits a disproportionate influence on model accuracy when its values are rearranged, suggesting an underlying complexity in its relationship with terra preta distribution.

The jackknife test results further substantiate the significance of FAO soil type and downslope in model training and testing. The decline in training gain upon the omission of these variables indicates that they hold unique information that is not captured by other variables in the model. In contrast, aspect, flow direction, and elevation showed negligible gains, questioning their relevance in the predictive modeling for this context. The elevated importance of the slope in single-variable models, as opposed to its minor role in multivariate models, points to a nonlinear and possibly synergistic interaction with other factors.

The findings from this research have several implications for the field of archaeological predictive modeling. Firstly, they highlight the significance of integrating diverse environmental variables to enhance the predictive accuracy of models. Secondly, the differential importance of these variables, both independently and in combination, underscores the complex interplay of factors that influence terra preta site distribution.

5.2 Second Run with 15 Sub-Samples

The secondary analysis of the predictive modeling for terra preta sites reinforces and elaborates upon the findings from the initial model. The average omission and predicted area graph show a strong correlation between predicted omission and cumulative threshold, indicating that as the threshold increases, the model becomes more conservative in predicting presences. The shaded area representing one standard deviation from the mean demonstrates the model's consistency across different threshold levels.

The average sensitivity versus specificity curve, with an AUC of 0.706, reveals that the model maintains a fair discriminative ability across its operational range. Although this AUC is slightly lower than that reported in the initial run, it remains significantly above random prediction, supporting the model's validity. The shaded region in this curve also suggests some variability in the model's performance across different runs, which is an expected aspect of any model that relies on real-world data where variability is inherent.

The consistency in the model's variable contributions, particularly with respect to slope and FAO soil type, underscores the importance of topographical and soil-related variables in the distribution of terra preta. This consistency is critical, as it suggests that these factors have a stable influence on the presence of terra preta, irrespective of the model iteration or the specific subset of data used.

The jackknife tests provide insightful revelations about the individual contribution of each environmental variable. For example, slope's significant individual contribution suggests that it has a unique and substantial influence on the model's predictions. In contrast, elevation appears to have a negligible effect, both when included with other variables and when tested in isolation.

5.3 Second Run with 13-fold Cross-validation

Results of the 13-fold cross-validation show a continuation of the model's performance evaluation, focusing on the reliability and consistency of predictions across different variables and thresholds. The average omission and predicted area plots underscore the variability inherent in ecological and environmental modeling, highlighting the importance of considering uncertainty in model predictions.

The average omission and predicted area graph showcases the variability in the model's performance at different thresholds. The mean area under the prediction curve, along with its standard deviation, provides an estimate of the model's reliability. It indicates that while the model performs well on average, there is variability around this performance, likely reflective of natural heterogeneity in the distribution of terra preta or in the environmental variables themselves.

The variable response curves offer a clear visual representation of each environmental factor's influence on the model. For example, the curves for slope and FAO soil type variables demonstrate a distinct trend, suggesting a strong correlation with terra preta presence, consistent with the ecological understanding of soil and topographical influence on such anthropogenic soils. On the other hand, variables such as aspect and catchment area show flat response curves, indicating little to no change in model prediction with varying levels of these variables.

The permutation importance results offer further insight into the model's reliance on each variable. The large discrepancy between the percent contribution and permutation importance for variables like FAO soil type and slope confirms their critical roles in the model. Notably, a significant drop in model performance upon permutation of the slope variable (49.4%) suggests that the model is highly sensitive to changes in this particular environmental factor, echoing the significance of topography in terra preta distribution.

The cross-validation results, reflected in Table 16, underline the robustness of FAO soil type and slope variables, with permutation importance showing high dependence on these factors. This reinforces the initial findings, affirming that soil type and slope are decisive in predicting the presence of terra preta. The low contribution of other variables such as catchment area and aspect during cross-validation further cements the limited predictive power of these variables.

Cross-validation and split-sample testing are pivotal in evaluating the model's reliability and the generalizability of its predictions. The divergence in the importance of river slope and slope between the 15 split-sample models and the cross-validation results highlights the model's sensitivity to the sampling and testing strategy. Notably, the cross-validation approach, which tests the model against multiple subsets of data, suggests that river slope may be a more reliable predictor than initially anticipated.

5.4 Implications

The predictive model developed in this study has demonstrated notable accuracy in identifying terra preta sites, as evidenced by the close alignment of the Area Under the Curve (AUC) for both training (0.806) and test (0.813) datasets in the first run. This level of performance is indicative of the model's strong generalization capabilities, which is crucial for ecological and archaeological predictive modeling (Elith et al., 2011). The generalization of the model suggests that it has effectively learned the underlying distribution patterns without overfitting to the training data.

The importance of specific environmental variables, such as FAO soil type and average downslope from streams, in predicting the presence of terra preta underscores the nuanced relationship between soil properties and hydrological factors in the formation and distribution of these anthropogenic soils. This finding aligns with studies that highlight the significance of edaphic conditions in the Amazon and their influence on human land use and soil modification practices (McMichael et al. 2014).

Interestingly, the model's reliance on variables like slope and NDVI, despite their initial appearance as minor contributors, points to a complex interplay of factors influencing terra preta distribution. This complexity echoes findings from ecological niche modeling, where seemingly marginal variables can significantly impact model outcomes when their interactions with other factors are considered (Austin 2007).

The predictive accuracy of the model, particularly its success at certain thresholds, offers a powerful tool for archaeological exploration and research. By efficiently identifying potential terra preta sites, the model can guide field surveys and excavation efforts, optimizing resource allocation and enhancing the discovery of new sites (Chase et al., 2012). Moreover, the model's insights into the environmental conditions conducive to terra preta formation can contribute to ongoing debates regarding the extent and impact of pre-Columbian land use in the Amazon (Denevan, 1992).

