Potential geographic distribution of two invasive cassava green mites

Soroush Parsa[1], Aymer Andrés Vásquez-Ordóñez[1], Qing Chen[2], Fuping Lu[2], Beatriz Vanessa Herrera Campo[1], John Stephen Yaninek[3]

[1]Centro Internacional de Agricultura Tropical (CIAT), Apartado Aéreo 6713, Cali, Colombia

[2]Environment and Plant Protection Institute, China Academy of Tropical Agriculture Sciences (CATAS), Haikou, China

[3] Department of Entomology, Purdue University, 901 W. State Street, West Lafayette, IN 47907, United States

Address correspondence to:

Soroush Parsa
CIAT (Centro Internacional de Agricultura Tropical)
A.A. 6713, Cali, Colombia, S.A.
Phone: +57 (2) 4450000
Fax: +57 (2) 4450073
Email: s.parsa@cgiar.org

Abstract

The cassava green mites *Mononychellus tanajoa* and *M. mcgregori* are highly invasive species that rank among the most serious pests of cassava globally. To guide the development of appropriate risk mitigation measures preventing their introduction and spread, this article estimates their potential geographic distribution using the maximum approach to distribution modeling. We compiled 1,232 occurrence records for *M. tanajoa* and 99 for *M. mcgregori*, and relied on the CliMond climate database as a source of environmental predictors. In addition to the distribution models, we conducted statistical analyses comparing the climates where they occur. The models predicted different potential distribution patterns for the two. Outside their native range in the Americas, *M. mcgregori* seems better adapted to survive in Southeast Asia and *M. tanajoa* to Africa. The statistical analyses suggested that unlike *M. tanajoa*, *M. mcgregori* can survive locations without a pronounced dry season, potentially explaining its predicted distribution across equatorial climates. Our results should help decision-makers assess the site-specific risk of cassava green mite establishment, and develop proportional risk mitigation measures to prevent their introduction and spread. These results should be particularly timely to help address the recent detection of *M. mcgregori* in Southeast Asia.

Keywords: cassava green mite, *Manihot esculenta*, *Mononychellus tanajoa*, *Mononychellus mcgregori*, pest risk map, species distribution modeling

Introduction

About 800 million people in the tropics depend on cassava (*Manihot esculenta*) as a source of food and income (Lebot 2009). Its production, however, can be severely limited by a complex of arthropod pests (Bellotti and van Schoonhoven 1978; Bellotti et al. 1999). Top among these pests are a few Neotropical mite species of the genus *Mononychellus*, commonly known as the “cassava green mites” (Bellotti et al. 2012). The most notorious species is *M. tanajoa*, whose accidental introduction into Africa in the 1970s reduced cassava yields by up to 80% (Yaninek 1988; Yaninek and Herren 1988). Although largely understudied, *M. mcgregori* follows in importance. This species was first detected in China in 2008 (Lu et al. 2014a), and shortly thereafter begun causing yield losses reaching up to 60% (Chen et al. 2010: cited in Lu et al., 2014). A year later, *M. mcgregori* was reported in Vietnam and Cambodia (Bellotti et al. 2012; Vásquez-Ordóñez and Parsa 2014), raising concerns over its potential spread throughout the region.

Cassava green mites feed only on cassava (Bellotti et al. 2012). They are most abundant at the top of the canopy, from the shoot tip to the youngest unfolded leaves (Bellotti and van Schoonhoven 1978). Their feeding kills leaf cells and reduces photosynthesis, interfering with normal leaf development (Yaninek and Herren 1988). Under field conditions in the tropics, cassava green mites have overlapping generations, each completed in less than one month, and are most abundant during dry seasons and at the beginning of the rain season (Bellotti and van Schoonhoven 1978). Early rains cause a flush of new leaf growth that promotes their rapid population growth (Yaninek et al.

