



## Spatial distribution and environmental preferences of 10 economically important forest palms in western South America



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### ABSTRACT

Sustainable management strategies for tropical forest ecosystems require a detailed understanding of the distribution of tropical forest species, limitations on distribution, as well as occurrence patterns in the absence of limitations. In the Americas, many tropical palms (Arecaceae) are locally abundant keystone species that provide a number of non-timber forest products. Here we focus on 10 such species (*Aphandra natalia*, *Attalea phalerata*, *Euterpe oleracea*, *Iriartea deltoidea*, *Mauritia flexuosa*, *Oenocarpus bataua*, *Phytelephas aequatorialis*, *Phytelephas macrocarpa*, and *Phytelephas seemannii*) found in western South America. This study aimed to determine: (i) what variables control potential species distribution, (ii) whether their distribution is spatially constrained and if so, (iii) how their potential ranges compare to their actual ranges. We built species distribution models using Maxent software with three groups of predictor variables: C (climatic), N (non-climatic environmental), S (spatial), and combinations thereof: C, CN and CNS. The CNS predictor variable combination gave superior predictive ability based on median Area Under the Curve (AUC) values and was consistent with available range maps. In contrast, individual C and CN predictor variables gave inferior AUC values and showed less similarity to range maps. We concluded that the CNS model that combined climatic, non-climatic, and spatial variables best represented the actual distribution of the 10 palm species, whereas C and CN models approached their potential distribution. Precipitation during the driest quarter and annual precipitation were the most important predictors of the potential distribution, whereas temperature of the coldest month, soil, and the Normalized Difference Vegetation Index (NDVI) were less important. We found that the actual distributions of palm species were spatially constrained, and that the spatial variables largely coincided with the dispersal barriers of the Andean Cordillera and past climatic fluctuations. The estimated potential range varied from nearly equal to the actual range, to up to  $0.55 \times 10^6$  km<sup>2</sup> ( $55.1 \times 10^6$  ha) larger than the actual range, depending on model, threshold settings, and species. We thus concluded that current palm resources in the forests of western South America have major potential for ecological expansion. These results are relevant to current palm management and resource conservation planning, as well as future strategies that will have to address climate change and increasing human disturbance.

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### 1. Introduction

Tropical forests provide a wide array of ecosystem services and non-market foods, which can account for 47–89% of the “GDP of the poor” (TEEB, 2010). Under these circumstances, tropical forests are often overexploited for their timber (MA, 2005). Development of non-timber forest products (NTFPs) is a potential sustainable alternative to timber extraction. NTFPs contribute capital to local economies and provide a safety net for poor inhabitants of nearby

settlements (SCBD, 2010). For many years NTFP extraction has been promoted as “conservation through use”, though it may not always function as such (SCBD, 2010). Whether promoted as a conservation mechanism or not, NTFP extraction from tropical forests should be developed and refined as a tool for preventing overexploitation and depletion of forest resources. Sustainable management of NTFPs should be implemented whenever possible.

Large scale sustainable management of economically important tropical forest species requires information on their spatial distributions, which also serves as a proxy for their availability as resources. The study of what drives distribution, including climatic, environmental or historical factors, provides insight into the species’ environmental preferences. Given the uncertain future of climate change and increasing human impacts (Wright, 2005), monitoring change in tropical forest ecosystems requires more

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detailed knowledge of ecological niches. Understanding of ecosystem constraints can also inform sustainable management plans intended to mitigate the consequences of climate change (Guisan and Thuiller, 2005). Most tropical species' distributions and requirements remain undocumented (Whittaker et al., 2005). Efforts in recent years to digitally catalog geo-referenced palm locality data in western South America have provided excellent opportunities for modeling spatial distributions and palm resource potential. Species distribution modeling (SDM) provides clues concerning distributional drivers and produces maps of habitat suitability that suggest probability of occurrence. SDM is a widely used method for developing conservation strategies and ecosystem management plans (Franklin, 2009; Guisan and Thuiller, 2005; Whittaker et al., 2005). In resource management for example, SDM's have been used to identify suitable locations for reintroduction of threatened species (Franklin, 2009; Pearce and Lindenmayer, 1998).

For the purpose of modeling the distribution of economically important, tropical American palms, we define *fundamental niche* following Hutchinson (1957), as a multidimensional environmental space within which abiotic conditions are suitable for the species. In geographical space, the fundamental niche corresponds to the *potential distribution*. The related *actual distribution* is the area in geographical space where the species has been observed (Pearson, 2007). In environmental space, this corresponds to the *occupied niche* (or *realized niche* according to Guisan and Thuiller (2005)). The actual distribution of most populations differs from their potential distribution (Svenning and Skov, 2004) due to exclusion by biotic interactions and dispersal barriers (Guisan and Thuiller, 2005; Pearson, 2007). Spatial constraints are often ignored in SDM's (Guisan and Thuiller, 2005). Recent studies have shown however that implementation of spatial filters can yield more accurate estimates of actual distribution ranges (Blach-Overgaard et al., 2010).