The predictive modeling results for the second run of terra preta distribution offer valuable insights into the environmental predictors of these anthropogenic soils. The average omission and predicted area graphs provide a nuanced understanding of the model's performance across various threshold values. Such an approach aligns with methodologies that consider the stochastic nature of presence predictions, acknowledging inherent uncertainties and emphasizing the importance of mean performance indicators alongside variability measures (Hastie et al., 2009).

The variable response curves for slope and soil types underscore the ecological significance of these factors. Slope, in particular, has been identified as a key variable in landscape ecology, influencing soil development and hydrological processes (Brown et al. 2017). The strong correlation between slope and terra preta presence suggests that these soils are likely found in areas where topographical gradients influence the accumulation of organic matter and pedogenetic processes (2017).

The soil types represented by the FAO soil type variable reaffirm the critical role that edaphic factors play in the distribution of anthropogenic soils (McMichael et al. 2014). These findings are in line with previous research indicating that soil properties can influence the spatial patterns of archaeological sites (Cutright 2009).

Cross-validation is a robust statistical technique for model validation, often used to assess the generalizability of predictive models. The strong performance of the FAO soil type and slope variables across 13-fold cross-validation suggests that these factors are reliable predictors of terra preta presence. This is consistent with the literature that highlights the significance of cross-validation in evaluating model consistency (Dietterich, 1998).

The model's reliance on key environmental variables such as soil type and slope has important implications for archaeological predictive modeling. These variables can guide survey strategies, informing targeted excavations and conservation efforts (Evans et al., 2013). Furthermore, understanding the environmental contexts of terra preta contributes to broader discussions on pre-Columbian land use and its legacy on Amazonian landscapes (Denevan 1992).

CHAPTER 6

CONCLUSION

The combined effects of highly seasonal rainfall, its effects on the discharge rates of three major Amazonian tributaries, and the resulting strong backwater effects on the Amazonas, are likely to affect its mean river slope. I propose here that this latter fact results in proximity to rivers not being consistent predictors of terra preta sites. Rather, conditions are more likely to be consistently suitable and transferable to other models when mean slope in interfluvial zones is at 21 degrees, or 11.86 degrees. In contrast to other, much larger scale predictive models, this study finds that statistically significant environmental variables in Basin-wide predictive models, like elevation, are not predictors of terra preta presences in the smaller region of Gurupá. The findings presented here suggest that large scale predictive models may not reflect suitability conditions and their dynamics at play for terra preta distributions at the micro-regional level.

The reliance on current environmental data to predict historical phenomena introduces an inherent uncertainty. Future research could enhance model accuracy by incorporating paleoenvironmental data, offering a more nuanced understanding of terra preta formation conditions over time.

Furthermore, expanding the model to include additional or alternative environmental variables (e.g., remotely sensed data), as suggested by the surprising importance of NDVI and NDWI in these findings, could uncover other significant predictors of terra preta presence. The exploration of different modeling frameworks or algorithms could also provide new insights into the predictive modeling of archaeological phenomena. The consistency in variable importance across different validation methods reinforces the potential application of the model for predictive purposes in identifying new terra preta sites. However, the variation observed in the model's performance at different thresholds suggests that future research should explore adaptive thresholding techniques that might better capture the complexities of terra preta distribution. Furthermore, incorporating additional environmental or anthropogenic variables could improve the model's predictive accuracy and offer more detailed insights into the conditions favoring terra preta formation.

Of additional concern is the selection of DEM datasets for predictive models in the Amazon. While the performance of a model may stay stable across multiple runs, it is questionable whether this would be the case when using different DEMs with varying spatial resolutions. It is worth carefully investigating DEMs with coarser spatial resolutions and comparing the performance of that model with that of a model using a DEM with a finer spatial resolution (e.g. 90m vs. 30m).

I did some additional processing on the DEM, namely hydrologic terrain analysis (TauDEM) in order to remove some artifacts in the DEM (like pits). It seems prudent to me that future predictive models not only aim for a comparison of multiple DEMs at differing resolutions in the Amazon, but that hydro-terrain analysis functions from TauDEM are included.

The approach used in this paper has some additional limitations. Ideally, a multitude of machine learning techniques would be used to produce multiple predictive models that are not limited to the presence-background model used here. Of particular interest was a random forest classification. Unfortunately, the number of input samples here are short of the minimum of 20 required for the classifier to run. The single most powerful addition to any predictive model of a similarly small scale as this one would be LiDAR data. These data products should be used when/if they become available because there is an indisputable advantage to having such high-resolution terrain data available.

REFERENCES

Adem, A. A., Dile, Y. T., Worqlul, A. W., Ayana, E. K., Tilahun, S. A., & Steenhuis, T.S. 2020. “Assessing digital soil inventories for predicting streamflow in the headwaters of the blue nile”. *Hydrology*, 7(1), 8. https://doi.org/10.3390/hydrology7010008

Assis, R., Haugaasen, T., Schöngart, J., Montero, J., Piedade, M., & Wittmann, F. 2014. “Patterns of tree diversity and composition in amazonian floodplain paleo-várzea forest.” *Journal of Vegetation Science*, 26(2), 312-322. https://doi.org/10.1111/jvs.12229

Austin, Mike. 2007. “Species Distribution Models and Ecological Theory: A Critical Assessment and Some Possible New Approaches.” *Ecological Modelling*. 200. 1-19. 10.1016/j.ecolmodel.2006.07.005.

Basso, Keith. 1988. "Speaking with Names": Language and Landscape among the Western Apache. Cultural anthropology, Vol. 3, No. 2, pp. 99-130.