1989). Continued rains eventually help suppress them to sub-economic levels through a combination of plant compensation and rainfall mortality (Yaninek et al. 1989). Green mites can also be suppressed to sub-economic levels by phytoseiid mites (Bellotti et al. 2012), which have been successfully deployed in classical biological control against *M. tanajoa* in Africa (Yaninek and Hanna 2003). A similar effort has been advocated to control *M. mcgregori* in Asia (Bellotti et al. 2012), but its potential remains to be investigated.

Pest risk maps, based on models estimating climatic suitability for a species, are important decision-support tools for the management of invasive pests (Venette et al. 2010). They can be based on two complementary approaches: (1) the mechanistic or deductive approach, which relies on the species' physiological data (Kearney and Porter 2009); and (2) the correlative or inductive approach, which relies on the species' occurrence data (Elith and Leathwick 2009). When a pest's biology is still poorly known, correlative models provide the most rapid and effective means to develop risk maps (Venette et al. 2010).

This article responds to the need to better assess and address the risk of invasive cassava green mites, emphasizing the invasion of *M. mcgregori* in Asia. Our principal objective was to develop correlative models predicting their potential geographic distribution, therefore guiding site-specific risk mitigation strategies. The resulting risk maps could also be used to identify exploration sites for natural enemies with a high probability of establishment in the affected locations.

Materials and methods

Occurrence data

We compiled occurrence data (i.e. presence-only) from three sources. Native distribution records for both species originated from a database submitted by the International Center for Tropical Agriculture (CIAT, its Spanish acronym) to the Global Biodiversity Information Facility (GBIF; Vásquez-Ordóñez and Parsa 2014). Because this source covers areas where the species co-occur, and may be confounded without proper mounting, we only extracted specimen-based records from it. Exotic distribution records of *M. tanajoa* in Africa originated from a database compiled by the International Institute of Tropical Agriculture (IITA), as part of the monitoring efforts of their Africa-wide Biological Control Programme (ABCP; Yaninek 1988; Yaninek and Herren 1988). Exotic distribution records of *M. mcgregori* in Asia originated partly from specimen-based records submitted to GBIF (Vásquez-Ordóñez and Parsa 2014) and partly from published records reporting its invasion in Hainan, China (Lu et al. 2012). This last source originally misreported the species as *M. tanajoa*, subsequently correcting its identification after submitting samples for verification to CIAT's Arthropod Reference Collection. Subsequent publications by the authors report the species as *M. mcgregori* (e.g., Lu et al. 2014a).

Environmental data

Our source of environmental data for species distribution modeling was the CliMond database (Kriticos et al. 2012), from which we derived 19 global bioclimatic variables summarizing annual trends, seasonality and extreme conditions during 1961-1990 at a 10’ spatial resolution. We favored CliMond as a source of environmental data because it is thought to combine the best features of the WorldClim CRU climatic databases (Kriticos et al. 2012).

Distribution modeling

Our species distribution modeling relied on the maximum entropy approach implemented in Maxent (version 3.3.3k; Elith et al. 2011; Phillips et al. 2006; Phillips et al. 2004), one of the best performing methods to model presence-only occurrence data (Elith et al. 2006). The bioclimatic variables were used as environmental layers to predict the occurrences. The models for both species were run selecting the auto features, logistic output and random seed, with the regularization multiplier maintained at 1 and the maximum number of background points maintained at 10,000. To ensure model convergence, we increased the maximum iterations to 5,000, maintaining the convergence threshold at 0.00001. The test values were obtained by running 15 subsampled replicates of the model with 25% of observations held out for validation. We used the Area Under the Curve (AUC) to assess model performance and the jackknife functionality to assess variable importance. Following the guidelines of Thuiller et al. (2005), we considered models with $0.8<AUC<0.9$ “fair,” $0.9<AUC<0.95$: “good,” and $0.95<AUC<1$: “very good.”

Statistical analyses

To test for differences between *M. tanajoa* and *M. mcgregori* climatic niches, we used the statistical software JMP (v 8.0.2.) to implement one-way analyses of variance (ANOVA) of each bioclimatic variable against a categorical variable for the two species.

