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Ecological Theory and its Applicability in the Brazilian Cerrado

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Abstract

The value of modeling as a tool to analyze species distribution in geographic space has been well documented. In the present study, we predicted potential distribution of *Davilla elliptica* a typical Brazilian Cerrado plant, to determine if the niche specified by the model was favorable habitat, and confirmed by actual occurrence data throughout the geographic range of the specie. We constructed an overlay of the modeling results in a Google Earth program as a field guide for re-sampling occurrence data of actual plant localities. We detected this specie in localities indicated as potential niches by the model. A comparison between theory and practice by re-sampling is important to assess the extent of the niche occupied by specie, as well as provide additional ecological data, providing confidence in the use of modeling in areas of high biodiversity, which are under continued threat, such as the Brazilian Cerrado.

Keywords: Plant ecology; Cerrado; Species distributions

Introduction

There is a long history in quantifying the relationship between species distribution and your interactions with biotic and abiotic environmental variables in ecological research [1]. In addition, it is now an integral tool in providing biogeographic data in species assembly, particularly in cases where data is lacking [2]. The SDM approach is based on the principles of ecological niche theory, including the "fundamental niche", which is primarily a function of physiological tolerance and ecosystem limitations; and "realized niche", which comprises to the effects of biotic interactions and competitive exclusion [3]. An ecological niche is defined as follows: the set of conditions and resources in which individuals of specie survive, grow, and reproduce; and the environmental variables and ecological interactions that control the species distribution [4-6]. Consequently, the SDM approach was developed as a probability distribution in geographic space, predicting complete spatial coverage of a particular species distribution, including locations where no event data is available [7]. Therefore, if understanding species geographic distributions are fundamental ecological questions, these predictions are essential for species conservation and management, particularly for endangered species [8]. SDM has broad applicability, including the capacity to assess the status of conservation reserves; efficiently locate areas of conservation priority; establish rare and endangered species distribution; biogeographic studies; analyze climate change affects on species distribution; and SDM serves to guide in efficient field data and specimen collection [1,5,9,10]. Despite widespread application, [9] points out that even for well-studied groups such as birds, some fundamental approaches (e.g. geographic ecology) remain poorly understood. It must be noted that since the inception of modeling in the 1970s [10] enormous advances have occurred, and technological achievements have aided the field's progression, which shows continued development. The most problematic issues identified in SDMs are the predominant use of biotic variables [11] to improve prediction efficiency. Another issue discussed often is data quality (location accuracy) versus quantity (occurrence number) [12], where efforts to create efficient models from incomplete data are questioned [13]. There is no doubt that model success depends critically on the available data [14].

Although several empirical guides are available to select models based on a set of specific criteria, it can be narrowed to an even smaller set of aspects to consider. For example, studies have reported Maximum Entropy (Maxent) exhibits increased accuracy in results. The method reduces false positive errors (i.e. type I error or commission error), which are not having species presence [15]. A type 1 error is less severe than a type II error or omission error, which indicates a smaller occurrence area [16]. If we consider statistical robustness, the Maxent algorithm produces high AUC values (area under the curve), which demonstrates accurate prediction [17]. Another criterion is accuracy in locating priority conservation areas, where once again Maxent demonstrates superior performance [6,17]. The approach has also been shown to perform well with small sample sizes and incomplete data [7]. However, simple methods, including Bioclim and Domain demonstrated inconsistent results in terms of positioning errors compared the successors or new methods such as Maxent and others [18]. Consequently, we concluded that neither model was satisfactory for all conditions [14], the user was forced to choose the approach that best suited the studies' requirements and objectives [3]. Lobo JM et al. [19] emphasized that variation in model accuracy depends more on the quality of biological data than the model. Even if the model performs well under limitations, their data and subsequent results must be interpreted to answer questions initially proposed in the study. According to [20], many modeling studies eventually lead to unanswered questions, and other studies employ modeling for purposes other than predicting species distributions. However, important contributions have indeed been made that clarify niche concepts via modeling approaches [3,21]. A simple means to evaluate any model is to compare predictions with observed data [1], and seek to answer theoretical questions using predictive methodologies. This approach can illuminate new environmental abiotic and biotic factors

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that affect species temporal or spatial distribution, and add to ecological niche theory.

The aim of this study was to test the consistent modeling results produced with the Maxent algorithm, and its practical value based as a field approach. We further verified the niche breadth occupied by *D. elliptica* for confirmed their presence in locations indicated as suitable habitat, but where we still did not have presence data. The suitable habitats analyses are important for guide further effective field data collections, and so that such information can strengthen and increase the use of this technique for biodiversity conservation in the Cerrado region, which is threatened by anthropogenic process [22].