Balée, W., Swanson, T. D., Zurita-Benavides, M. G., & Macedo, J. C. R. 2023. “Evidence for landscape transformation of ridgetop forests in amazonian ecuador.*” Latin American Antiquity*, 1-15. https://doi.org/10.1017/laq.2022.94

Bandeira, Í., Conceição, R., Andrade, M., Teixeira, S., Fonseca, D., Lima, J., Azambuja, A., Gregorio, A., Miyagawa, L., Silva, S.,Aguiar, P. 2021. “FLUVIAL EROSION RISK ANALYSIS: AN AMAZON STUDY CASE.” *Revista Geonorte* 12. 01-25. 10.21170/geonorte.2021.V.12.N.39.01.25.

Becker, T. and Siegmüller, A. 2021. „The coastal lowland of northwestern germany as an archive of holocene landscape evolution: basis for a spatial evaluation of stone age settlement patterns in the dornumer tidal basin.” *Netherlands Journal of Geosciences*, 100. https://doi.org/10.1017/njg.2020.17

Bobrowiec, P., Rosa, L., Gazarini, J., & Haugaasen, T. 2014. “Phyllostomid bat assemblage structure in amazonian flooded and unflooded forests.” *Biotropica*, 46(3), 312-321. https://doi.org/10.1111/btp.12102

Bush, M., Silman, M., Toledo, M., Listopad, C., Gosling, W., Williams, C., … & Krisel, C. 2007. “Holocene fire and occupation in Amazonia: records from two lake districts.” *Philosophical Transactions of the Royal Society B Biological Sciences*, 362(1478), 209-218. https://doi.org/10.1098/rstb.2006.1980

Bush, M., McMichael, C., Piperno, D., Silman, M., Barlow, J., Peres, C., … & Palace, M. 2015. “Anthropogenic influence on amazonian forests in pre-history: an ecological perspective.” *Journal of Biogeography*, 42(12), 2277-2288. https://doi.org/10.1111/jbi.12638

Brown, A. G., Tooth, S., Bullard, J. E., Thomas, D. S. G., Chiverrell, R. C., Plater, A. J., Murton, J., Thorndycraft, V. R., Tarolli, P., Rose, J., Wainwright, J., Downs, P., and Aalto, R. 2017. “The geomorphology of the Anthropocene: emergence, status

and implications." *Earth Surf. Process. Landforms*, 42: 71–90. doi: 10.1002/esp.3943.
Browne Ribeiro, A., H. P. Lima, F. L. T. Marques, M.J. Schmidt and K.S. McDaniel. 2016. "Results from pilot archaeological fieldwork at the Carrazedo site, Lower Xingu River, Amazonia." *Latin American Antiquity*. 27(3):318-339
Carrer, F. 2013. "An ethnoarchaeological inductive model for predicting archaeological site location: A case-study of pastoral settlement patterns in the Val di Fiemme and Val di Sole". *Journal of Anthropological Archaeology*. 32: 54–62.
Chase, Arlen & Chase, Diane & Fisher, Christopher & Leisz, Stephen & Weishampel, John. 2012. "Geospatial Revolution and Remote Sensing LiDAR in Mesoamerican Archaeology." *Proceedings of the National Academy of Sciences of the United States of America*. 109. 12916-21. 10.1073/pnas.1205198109.
Chia CH, Munroe P, Joseph S, Lin Y.2010. "Microscopic characterisation of synthetic Terra Preta." *Australian Journal of Soil Research* 48, 593–605.
Choi, J., Wright, D. K., and Lima, H. P. (2020). A new local scale prediction model of Amazonian landscape domestication sites. *J. Archaeol. Sci.* 123, 105240. doi:10.1016/j.jas.2020.105240
Costa, M., Kern, D., Pinto, A., & Souza, J. 2004. "The ceramic artifacts in archaeological black earth (terra preta) from lower amazon region, brazil: mineralogy." *Acta Amazonica*, 34(2), 165-178. https://doi.org/10.1590/s0044-59672004000200004
Cruz, A., Giehl, E., Levis, C., Machado, J., Bueno, L., & Peroni, N. 2020. "Pre-colonial amerindian legacies in forest composition of southern brazil." *Plos One*, 15(7), e0235819. https://doi.org/10.1371/journal.pone.0235819
Cutright, Robyn E. 2009. *Between the Kitchen and the State: Domestic Practice and Chimú Expansion in the Jequetepeque Valley, Peru.* Doctoral Dissertation, University of Pittsburgh.
Daly, D. C., and J. D. Mitchell. 2000. *Lowland vegetation of tropical South America*. Pages 391-453 in D. L. Lentz, editor, Imperfect Balance: Landscape transformations in the Precolumbian Americas. New York, Columbia University Press.
Denevan, W. M. 1992. "The Pristine Myth: The Landscape of the Americas in 1492." *Annals of the Association of American Geographers*, *82*(3), 369–385. http://www.jstor.org/stable/2563351
Dietterich TG. 1998. "Approximate Statistical Tests for Comparing Supervised Classification Learning Algorithms." *Neural Comput*.10(7):1895-1923. doi: 10.1162/089976698300017197. PMID: 9744903.
de Souza, J.G., Schaan, D.P., Robinson, M. *et al.* 2018. „Pre-Columbian earth-builders settled along the entire southern rim of the Amazon. "*Nat Commun* **9**, 1125. https://doi.org/10.1038/s41467-018-03510-7
Eckstein, Barbara. 2019. "Formal encounters in two tales of toxicity". In: Christoph Lindner and Miriam Meissner, eds. *The Routledge Companion to Urban Imaginaries*, pp. 90-102. New York: Routledge.
Edelstein, D. M. and Tonjes, D. J. 2012. „Modeling an improvement in phosphorus utilization in tropical agriculture." *Journal of Sustainable Agriculture*, 36(1), 18-35. https://doi.org/10.1080/10440046.2011.627993
Elith, J., Phillips, S.J., Hastie, T., Dudík, M., Chee, Y.E. and Yates, C.J. 2011. "A

statistical explanation of MaxEnt for ecologists. "*Diversity and Distributions,* 17: 43-57. https://doi.org/10.1111/j.1472-4642.2010.00725.x