Results

A total of 1,232 occurrence records for *M. tanajoa* and 99 for *M. mcgregori* were compiled. Their distribution shows some level of geographic overlap within their native range in South America (Fig. 1). Outside this range, *M. tanajoa* occurrence is restricted to Africa and *M. mcgregori* to Southeast Asia (Fig. 1).

Maxent-based predicted distributions are presented in Figure 2. The average test AUC for the 15 replicate runs was 0.961 for *M. tanajoa* and 0.979 for *M. mcgregori*, indicating "very good" model performance. As would be expected for tropical species, their global distribution was best explained by (low) Temperature seasonality (> 40% contribution), followed by Annual precipitation for *M. tanajoa* and Isothermality for *M. mcgregori* (Table 1). The environmental variables that produced the highest gain when used in isolation were Temperature seasonality for *M. tanajoa* and Temperature annual range for *M. mcgregori*. On the other hand, the environmental variables that decreased the gain the most when omitted were Precipitation of the coldest quarter for *M. tanajoa* and again Temperature annual range for *M. mcgregori*.

On average, *M. tanajoa* and *M. mcgregori* were found in locations with relatively similar temperatures (Table 1). The locations differed, however, with respect to several precipitation variables, with *M. mcgregori* found in locations with greater and more continuous rainfall than *M. tanajoa* (Table 1). Interestingly, *M. mcgregori* was found in locations with no pronounced dry season, with up to 186 mm of rainfall in their driest month (Bio14; e.g., 6°03'23.4"N 75°11'06.4"W). Where it was reported as an invasive pest, however, rainfall in the driest month averaged 20 mm. By contrast, and despite a much larger number of observations, *M. tanajoa* was not found in any location with more than 85 mm of rainfall in its driest month. This difference is also reflected in the predicted distribution map (Fig. 2). For example, the Congo Basin, an area where high rainfall limits the establishment of the cassava mealybug *Phenacoccus manihoti* (Parsa et al. 2012), was rendered suitable for *M. mcgregori* but not for *M. tanajoa* (Fig. 2). The same is true for areas around the equator in Southeast Asia.

Discussion

Our main objective was to predict the potential distribution of *M. tanajoa* and *M. mcgregori* in order to guide the development of appropriate risk mitigation measures. These measures could include the passage of phytosanitary regulations, the establishment of pest-surveillance networks, and the development of emergency response plans to address their potential incursion (Venette et al. 2010). Our predictions should therefore be most valuable for high-risk locations where the species are still absent. In Southeast Asia, for example, these locations include the south of Vietnam for *M. tanajoa* and Indonesia for *M. mcgregori*.

Given the magnitude and spatial coverage of our database, we suspect the risk maps presented here represent the best approximation to *M. tanajoa* and *M. mcgregori's* fundamental niche available to date. A previous effort to model *M. tanajoa* relied on only 215 occurrence records (Herrera Campo et al. 2011), and generated broadly similar predictions to ours, albeit rendering high-rainfall locations more suitable for the species than our model. Our predictions, based on 1,232 records, rendered the same locations relatively unsuitable, but are more consistent with previous research demonstrating rainfall is a primary mortality factor limiting *M. tanajoa* populations (Gutierrez et al. 1988; Yaninek et al. 1989). Previous models of *M. mcgregori* may be less reliable, as they utilized *M. tanajoa* and *M. mcgregori* occurrence records jointly as data inputs (Lu et al. 2014b; Lu et al. 2012), potentially confounding their predicted distributions.

Our results suggest that unlike *M. tanajoa*, *M. mcgregori* typically occurs in locations with no pronounced dry season. Its ability to survive in those locations, however, does not necessarily imply an ability to reach economic status. It is generally believed that cassava green mites need a dry season lasting 2-6 months with rainfall below 60 mm/month to become economic pests (Bellotti et al. 2012; Bellotti et al. 1987). This condition is met across the locations where *M. mcgregori* was reported as an invasive pest in Asia. However, the extent to which *M. mcgregori* may impact cassava during the wet season, or in locations without a dry season, merits empirical attention.

