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Potential geographical distribution of the red palm mite in South America

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Abstract Among pests that have recently been introduced into the Americas, the red palm mite, *Raoiella indica* Hirst (Prostigmata: Tenuipalpidae), is the most invasive. This mite has spread rapidly to several Caribbean countries, United States of America, Mexico, Venezuela, Colombia and Brazil. The potential dispersion of *R. indica* to other regions of South America could seriously impact the cultivation of coconuts, bananas, exotic and native palms and tropical flowers such as the Heliconiaceae. To facilitate the development of efficacious *R. indica* management techniques such as the adoption of phytosanitary measures to prevent or delay the dispersion of this pest, the objective of this paper was to estimate the potential geographical distribution of *R. indica* in South America using a maximum entropy model. The *R. indica* occurrence data used in this model were obtained from extant literature, online databases and field sampling data. The model predicted potential suitable areas for *R. indica* in northern Colombia, central and northern Venezuela, Guyana, Suriname, east French Guiana and many parts of Brazil, including Roraima, the eastern Amazonas, northern Pará, Amapá and the coastal zones, from Pará to north of Rio de Janeiro. These results indicate the potential for significant *R. indica* related economic and social impacts in all of these countries, particularly in Brazil, because the suitable habitat regions overlap with agricultural areas for *R. indica* host plants such as coconuts and bananas.

Keywords *Raoiella indica* · Niche modeling · Environment suitability · Coconut

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Introduction

The red palm mite, *Raoiella indica* Hirst (Prostigmata: Tenuipalpidae), is an invasive pest recently introduced into neotropical regions. In the Old World, it was initially reported in India (Hirst 1924) and later in northeast Africa (Pritchard and Baker 1958), southern Africa (Moutia 1958) and the Middle East (Gerson et al. 1983). In the neotropics, *R. indica* was first reported in 2004 in Martinique (Flechtmann and Etienne 2004) and despite quarantine measures established by some countries, it rapidly dispersed to several Caribbean islands (Kane et al. 2005; Etienne and Fletchmann 2006), southern Florida (Welbourn 2006), Mexico (NAPPO 2009), Venezuela (Vásquez et al. 2008), Colombia (Carrillo et al. 2011b) and northern Brazil (Navia et al. 2011; Rodrigues and Antony 2011). Following the discovery of *R. indica* in the Brazilian state of Roraima in 2009, the Brazilian Ministry of Agriculture, Livestock and Supply established quarantine measures restricting the transit of host plants and their parts (fruits and leaves) to other states. However, 2 years ago, *R. indica* was also found to be infesting coconuts (*Cocos nucifera* L.), dwarf royal palms [(*Veitchia merrillii* (Becc.) H. E. Moore] and fishtail palm trees (*Caryota mitis* Lour.) (Rodrigues and Antony 2011).

The initial reported host range of *R. indica* was limited to Arecaceae plants such as coconut (Sayed 1942; Moutia 1958; Kapur 1961). However, since its introduction in the Americas, this mite has expanded its host plant range to 96 reported plant species: Arecaceae (75 species), Cannaceae (1), Heliconiaceae (5), Musaceae (6), Pandanaceae (1), Strelitziaceae (2) and Zingiberaceae (6) (Cocco and Hoy 2009; Navia et al. 2012).

The potential impact of *R. indica* in South America is high, particularly for coconuts, bananas and flowers of the Heliconiaceae, Musaceae, Zingiberaceae and Strelitziaceae families. The presence of *R. indica* in the production areas for these host plants may affect exportation of these plants to other counties and non-infested areas due to the imposition of sanitary barriers (Navia et al. 2012). Additionally, particularly in the northern and northeastern regions of Brazil, exotic and native palms such as açaí (*Euterpe oleracea* Mart.), moriche palms (or burit, *Mauritia flexuosa* L.) and peach palm (*Bactris gasipaes* Kunth.), play important economic and social roles, especially for low-income populations that depend on their fruit.