Evans DH, Fletcher RJ, Pottier C, Chevance JB, Soutif D, Tan BS, Im S, Ea D, Tin T, Kim S, Cromarty C, De Greef S, Hanus K, Bâty P, Kuszinger R, Shimoda I, Boornazian G. 2013. "Uncovering archaeological landscapes at Angkor using lidar." *Proc Natl Acad Sci USA*.; 110(31):12595-600. doi: 10.1073/pnas.1306539110. Epub 2013 Jul 11. PMID: 23847206; PMCID: PMC3732978.

Fairhead, J., Leach, M. 2009. *Amazonian Dark Earths in Africa?*. In: Woods, W.I.,

FAO & IIASA. 2023. Harmonized World Soil Database version 2.0. Rome and Laxenburg. https://doi.org/10.4060/cc3823en

Glaser, B. 2006. "Prehistorically modified soils of central amazonia: a model for sustainable agriculture in the twenty-first century." *Philosophical Transactions of the Royal Society B: Biological Sciences*, 362(1478), 187-196. https://doi.org/10.1098/rstb.2006.1978

Glaser, B. and Birk, J. J. 2012) "State of the scientific knowledge on properties and genesis of anthropogenic dark earths in central amazonia (terra preta de índio)." *Geochimica Et Cosmochimica Acta*, 82, 39-51. https://doi.org/10.1016/j.gca.2010.11.029

Gasché, J. 2008. "Agricultura vs. horticultura, campesino vs. bosquesino. balance y proyección." *Folia Amazónica*, 4(2), 65. https://doi.org/10.24841/fa.v17i1-2.268

Guillera-Arroita, Gurutzeta & Lahoz-Monfort, Jose & Elith, Jane. 2014. "Maxent is not a presence-absence method: a comment on Thibaud et al ." *Methods in Ecology and Evolution*. 5. 10.1111/2041-210X.12252.

Hastie T , Tibshirani R , Friedman J. 2009. *The Elements of Statistical Learning*. New York: Springer

Harvey, David. 1996. "From Space to Place and Back Again". In: *Justice, Nature and the Geography of Difference*, pp. 291-326. Blackwell

Haugaasen, T. and Peres, C. A.

2005 "Tree phenology in adjacent amazonian flooded and unflooded forests." *Biotropica*, 37(4), 620-630. https://doi.org/10.1111/j.1744-7429.2005.00079.x

2006 "Floristic, edaphic and structural characteristics of flooded and unflooded forests in the lower rio purús region of central amazonia, brazil." *Acta Amazonica*, 36(1), 25-35. https://doi.org/10.1590/s0044-59672006000100005

Kammann, C. 2013. "Moving forward from "biochar revolution" to "biochar evolution": shaping a promising mitigation tool demands future research efforts." *Agricultural and Food Science*, 22(4), 371-372. https://doi.org/10.23986/afsci.9328

Koziell, Izabella; Inoue, Christina Y. A. 2002. *Mamirauá Sustainable Development Reserve, Brazil*. IIED

Krofcheck, D. J., Eitel, J. U. H., Lippitt, C. D., Vierling, L. A., Schulthess, U., & Litvak, M. E. 2015. "Remote sensing based simple models of gpp in both disturbed and undisturbed piñon-juniper woodlands in the southwestern u.s." *Remote Sensing*, 8(1), 20. https://doi.org/10.3390/rs8010020

Knoop, S. B., Morcatty, T. Q., Bizri, H. R. E., & Cheyne, S. M. 2020. "Age, religion, and