For locations where cassava green mites are already established as invasive pests, classical biological control by phytoseiid predators should be considered. Based on their climatic homology to potential target areas, our predictions suggest Colombia's inter-Andean valleys rank among the best sites to import them from. Explorations conducted in Colombia during the mid 1980s identified 46 phytoseiid species associated with cassava mites (Bellotti et al. 1987). The list includes *Typhlodromalus aripo*, a predator introduced into Africa to target *M. tanajoa*, resulting in a highly successful case of classical biological control (Yaninek and Hanna 2003). Efforts to test the potential of *T. aripo* or an alternative phytoseiid predator against *M. mcgregori* in Asia are therefore warranted.

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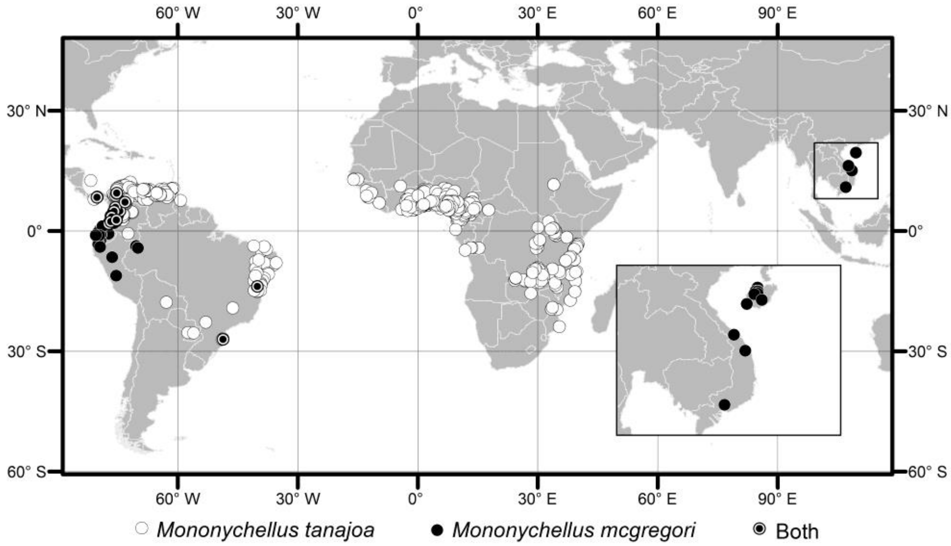
Figure 1. Global occurrence records for *Mononychellus tanajoa* and *M. mcgregori*.

Figure 2. Predicted distribution maps for *Mononychellus tanajoa* (A, C) and *M. mcgregori* (B, D).

Table 1. Environmental predictor variables used to model *Mononychellus tanajoa* and *M. mcgregori* geographic distributions.

		Mean		ANOVA[2]		Maxent % contribution	
Variable	Description[1]	*M. mcgregori*	*M. tanajoa*	F	*p*	*M. mcgregori*	*M. tanajoa*
Bio01	Annual Mean Temperature	24.2	25.0	7.7	0.0056	0	0.5
Bio02	Mean Diurnal Range (Mean of monthly (max temp - min temp))	10.1	10.2	0.7	0.3975	2.5	2.3
Bio03	Isothermality (BIO2/BIO7) (* 100)	79.0	71.7	49.3	0.0000	25	4.8
Bio04	Temperature Seasonality (standard deviation *100)	88.8	114.0	14.1	0.0002	43.1	55.2
Bio05	Max Temperature of Warmest Month	30.7	32.4	24.1	0.0000	0	0.6
Bio06	Min Temperature of Coldest Month	17.7	18.1	0.9	0.3343	4.1	0.7
Bio07	Temperature Annual Range (BIO5-BIO6)	13.0	14.3	13.7	0.0002	4.1	4.1
Bio08	Mean Temperature of Wettest Quarter	24.5	24.8	1.0	0.3170	0.1	1.9
Bio09	Mean Temperature of Driest Quarter	23.4	24.8	14.7	0.0001	0.6	0.9
Bio10	Mean Temperature of Warmest Quarter	25.1	26.4	15.4	0.0000	0.3	0.9
Bio11	Mean Temperature of Coldest Quarter	22.9	23.4	2.3	0.1255	2.5	6.3
Bio12	Annual Precipitation	1,758.7	1,388.9	40.9	0.0000	5	10.3
Bio13	Precipitation of Wettest Month	265.1	247.7	3.5	0.0619	0.7	0
Bio14	Precipitation of Driest Month	58.4	16.4	351.2	0.0000	6.8	2.6
Bio15	Precipitation Seasonality (Coefficient of Variation)	49.8	69.0	85.2	0.0000	2.1	0.3
Bio16	Precipitation of Wettest Quarter	701.6	638.6	6.4	0.0114	0.6	0.3
Bio17	Precipitation of Driest Quarter	210.3	73.7	260.0	0.0000	0.1	0.2
Bio18	Precipitation of Warmest Quarter	479.5	274.5	174.1	0.0000	1.1	4.9
Bio19	Precipitation of Coldest Quarter	429.5	413.5	0.2	0.6379	1.1	3