To reduce problems associated with *R. indica* infestation in areas in which it has already been introduced, control methods such as plant resistance (Rodrigues and Irish 2011), chemical controls (Rodrigues and Peña 2012) and biological controls (Peña et al. 2009; Carrillo et al. 2010, 2011a, 2012; Carrillo and Peña 2011; Hoy 2012) have been investigated. The prediction of potential suitable habitats for this invasive species is important to support these studies and the implementation of phytosanitary measures to prevent or delay the dispersion of *R. indica* in South America.

Species distribution modeling (SDM), in which predictive models of geographic distributions of species are developed based on the environmental conditions (suitable habitat) of sites where the species is known to be present, has applications in conservation planning, ecology, evolution, epidemiology, invasive-species management and other fields (Yom-Tov and Kadmon 1998; Corsi et al. 1999; Peterson et al. 1999; Scott et al. 2002; Welk et al. 2002; Peterson and Shaw 2003).

When both absence and presence data are available for modeling, general-purpose statistical methods such as generalized linear models (GLM), generalized additive models (GAM), classification and regression trees (CARTs), principal component analysis (PCA) and artificial neural networks (ANNs) (Guisan and Zimmermann 2000; Moisen and Frescino 2002; Guisan et al. 2002; Berg et al. 2004) can be used. However, while presence-only data are abundant, absence data are limited (Soberón 1999; Ponder et al. 2001; Anderson et al. 2002). In addition, even when absence data are available, they may be of questionable value in many situations (Anderson et al. 2003). Thus, modeling techniques that require only presence data are extremely valuable (Graham et al. 2004). Therefore, a second group of methods, including genetic algorithms (GARP) (Stockwell and Peters 1999) and Bioclim (Busby 1991), is gaining more consideration. The recently proposed maximum entropy (Maxent) algorithm (Phillips et al. 2006) permits the use of presence-only data and categorical predictors.

Maxent outperforms many different modeling methods (Elith et al. 2006; Ortega-Huerta and Peterson 2008) and may remain effective despite small sample sizes (Hernandez et al. 2006; Pearson et al. 2007; Papes and Gaubert 2007; Wisz et al. 2008; Benito et al. 2009). Elith et al. (2006) demonstrated that Maxent performed better than more established methods such as Bioclim, GARP, GAM and GLM. In addition, Barry and Elith (2006) noted that Maxent, GLM and GAM were similar in their ability to fit nonlinear response surfaces, which are frequently observed in biological data. Hernandez et al. (2006) tested four modeling methods and demonstrated that Maxent had the strongest performance among the tested methods because it performed well and its prediction accuracy remained reasonably stable across all sample size categories, producing maximal accuracy levels for the smallest sample size categories. Sérgio et al. (2007) showed that Maxent outperformed GARP when applied to presence-only herbarium collection data.

Maxent is a machine learning algorithm which estimates the distribution of the species by finding the probability distribution of maximum entropy (i.e., the closest uniform as possible) subject to constraints representing the incomplete information about the distribution. The constraints are that the expected value of each environmental variable should match its average over sampling locations from environmental layers (Phillips et al. 2006). Maxent searches for the statistical model that produces the most uniform distribution but still infers as accurately as possible the observed data. To do that, it compares the presence-only records with random data extracted automatically from all the background (including the species records; see Phillips et al. 2006), or ‘pseudo-absence” data.

The pseudo-absences represent true absences, being considered an intermediate methodological approach between presence-only and presence-absence distribution modes (Pearce and Boyce 2006; Sillero et al. 2010). The aim here is to assess differences between the occurrence localities and a set of localities chosen from the study area that are used in place of real absence data. The pseudo-absences points may be selected randomly (Stockwell and Peters 1999) or according to a set of weighting criteria (Engler et al. 2004; Zaniewski et al. 2002). Random selection of pseudo-absences has recently been found to outperform selection of pseudo-absences in low suitability areas (Wisz and Guisan 2009).

To facilitate the development of a strategy for the surveillance, quarantine and control of *R. indica*, the purpose of this paper was to estimate the potential geographical distribution of this mite using the Maxent model.