Material and Methods

A predicted distribution for *Davilla elliptica* A. St. Hil. (Dilleniaceae), commonly known as lixeirinha or sambaibinha was performed. This species was chosen because it is representative of the Cerrado Biome, occurring primarily in the open savanna vegetation (cerrado), which exhibits high biodiversity, but is under increased anthropogenic pressures. Therefore, the species was a viable choice to serve as a model for conservation studies. *D. elliptica* is well circumscribed taxonomically, and 160 occurrence records have been reported. We used environmental data based on the criteria that a higher correlation within variables and also significant for studied species. We used the following bioclimatic variables: average annual temperature - Bio1; seasonal temperature (standard deviation * 100) - Bio4; coldest quarter average temperature - Bio11; annual precipitation - Bio12; seasonal precipitation (coefficient of variation) - Bio15; and altitude and soils from AMBIDATA (Division of INPE's Image Processing (DPI), available at

http://www.dpi.inpe.br/Ambdata/download.php).

The Maxent algorithm [23] is based on the maximum entropy modeling of a species geographic distribution. The method uses the option to output results of a logistic and random testing rate of 50%, while other functions are standard to the program. The results illustrate images representing probability of occurrence in color ranges indicating suitable habitat (near 1) gradually changing to unsuitable habitat (values close to 0). In the present study, we subsequently transformed the images to maps using Diva-GIS 7.1.7 to delimit political and environmental units in geographic space, that were later saved in a kmz format for use in Google Earth. In the Google Earth program, a transparency was set for the image by right clicking above the image icon following the upload. Image properties were subsequently used to allow a transparent visualization above the satellite image as a navigation field guide (Figure 1). We were therefore able to compare the modeling results with 10 re-sampling field points set on our image, and verify habitat suitability, i.e., did the model accurately predict suitable habitat for *D. elliptica*?

Results

Potential distribution of *D. elliptica* is shown in a color scale that represents the species probability of occurrence, where increased probability of occurrence were values close to 1, and decreased probability were values close to 0 (Figures 1 and 2). Note that the core suitable habitat areas were distributed within a wide range of Goias State, which included the core Cerrado. Smaller, insulated areas with different habitat suitability were also indicated in several other areas (Figure 2). The distribution map indicates points of registered incidence (circles), and re-sampling points (crosses). Results showed many habitat suitability areas and re-sampling points coincided with actual *D. elliptica* field occurrence localities, which confirmed model accuracy at crosses (Figure 2).

In addition to the standard procedure described in the methods, two other analyses were performed. In one, the points of re-sampling were modeled a second time to ascertain possible effects on the results, but no significant influence was detected in modeling, only the AUC was improved from 0.949 to 0.952. In a third analysis, following [23] 30 points were randomly selected from 160 evenly spaced points to avoid spatial auto-correlation. No significant differences were detected in all the results.

Discussion

D. elliptica modeling results were consistent with the environmental variables and occurrence data, and statistically confirmed by a exceptional area under the curve value (AUC=0.946) [24], based on the model to classify the species presence or absence [25]. Our analysis tested model accuracy by directly re-sampling in the field. Despite the expense of new data sample collection [26], this technique revealed the localities as suitable habitats, or the sites exhibited niche potential.

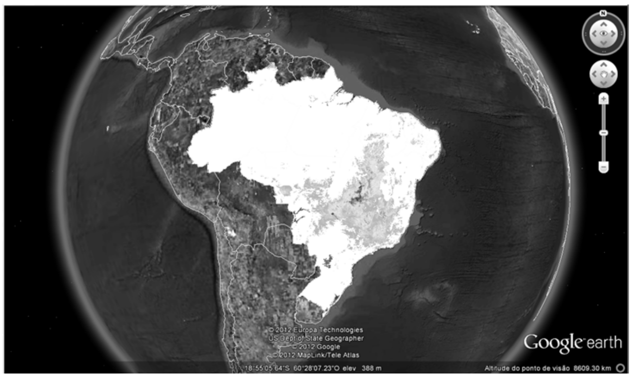

Figure 1: Google Earth program for visualization and usage as field guide for analysis of the modeling results.