taboos influence subsistence hunting by indigenous people of the lower madeira river, brazilian amazon." *Journal of Ethnobiology*, 40(2), 131-148. https://doi.org/10.2993/0278-0771-40.2.131
Lathrap, Donald W. 1970. *The Upper Amazon.* Thames & Hudson, London.
Law, W. B., Slack, M., Ostendorf, B., & Lewis, M. K. 2017. "Digital terrain analysis reveals new insights into the topographic context of australian aboriginal stone arrangements." *Archaeological Prospection*, 24(2), 169-179. https://doi.org/10.1002/arp.1567
Lehmann, J. 2009. "*Terra Preta* Nova – Where to from Here?" In: Woods, W.I., Teixeira, W.G., Lehmann, J., Steiner, C., WinklerPrins, A., Rebellato, L. (eds) *Amazonian Dark Earths: Wim Sombroek's Vision.* Springer, Dordrecht. https://doi.org/10.1007/978-1-4020-9031-8_28
Lepodise, LM., Lewis, R., Constable, E., Pogson, E., Joseph, S., & Horvat, J. 2022. "Characteristic spectral features of terra preta (tp) in the 5–15 terahertz range." *Applied Spectroscopy*, 76(3), 300-309. https://doi.org/10.1177/00037028211060384
Lieshout, S., Kirkby, C., & Siepel, H. 2016. "Avian distribution and life-history strategies in amazonian terra-firme and floodplain forests." *Tropical Conservation Science,* 9(1), 465-502. https://doi.org/10.1177/194008291600900125
Li L, Li Y, Chen X, Sun D. "A Prediction Study on Archaeological Sites Based on Geographical Variables and Logistic Regression—A Case Study of the Neolithic Era and the Bronze Age of Xiangyang." *Sustainability*. 2022; 14(23):15675. https://doi.org/10.3390/su142315675
Liu, C., White, M. and Newell, G. 2013. "Selecting thresholds for the prediction of species occurrence with presence-only data." *J. Biogeog*r., 40: 778-789. https://doi.org/10.1111/jbi.12058
Low, Setha M. and Lawrence-Zuñiga, Denise. 2003. *The Anthropology of Space and Place: Locating Culture*. Malden, Massachussetts, and Oxford: Blackwell Pub
McMichael, Crystal N.H., Frazer Matthews-Bird, William Farfán-Ríos, and Kenneth J. Feeley, 2017. "Ancient human disturbances may be skewing our understanding of amazonian forests", *Proceedings of the National Academy of Sciences*(3), 114:522-527. https://doi.org/10.1073/pnas.1614577114
McMichael, C., Palace, M., Bush, M., Braswell, B., Hagen, S., Neves, E., … & Czarnecki, C. 2014. "Predicting pre-columbian anthropogenic soils in amazonia." *Proceedings of the Royal Society B Biological Sciences*, 281(1777), 20132475. https://doi.org/10.1098/rspb.2013.2475
McMichael, C. N., Palace, M. W., & Golightly, M. 2014. "Bamboo-dominated forests and pre-columbian earthwork formations in south-western amazonia." *Journal of Biogeography*, 41(9), 1733-1745. https://doi.org/10.1111/jbi.12325
Meade, R.H., Rayol, J.M., Da Conceicão, S.C. *et al.* 1991. "Backwater effects in the Amazon River basin of Brazil." *Environ. Geol. Water Sci* **18**, 105–114. https://doi.org/10.1007/BF01704664
Meggers, B.J. 1971. *Amazonia: Man and Culture in a Counterfeit Paradise*. Aldine, Chicago, IL.
Müller, L., Kipnis, R., Ferreira, M., Marzo, S., Fiedler, B., Lucas, M., … & Roberts, P.

2022. “Late holocene dietary and cultural variability on the xingu river, amazon basin: a stable isotopic approach.” *Plos One*, 17(8), e0271545. https://doi.org/10.1371/journal.pone.0271545
NASADEM Merged DEM Global 1 arc second V001. Distributed by OpenTopography. https://doi.org/10.5069/G93T9FD9. (Accessed: 2023-03-11).
Negreiros, G.H. DE, A.C. Alencar, P. Schlesinger, D.C. Nepstad, and P.A. Lefebvre. 2009. Pre-LBA RADAMBRASIL Project Data. ORNL DAAC, Oak Ridge, Tennessee, USA. https://doi.org/10.3334/ORNLDAAC/941)
Novotny, E., deAzevedo, E., Bonagamba, T., Cunha, T., Madari, B., Benites, V., … & Hayes, M. 2006. “Studies of the compositions of humic acids from amazonian dark earth soils.” *Environmental Science & Technology* 41(2), 400-405. https://doi.org/10.1021/es060941x
Peña-Venegas, C., Stomph, T., Verschoor, G., & Struik, P. 2015. “Classification and use of natural and anthropogenic soils by indigenous communities of the upper amazon region of colombia.” *Human Ecology*, 44(1), 1-15. https://doi.org/10.1007/s10745-015-9793-6
Petersen JB, Neves EG , Heckenberger MJ. 2001. “Gift from the past: terra preta and prehistoric Amerindian occupation in Amazonia” In: McEwan C, Barreto C, Neves EG (eds). *Unknown Amazon: culture in nature in ancient Brazil*. British Museum Press, London, pp 86–105
Piperno, D., McMichael, C., & Bush, M. 2017. “Further evidence for localized, short-term anthropogenic forest alterations across pre-columbian amazonia.” *Proceedings of the National Academy of Sciences,* 114(21). https://doi.org/10.1073/pnas.1705585114
Pöhlker, C., Walter, D., Paulsen, H., Könemann, T., Rodríguez-Caballero, E., Morán-Zuloaga, D., … & Andreae, M. 2019. “Land cover and its transformation in the backward trajectory footprint region of the amazon tall tower observatory.” *Atmospheric Chemistry and Physics*, 19(13), 8425-8470. https://doi.org/10.5194/acp-19-8425-2019
Rhodes, C. J. 2012. “Biochar, and its potential contribution to improving soil quality and carbon capture.” *Science Progress*, 95(3), 330-340. https://doi.org/10.3184/003685012x13445960110308
Sales, R., McMichael, C., Flantua, S., Hagemans, K., Zondervan, J., González-Arango, C., … & Bush, M. 2022. “Potential distributions of pre-columbian people in tropical andean landscapes.” *Philosophical Transactions of the Royal Society B Biological Sciences*, 377(1849). https://doi.org/10.1098/rstb.2020.0502
Salomon, Frank, and Stuart B. Schwartz, eds. 1999. *The Cambridge History of the Native Peoples of the Americas, vol.3*. Cambridge: Cambridge University Press.
Seibert, J. and McGlynn, B. L. 2007. “A new triangular multiple flow direction algorithm for computing upslope areas from gridded digital elevation models.” *Water Resources Research*, 43(4). https://doi.org/10.1029/2006wr005128
Soentgen, J., Hilbert, K., Groote-Bidlingmaier, C., Herzog-Schröder, G., Pabst, E., & Timpf, S. 2017. “terra preta de índio: commodification and mythification of the amazonian dark earths.” *Gaia - Ecological Perspectives for Science and Society*, 26(2), 136-143. https://doi.org/10.14512/gaia.26.2.18
Souza, J. G. d., Robinson, M., Maezumi, S. Y., Capriles, J. M., Hoggarth, J. A.,

Lombardo, U., … & Iriarte, J. 2019. "Climate change and cultural resilience in late pre-columbian amazonia." *Nature Ecology &Amp; Evolution*, 3(7), 1007-1017. https://doi.org/10.1038/s41559-019-0924-0

Steven J. Phillips, Robert P. Anderson, Robert E. Schapire. 2006. "Maximum entropy modeling of species geographic distributions." *Ecological Modelling*, Vol 190/3-4 pp 231-259.