Materials and methods

Raoiella indica occurrence data

The geographical coordinates available for *R. indica* were obtained from existing literature, online databases (CABI 2012; EPPO 2012) and new field sampling data from the states of Roraima and Amazonas. When just a state or county was cited, the coordinates for a point near the center of the polygon representing that region were used. Altogether, 92 known *R. indica* locations were used in the model (Table 1 in supplementary material; Fig. 1).

Environmental variables

Twenty environmental variables were considered as potential predictors of *R. indica* habitat distribution (Table 1), including nineteen bioclimatic variables (Nix 1986) that are biologically meaningful for defining the eco-physiological tolerances of a species (Graham and Hijmans 2006; Murienne et al. 2009) and one topographic variable (digital elevation model—DEM), as a proxy for missing environmental variables. All variables were obtained from the WorldClim (http://www.worldclim.org/) current (~1950–2000) database version 1.4, release 3 (Hijmans et al. 2005), as generic 2.5 arc-min grids.

Modeling procedure

Maxent software version 3.3.3 k was used with the following settings: auto features (feature types are automatically selected depending on the training sample size), logistic output format (provides an estimate of presence probability), random seeds, replicates = 5, replicate run type = cross validate (Hope et al. 2010), regularization multiplier = 1, maximum iterations = 2,000, convergence threshold = 10^{-5} and maximum number of background points = 20,000 (Phillips and Dudik 2008). The model was developed based on all *R. indica* occurrences and projected onto South America to assess the potential geographic distribution of *R. indica*.

Cross-validation is a straightforward, rapid and useful method for resampling data for training and testing models (Kohavi 1995; Hastie et al. 2009). In cross-validation, the occurrence data is randomly split into a number of equal-sized groups called "folds" and models are created sequentially by omitting each fold. The removed folds are used for evaluation. Cross-validation has one important advantage over using a single training/test split: it uses all of the data for validation, thus making better use of small data sets (Phillips et al. 2012).

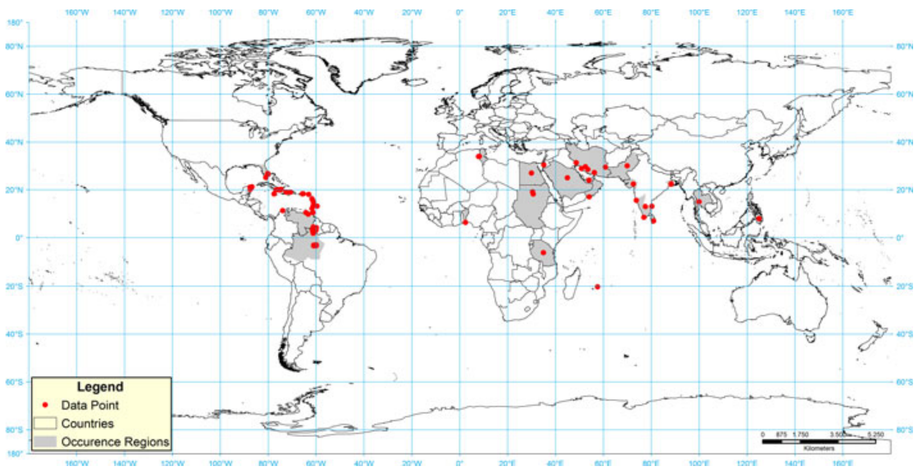

Fig. 1 *Raoiella indica* occurrence worldwide

Table 1 Environmental variables used and estimative of its relative contributions to the Maxent model

Variable mnemonic	Variable	% contribution
Alt	Altitude (digital elevation model)	17.7
Bio01	Annual mean temperature	3.1
Bio02	Mean diurnal range [mean of monthly (max − min)]	0.7
Bio03	Isothermality (Bio02/Bio07) × 100	2.6
Bio04	Temperature seasonality (standard deviation × 100)	5.1
Bio05	Max temperature of warmest month	0.1
Bio06	Min temperature of coldest month	22.5
Bio07	Temperature annual range (Bio05–Bio06)	3.1
Bio08	Mean temperature of wettest quarter	0.2
Bio09	Mean temperature of driest quarter	2.5
Bio10	Mean temperature of warmest quarter	0.7
Bio11	Mean temperature of coldest quarter	20.4
Bio12	Annual precipitation	2.5
Bio13	Precipitation of wettest month	0.4
Bio14	Precipitation of driest month	4.6
Bio15	Precipitation seasonality (coefficient of variation)	4.9
Bio16	Precipitation of wettest quarter	1.6
Bio17	Precipitation of driest quarter	0.1
Bio18	Precipitation of warmest quarter	2.3
Bio19	Precipitation of coldest quarter	4.8