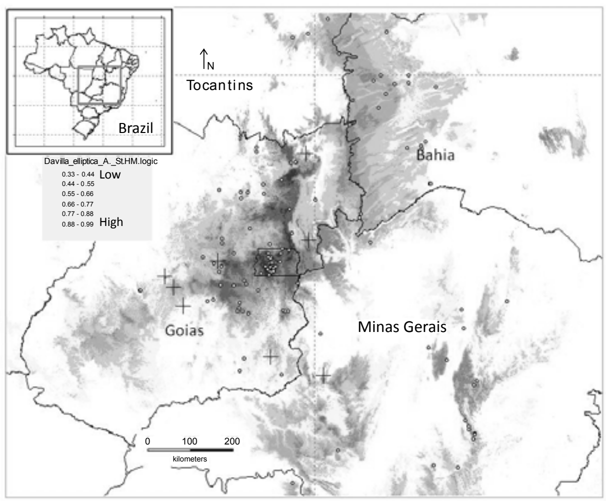

Figure 2: Ecological niche modeling for *Davilla elliptica*. The areas for *D. elliptica* most likely to occur, or the realized niche are depicted in the color scale (>0.66-0.99 high, and <0.44 low). The actual species occurrences (circle), and new areas re-sampled with field presence confirmed (cross) are indicated. Maxent: AUC = 0.949.

Furthermore, we verified actual occurrence of the species at these locales, which according to [12], indicates the accuracy and usability of the predictive modeling approach. Other case, e.g., we performed fieldwork in the Sierra of Mantiqueira in the State of São Paulo, and detected new populations based on model prediction as indicated in suitable habitat 300 km straight south of known populations for *D. angustifolia*, an endemic restricted Dilleniaceae specie to the higher altitudes of the Cerrado.

Ecological discussions involving species distributions are complex, however simplifications are inherent in SDM modeling. Therefore, assuming an ecological niche is analogous to a volume in environmental space, which enables positive population growth, we can follow a distribution analysis [27]. SDMs can only measure the realized niche [3], and where species are found in their realized distribution [5]. Therefore, the realized niche (or distribution) of *D. elliptica* corresponds to areas indicated on the map as suitable habitat (Figure 2). However, often variables and / or models fail to answer some questions with certainty, due to limitations, and niche complexity, which results in additional questions like the climatic changes and dynamic species distributions. Although proposals aimed at making more robust species distribution predictions using SDMs, which include new and more refined data [28], will likely result in more reliable predictions [28]. But, often only a few environmental variables (direct predictors) are sufficient and the best approaches clarify the ecological parameters of distributions, species and communities. Discussed in detail how environmental variables and ecological interactions act directly or indirectly to affect species distribution. Species presence at a specific location meets three basic conditions [29]: (1) local conditions support population growth; (2) interactions with other species (predation, competition, and mutualism, among others) result in species persistence; and (3) the locality provides dispersal capacity for species. *D. elliptica* occurs along a latitudinal gradient of approximately 1500 km within the Cerrado, but the distribution is not homogeneous; the species is distributed in the Cerrado *sensu stricto* or open savannas. There are few geographic areas exhibiting suitable characteristics that lack the presence of the species. This is certainly due to one or more of the factors considered above; perhaps local environmental conditions not supporting population growth; or interactions with other species like competitions. *D. elliptica* occurs in isolated geographic areas, therefore, dispersion seems not to be a limiting factor in distribution. Typically, presence or absence of a species in a given location is a combination of many factors. Consider these three conditions spatially and temporally. The Brazilian Cerrado vegetation occupied almost the entire Amazon region as recently as 18,000-13,000 years ago [30], indicating a major biogeography event likely affected all three conditions noted above. Consequently, only species that adapted to changes in environmental conditions following the event (or events) persisted, whereas species unable to adapt migrated or went locally extinct [31]. That in the absence of migration, a species only survives if environmental conditions are favorable [32] while many species need to migrate if ecological and environmental changes arise. This process constitutes a dynamic, termed niche evolution [33], which species and communities constantly confront [31]. Despite the importance of niche factors contributing to species distribution, an understanding of the complexities of each factor can be challenging. For example, long fire-free intervals are rare in mesic savanna, increasing the probability that savanna will transition to forest, whereas low-resource sites are likely to remain as savanna even if fire is infrequent [34]. A species occupies its realized niche, which reflects ecological and environmental data that can be modeled. However, these factors are cumulatively dynamic processes, which exert limitations on modeling ecological niches. Ultimately, modeling serves to simplify our understanding, predict species distributions, and are viable tools required in conservation and management of special status species.

An expeditious, accurate, and cost effective method for predicting species geographic distributions is required in our current climate of rapid biodiversity loss. Our study using *D. elliptica* as a model species demonstrated the usefulness of Maxent in ecological modeling. The model exhibited a high degree of accuracy in its predictions, demonstrated by congruency with satellite image field survey. We conclude that the model should be used frequently for studies of distribution and conservation of Cerrado species that suffer high anthropogenic pressure, including deforestation, fire, and the affects of invasive species, among others factors that have the potential to reduce Brazilian Cerrado biodiversity [35]. The next steps, performing various other studies to the Cerrado region, which are promising to support its preservation.

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