Palms (Arecaceae) are abundant in tropical forests of the Americas. Their overarching influence on the structure and functioning of these ecosystems indicates that they are a keystone species (Balslev et al., 2011). Palms are significant in terms of their high local densities, biomass, vegetative cover, effects on recruitment of plants, influence on nutrient turnover, and their interactions with herbivores, dispersers, and pollinators (Montúfar et al., 2011). Palms also support the livelihood of local communities by providing food such as fruits and oil, construction materials, handicraft materials, and fibers (Balslev, 2011; Macía et al., 2011). Palm products satisfy a relatively high proportion of the basic needs of indigenous populations and subsistence farmers living in proximity to tropical forests (Macía et al., 2011). The export of wild palm products such as fiber, handicraft, and palm hearts to regional and international markets also provides local communities with cash income (Brokamp et al., 2011). These conditions have created incentives for destructive levels of palm extraction from natural forest stands. Several species are approaching local extinction in many areas of western South America due to unsustainable management practices (Bernal et al., 2011).

In this study we model the distribution of 10 native, medium-to wide-ranging, wild and commercially significant, keystone palm species in western South America (Table A1, Appendix A). The purpose of our study was to identify environmental preferences of the palms and map the potential extent of the resources they represent. As described above, this information can enhance decision-making in land use, conservation, and management planning. In this context, we asked the following specific questions: (1) what are the most important variables controlling the potential distributions of palms, (2) are they spatially constrained, and in the affirmative case, (3) how do their potential ranges compare to their actual ranges?

**Table 1**

Total occurrence records from datasets and unique occurrence records input into Maxent models of 10 economically important South American palm species. The data were downloaded from the GBIF data portal ([www.gbif.org](http://www.gbif.org); see Table 2 for data providers) on the 30th of August and the 26–27th of October 2011. Nomenclature follows Govaerts and Dransfield (2005), except for *Phytelephas macrocarpa*, which here includes *Phytelephas tenuicaulis*, originally described as a subspecies by Barfod (1991).

Species	Total occurrence records	Unique occurrence records
<i>Aphandra natalia</i>	895	32
<i>Astrocaryum chambira</i>	1128	149
<i>Attalea phalerata</i>	1176	60
<i>Euterpe oleracea</i>	66	42
<i>Iriartea deltoidea</i>	1546	240
<i>Mauritia flexuosa</i>	1776	102
<i>Oenocarpus bataua</i>	179,05	222
<i>Phytelephas</i> <i>aequatorialis</i>	31	27
<i>Phytelephas</i> <i>macrocarpa</i>	680	35
<i>Phytelephas</i> <i>seemannii</i>	26	13

## 2. Methods

### 2.1. Building species distribution models

Geo-referenced occurrence records of the 10 palm species (Table 1) were downloaded from the Global Biodiversity Information Facility (GBIF) data-portal (<http://data.gbif.org>) (Table 2). Although our study area spanned western South America (here defined as Colombia, Ecuador, Peru, and Bolivia), we built our models based on occurrence data from the entire equatorial to tropical region of South and Central America (15°N–23.4°S) in order to make them more robust (Elith et al., 2011; VanDerWal et al., 2009).

We used three groups of predictor variables to model probability of occurrence: C (climatic), N (environmental but non-climatic), S (spatial) and their combinations: C, CN, and CNS (Table 3). Each of these variables played a significant role in continent-scale distribution studies of African palms (Blach-Overgaard et al., 2010) and we therefore assume that they affect palm distribution in tropical ecosystems of the Americas as well.

We used Maxent software, which is a species distribution modeling program based on a general-purpose machine learning method (Phillips et al., 2006). Maxent has been shown to outperform other presence-only methods (Elith et al., 2006; Phillips and Dudík, 2008).

We selected *climatic variables* from the Worldclim dataset (Hijmans et al., 2005) based on Blach-Overgaard et al.'s (2010) study of distribution of African palms. The variables include annual mean temperature (Bio\_1), minimum temperature of the coldest month (Bio\_6), annual precipitation (Bio\_12), and precipitation of the driest quarter (Bio\_17) (Table 3; Fig. C1, Appendix C). Our *non-climatic variables* represent both environmental variability of the habitat and human impact. These include mean monthly values of Normalized Difference Vegetation Index (NDVI\_mean) and standard deviation of monthly NDVI (NDVI\_sd) (EDIT Geoplatform, 2010) (Table 3, Fig. C2, Appendix C). The non-climatic variable Soil was derived from the Harmonized Soil Database, which classifies global soil types into 28 different categories (Fisher et al., 2008) (Table 3; Fig. C2, Appendix C). The other non-climatic variable Slope was computed with the Surface Analysis tool in ArcGIS 10.0 (ESRI, Redlands, CA, USA) on the basis of elevation data produced by the digital elevation model from the Shuttle Radar Topography Mission (SRTM), and then post-processed in a 3 arc second grid (Jarvis et al., 2008) (Table 3; Fig. C2, Appendix C). We also included Human Influence Index (HII) derived

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