The jackknife approach (Yost et al. 2008; Phillips et al. 2012) was used to assess variable importance. This approach excludes one variable at a time when running the model, by training with each environmental variable first omitted and then used singly. In so doing, it provides information on the performance of each variable in the model in terms of how important each variable is at explaining the species distribution and how much unique information each variable provides.

The area under the curve (AUC) of the receiver operated characteristics (ROC) was used to test the agreement between observed species presence and projected distribution (Manel et al. 2001). The ROC plot relates the sensitivity (proportion of observed presences correctly predicted) with 1-specificity (proportion of observed absences/pseudo-absences incorrectly predicted). To develop a ROC plot, a certain percentage of the data is selected for training data; the other portion is used for test data. A good model is defined by a curve that maximizes sensitivity for low values of the false-positive fraction. The significance of this curve is quantified by the AUC and has values that typically range from 0.5 (no better than the expected by random) and 1.0 (perfect fit). Values <0.5 indicate that a model fits worse than random (Fielding and Bell 1997; Engler et al. 2004; Hernandez et al. 2006; Baldwin 2009).

Results

We performed Maxent modeling on 69 training and 17 testing presence records in a fivefold cross-validation run that considered all occurrence points. The average AUCs were

0.9691 and 0.9469 for the training and test data, respectively, suggesting that the model had high predictive power.

The environmental variables that most influenced the predictions were ‘Minimum temperature of coldest month’ (22.5 %), ‘Mean temperature of coldest quarter’ (20.4 %), ‘Altitude’ (17.7 %), ‘Temperature seasonality’ (5.1 %). The influence of all other variables was 5 % or less (Table 1). The environmental variable with the highest gain when used in isolation (red bars in Fig. 2) was the minimum temperature of the coldest month (Bio06). The variable that decreased the gain most when it was omitted (blue bars in Fig. 2) was the altitude (alt). The values in Fig. 2 are averages over five replicated runs.

A suitable habitat world map for *R. indica* is presented in Fig. 3. The predicted occurrence is in good agreement with the occurrence data. However, the model predictions suggest that there is more suitable habitat than is currently occupied and indicate that *R. indica* may still be in the early stage of invasion. According to the potential distribution in South America, the area suitable for *R. indica* is wider than the area defined thus far by the occurrence points. The modeled suitable habitat areas range from northern to central South America, with the greatest suitability in northern Colombia, east, west and central Venezuela, Guyana, Suriname, east French Guiana and parts of Brazil. Other countries have regions with moderate suitability, such as the coast of Ecuador, eastern Peru, central and northern Bolivia and central Paraguay (Fig. 4).

In Brazil, the most suitable areas were mainly restricted to the coastal zones and the Amazon basin. The projection of the occurrence data points onto Brazil showed that the predicted occurrence included the actual distribution in Roraima and Manaus (Amazonas) but also suggested that other areas in the Brazilian Amazon, such as the eastern Amazonas state, the northern Pará state, the southern Amapá state and northern Maranhão, may also be habitable (Fig. 4). The entire coasts of northeastern (from Piauí, Ceará, Rio Grande do Norte, Paraiba, Pernambuco, Alagoas to Bahia) and southeastern (Espírito Santo and Rio