Steven J. Phillips, Miroslav Dudík, Robert E. Schapire. [Internet] Maxent software for modeling species niches and distributions (Version 3.4.1). Available from url: http://biodiversityinformatics.amnh.org/open_source/maxent/. Accessed on 2023-3-11.

Summerell, G., Vaze, J., Tuteja, N., Grayson, R. B., Beale, G., & Dowling, T. I. 2005. "Delineating the major landforms of catchments using an objective hydrological terrain analysis method." *Water Resources Research*, 41(12). https://doi.org/10.1029/2005wr004013

Takata, Y., Funakawa, S., Akshalov, K., Ishida, N., & Kosaki, T. 2007. "Spatial prediction of soil organic matter in northern kazakhstan based on topographic and vegetation information." *Soil Science and Plant Nutrition*, 53(3), 289-299. https://doi.org/10.1111/j.1747-0765.2007.00142.x

Tarboton, David Gavin. 1997. "A new method for the determination of flow directions and upslope areas in grid digital elevation models." *Water Resources Research* 33:309 - 319.

Théry, Hervé; Maurence, Pascale. 1997. *HYDROLOGIE DU BASSIN AMAZONIEN*. ISBN 2-7011-1532-9.

Welivitiya, W. D. D. P., Willgoose, G., & Hancock, G. 2021. "Evaluating a new landform evolution model: a case study using a proposed mine rehabilitation landform." *Earth Surface Processes and Landforms*, 46(11), 2298-2314. https://doi.org/10.1002/esp.5175

WorldCover 2021
Zanaga, D.,Van De Kerchove, R., Daems, D., De Keersmaecker, W., Brockmann, C., Kirches, G., Wevers, J., Cartus, O., Santoro, M., Fritz, S., Lesiv, M., Herold, M., Tsendbazar, N.E., Xu, P.,Ramoino, F., Arino, O., 2022. ESA 10 m 2021 v200. doi:10.5281/zenodo.7254221.

Zahedi, S., Shahedi, K., Rawshan, M. H., Solimani, K., & Dadkhah, K. 2017. "Soil depth Modeling using terrain analysis and satellite imagery: the case study of qeshlaq mountainous watershed (kurdistan, iran)." *Journal of Agricultural Engineering*, 48(3), https://doi.org/10.4081/jae.2017.59