[1]Temperatures are in ºC and precipitation in mm.
[2]df=1329


60° W
30° W
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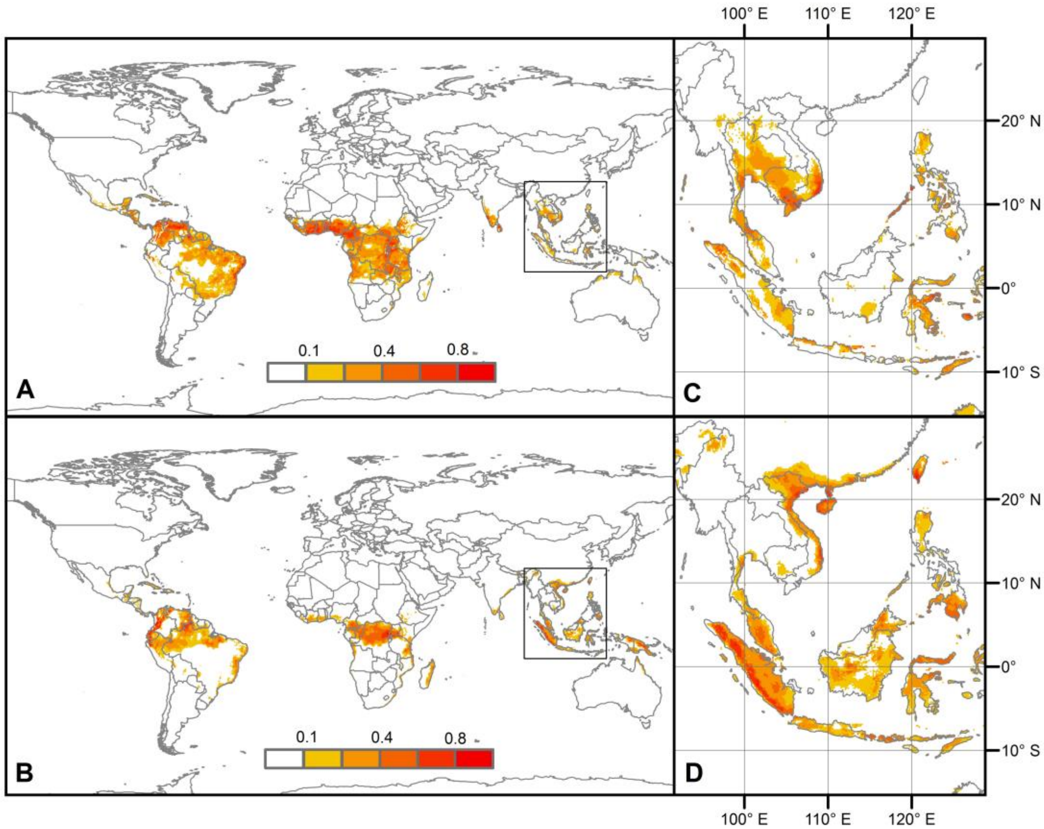
Mononychellus tanajoa
Mononychellus mcgregori
Both


100° E
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