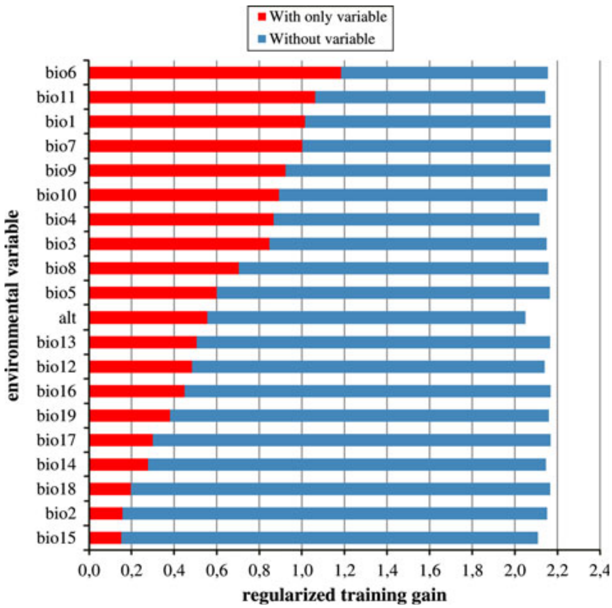

Fig. 2 Jackknife test of regularized training gain for *Raoiella indica* modeling

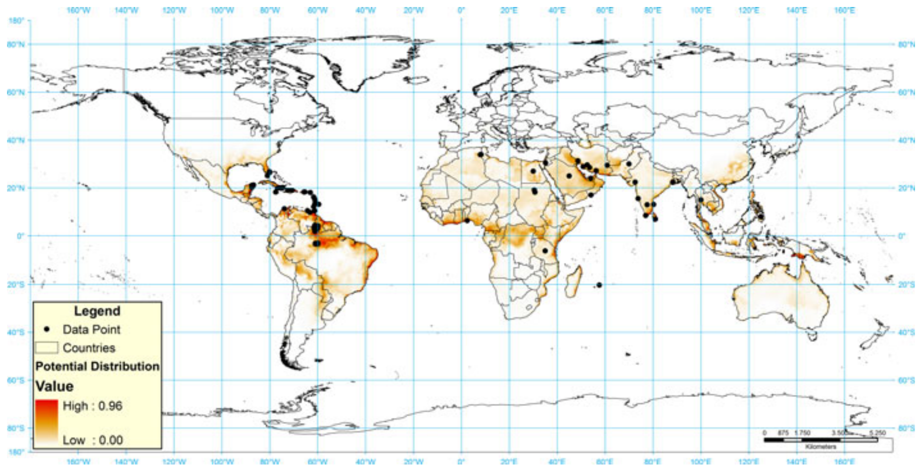

Fig. 3 Modeled potential *Raoiella indica* distribution around the world using Maxent

de Janeiro) Brazilian also exhibited a high probability of *R. indica* occurrence (Fig. 4). Mato Grosso do Sul and southeastern São Paulo exhibited moderate suitability.

Discussion

Raoiella indica SDM (Fig. 4) represents an approximation of the potential geographical distribution based in its fundamental ecological niche in the examined environmental dimensions (South America). The fundamental niche of a species consists of a set of all conditions that permit its long-term survival, whereas the realized niche of the species is the subset of the fundamental niche that is actually occupied (Hutchinson 1957). The realized niche of the species may be smaller than its fundamental niche, due to human influence, biotic interactions (e.g., inter-specific competition or predation), or geographic barriers that have hindered dispersal and colonization; such factors may prevent the species from inhabiting (or even encountering) conditions encompassing its full ecological potential (Pulliam 2000; Anderson and Martinez-Meyer 2004).

The selection of optimal areas within the fundamental niche may also limit the extent of the realized niche (Hutchinson 1978). A species may be absent from suitable habitats because of local extinction events or limited dispersal ability, or it may occur in a sink habitat in which its population growth rate is <1 and thus would disappear without constant immigration from source habitats (Guisan and Thuiller 2005). In this sense, SDM is used to inductively interpolate or extrapolate fundamental niches outside the locations where a species is present (i.e., the realized niche) by relating species presence to environmental predictors (Franklin 1995).