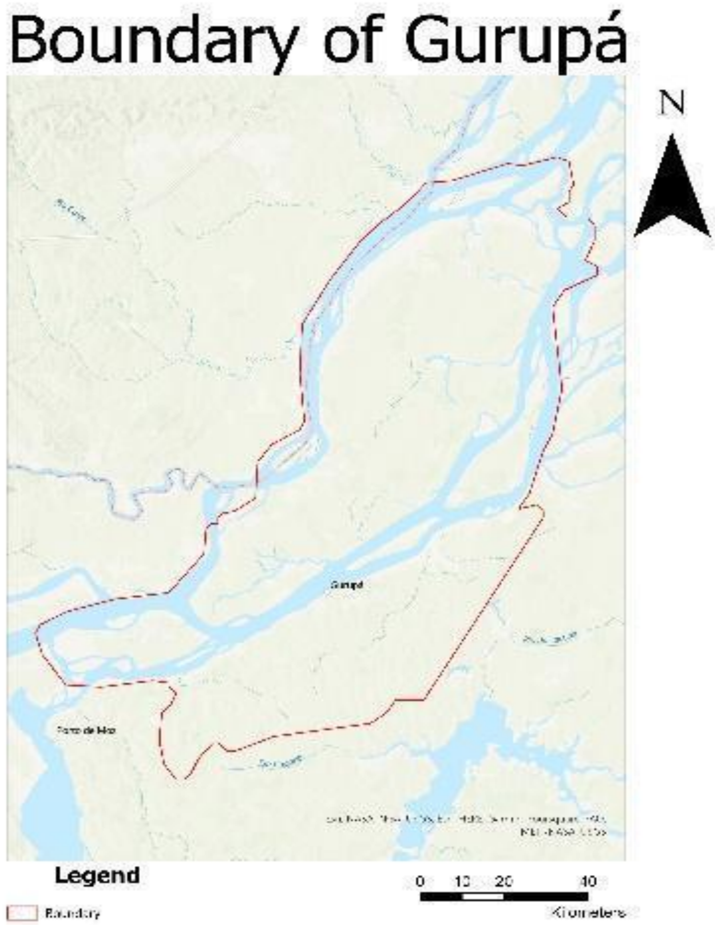
APPENDIX

I. Municipal Boundary coordinates used to create a Boundary polygon

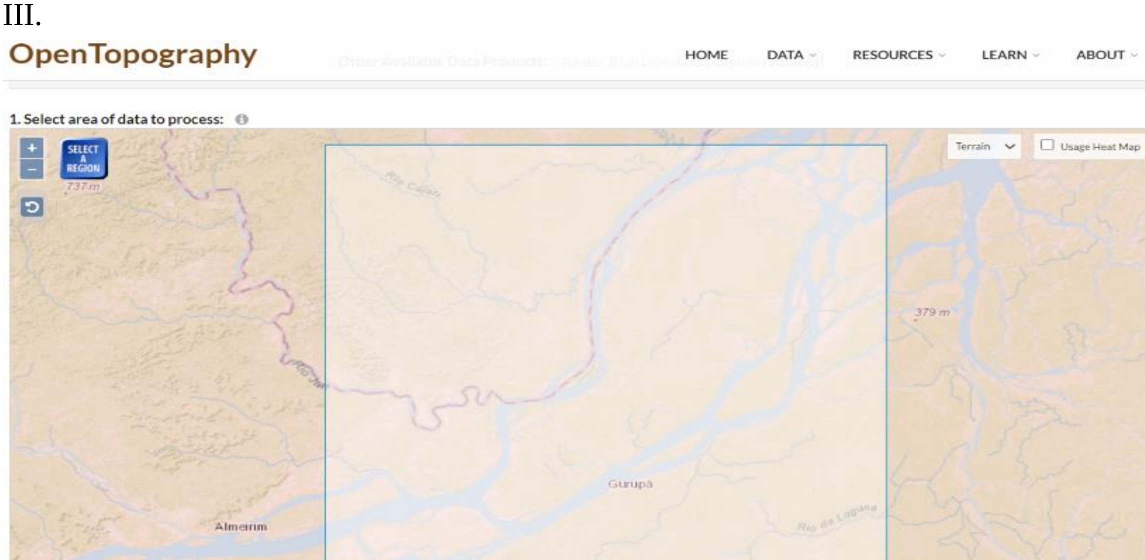
Latitude	Longitude
-52.265	-1.485
-52.21	-1.455
-52.105	-1.425
-51.99	-1.41
-51.915	-1.32
-51.91	-1.26
-51.9	-1.25
-51.885	-1.25
-51.885	-1.235
-51.875	-1.225
-51.85	-1.22
-51.805	-1.19
-51.8	-1.105
-51.77	-1.065
-51.71	-1.03
-51.7	-1.01
-51.71	-0.9
-51.705	-0.785
-51.645	-0.68
-51.58	-0.59
-51.54	-0.55
-51.485	-0.505
-51.44	-0.455
-51.385	-0.45
-51.265	-0.41
-51.235	-0.415

-51.16	-0.395
-51.135	-0.405
-51.125	-0.46
-51.135	-0.475
-51.135	-0.5
-51.16	-0.515
-51.14	-0.535
-51.095	-0.535
-51.08	-0.555
-51.08	-0.59
-51.1	-0.635
-51.075	-0.65
-51.075	-0.67
-51.145	-0.705
-51.17	-0.745
-51.15	-0.935
-51.17	-1.04
-51.19	-1.08
-51.22	-1.18
-51.24	-1.21

II.

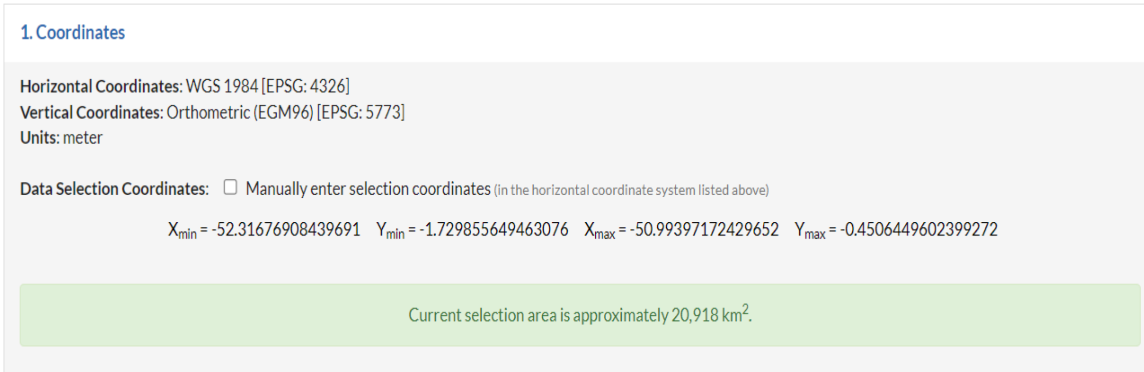


III.



Overview of the area requested. NASADEM Merged DEM Global 1 arc second V001.

IV.



1. Coordinates

Horizontal Coordinates: WGS 1984 [EPSG: 4326]
Vertical Coordinates: Orthometric (EGM96) [EPSG: 5773]
Units: meter