Temperature and altitude seem to be the limiting factors in *R. indica* dispersion. The minimum temperature of the coldest month, mean temperature of coldest quarter and altitude were the variables that most influenced the *R. indica* distribution predictions; accordingly, the most suitable niches for *R. indica* in South America overlapped warm regions with low temperature variation and low altitude. Dynamic population studies of *R. indica* performed in India on coconut and on areca palm indicated positive relationships

Fig. 4 Modeled potential *Raoiella indica* distribution in South America using Maxent

between the population density of this mite and temperature (Nagesha-Chandra and Channabasavanna 1983; Sarkar and Somchoudhury 1989; Yadavbabu and Manjunatha 2007; Taylor et al. 2011). In these studies, *R. indica* densities were significantly higher in April through June when the maximum temperature was approximately 38 °C, the minimum temperature was 22 °C and the average temperature was 30 °C. Relative humidity also affects *R. indica* and higher densities of this mite were found in drier and warmer conditions (Nagesha-Chandra and Channabasavanna 1983; Taylor et al. 2011). Taylor et al. (2011) observed that density increases during these months appeared to be related to mite dispersal. *R. indica* can disperse on wind currents, tropical storms and through the transport of infected plant material (Welbourn 2006; CABI 2012). On Caribbean islands and in Florida, this pest appears to have spread through the movement of infested palm souvenirs such as hats, baskets, rugs, bowls and purses (Mendonça et al. 2005).

If we conservatively assume that the predicted distribution map presented is a proxy for invasion potential, the Amazon states and the northeastern Brazilian coasts must be considered especially sensitive because they are important locations for the production of bananas, coconuts and other economically important palm species such as açaí, moriche palm (buriti) and peach palm. The coconut has been considered the main host of *R. indica* (Carrillo et al. 2010; Peña et al. 2009) and infestations of this plant with densities of up to 4,000 mites/leaflet have been reported (Duncan et al. 2010). *R. indica* causes a severe yellowing of the leaves followed by tissue necrosis (Flechtmann and Etienne 2004) and severe attacks have caused significant reductions in fruit production (Navia et al. 2011). Brazil is the fourth largest coconut producer in the world and has an estimated annual production of 2.7 million tons and a cultivation area of 287,000 ha and its production comprises more than 80 % of all coconuts cultivated in South America (FAO 2011). At least 70 % of Brazilian coconut production is located in the northern and northeastern coastal regions (IBGE 2012), which coincide with the most suitable regions for *R. indica*. In these regions, the coconut is cultivated by small family-based farmers who adopt few modern production technologies and therefore may be greatly affected by possible production losses due to *R. indica* infestation. High *R. indica* population levels on banana plantations have been reported and attacked plants exhibit yellow leaf margins (Cocco and Hoy 2009; Kane et al. 2005). The banana as a host plant is of special social and economic interest in South America because this continent accounts for approximately 19 % of worldwide banana production. Brazil and Ecuador, respectively, are the fourth and fifth largest banana producers in the world (FAO 2011). The suitable *R. indica* niches in Brazil overlap the four states with the largest banana production, Bahia, São Paulo, Ceará and Pernambuco (IBGE 2012).

The açaí may be the native palm most affected by the possible establishment of *R. indica* in the Brazilian Amazon. In 2012, Brazil produced 124,421 t of açaí. More than 85 % of the production was concentrated in Pará (IBGE 2012), a state with high suitability for *R. indica* habitat (Fig. 4). While there are no studies on the potential damage that this mite can cause to açaí plants, this is an area of potential concern that should be investigated.

The recent introduction of *R. indica* in Manaus (Amazonas, Brazil) (Rodrigues and Antony 2011) may facilitate the spread of this mite to other regions due to the large movement of people to and from this city, especially via boats to the state of Para. Additionally, the continuity of suitable *R. indica* regions may facilitate and accelerate its dispersion in Brazil. In particular, the entire northern region and the Brazilian coasts have ideal environmental conditions for *R. indica* and present a large and diverse population of potential hosts for this mite.

Both, an extensive suitable habitat and the high likelihood of human-aided spread, indicate that invasive species such as *R. indica* could have a large potential economic impact on production areas in South America. Researchers must develop extensive measures to avoid their rapid spread on this continent. Additionally, further research is needed to understand the population dynamics of *R. indica* in South America and the real host range of this mite because there are multiple potential native and exotic host species in this continent.

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