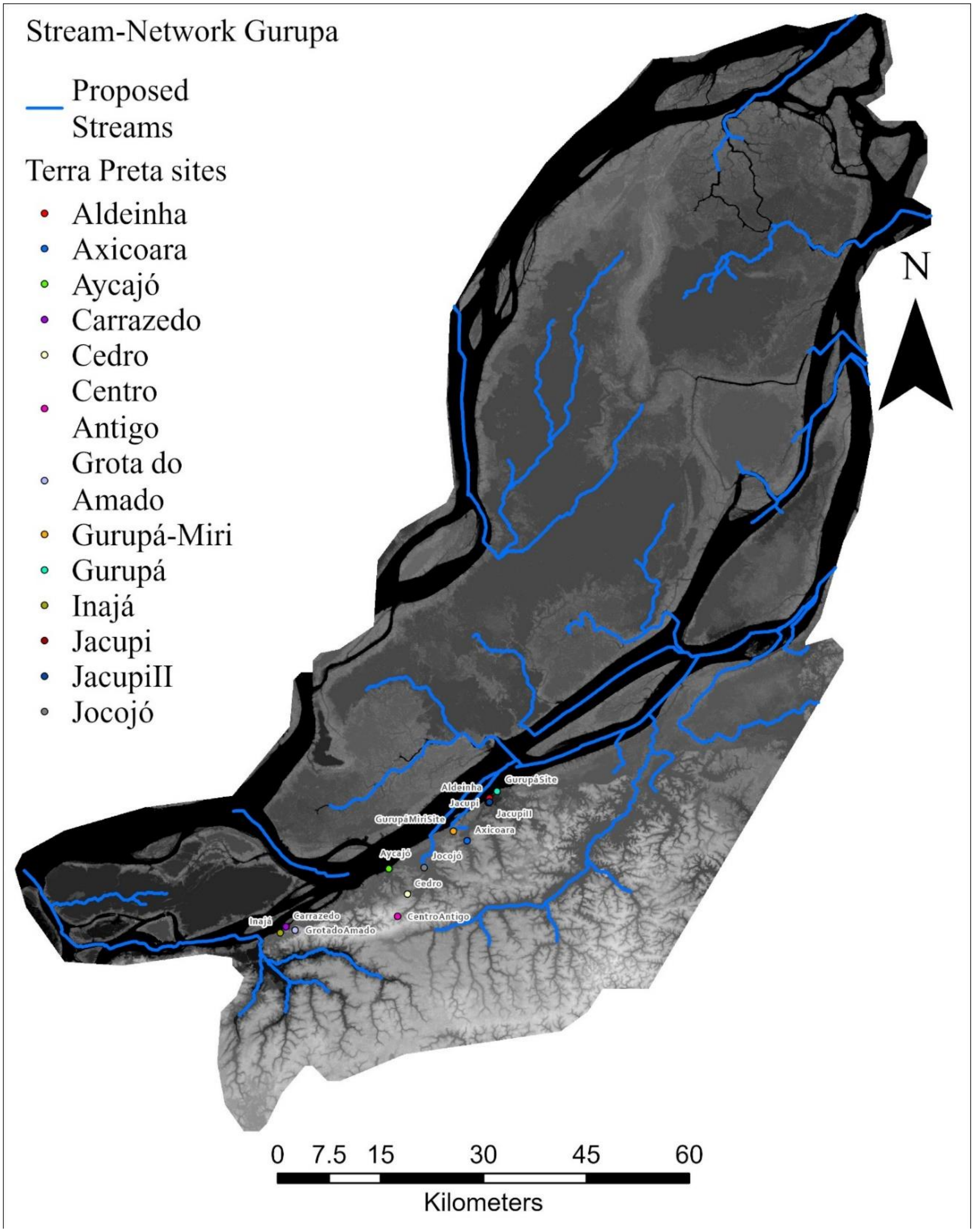
Data Selection Coordinates: ☐ Manually enter selection coordinates (in the horizontal coordinate system listed above)

X_{min} = -52.31676908439691 Y_{min} = -1.729855649463076 X_{max} = -50.99397172429652 Y_{max} = -0.4506449602399272

Current selection area is approximately 20,918 km^2.

Coordinate system, projection, units, and area size.

V. A proposition of locations of streams in Gurupá based on hydrology analysis.



CURRICULUM VITAE
Lauren Zacks

PROFESSIONAL EXPERIENCE

Metropolitan Interpreters and Translators Oct. 2022
Analytic Linguist

- Rendered the spoken word of a language into the written form of the same language, then saved the results in printed format.
- interpreted spoken words orally and simultaneously or consecutively from foreign language into English or to translated spoken words from English into foreign language.
- Provided typed concise and accurate synopsis of oral or written communications about allocations and events.

University of Louisville, Department of Anthropology August 2021
Archaeological Field School *Winchester, Kentucky*
Mentors: Ashley Smallwood Ph.D. & Thomas Jennings Ph.D.

- Conducted survey and shovel testing to identify- and map locations of buried archaeological deposits.
- Used total station & GPS to map possible use-sites.

Centre College, Department of Anthropology
Lab and Teaching Assistant | August 2019 – May 2020
Danville, Kentucky

- Familiarized students with human anatomy and osteology.
- Introduced students to the interpretation of fossil evidence through comparative studies.
- Graded osteology- bipedalism-, and human ancestry labs.

Centre College, Department of Classical Studies
Research Assistant | May 2017 – August 2017

- Contributed secondary sources for a commentary on Vergil's Eclogues and Georgics.
- Translated secondary sources from German- and French into English.
- Efforts resulted in a publication with Dickinson College Commentaries, 2021.

VOLUNTEERING

U.S. Geological Survey National Map Corps
Centre College After School Program (ASP) for ESL K-12 students

DISTINGUISHED ACHIEVEMENT

2021	Mentored Undergraduate Research Award
2019 – 2020	Emily Weixler McCay Annual Scholarship
2018 – 2020	Combs Achievement Scholarship
2016 – 2020	Deans’ List
2016 – 2020	Language Scholarship
2016 – 2020	Alumni Award Scholarship

EDUCATION

University of Louisville
May 2024
MA, Anthropology
Louisville, Kentucky

Centre College
May 2020
BA, Anthropology
BA, Classical Studies
Danville, Kentucky

- *Magna cum laude;* 3.6 GPA.

SKILLS AND CERTIFICATIONS

- Skills: Topographic mapping; Geographic Information Systems; Global Positioning System; Database Management; Leaflet; Python; LiDAR; Remote Sensing; Teaching; German native speaker; Translation; Lithic analysis; Fieldwork
- Certifications: Security Clearance; Advanced Diploma in Geographic Information Systems; Diplôme d’Etudes en Langue Française/Diploma in French Language Studies (DELF) Level B2-C1