Use of soil moisture active passive satellite data and WorldClim 2.0 data to predict the potential distribution of visceral leishmaniasis and its vector *Lutzomyia longipalpis* in Sao Paulo and Bahia states, Brazil

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Abstract

Visceral leishmaniasis (VL) is a neglected tropical disease transmitted by *Lutzomyia longipalpis,* a sand fly widely distributed in Brazil. Despite efforts to strengthen national control programs reduction in incidence and geographical distribution of VL in Brazil has not yet been successful; VL is in fact expanding its range in newly urbanized areas. Ecological niche models (ENM) for use in surveillance and response systems may enable more effective operational VL control by mapping risk areas and elucidation of eco-epidemiologic risk factors. ENMs for VL and *Lu. longipalpis* were generated using monthly WorldClim 2.0 data (30-year climate normal, 1-km spatial resolution) and monthly soil moisture active passive (SMAP) satellite L4 soil moisture data. SMAP L4 Global 3-hourly 9-km EASE-Grid Surface and Root Zone Soil Moisture Geophysical Data V004 were obtained for the first image of day 1 and day 15 (0:00-3:00 hour) of each month. ENM were developed using MaxEnt software to generate risk maps based on an algorithm for maximum entropy. The jack-knife procedure was used to identify the contribution of each variable to model performance. The three most meaningful components were used to generate ENM distribution maps by ArcGIS 10.6. Similar patterns of VL and vector distribution were observed using SMAP as compared to WorldClim 2.0 models based on temperature and precipitation data or water budget. Results indicate that *direct* Earth-observing satellite measurement of soil moisture by SMAP can be used *in lieu* of models calculated from classical temperature and precipitation climate station data to assess VL risk.

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Introduction

Visceral leishmaniasis (VL) is a neglected tropical disease (NTD) transmitted by *Lutzomyia longipalpis,* a sand fly species that is widely distributed in Brazil and the main vector for VL in this country. VL is mainly a childhood disease and cases are mandatorily reported to the Brazilian Ministry of Health through the National System on Diseases Notification (SINAN, http://portalsinan.saude.gov.br/). Despite efforts to strengthen the current VL national control program in Brazil, its incidence and geographical distribution has not yet been successfully reduced. VL is in fact expanding its range, particularly in newly urbanized areas (Lima *et al*., 2018). There is a need for more effective alternative methods for control. In Bahia state, VL is considered an endemic disease in rapid expansion. Between the years 2015 and 2017, this state was responsible for 8.9% of notifications of VL in the country. In 2016 and 2017, the highest number of reported new cases was in the Central-North, the West and south-eastern regions of the state. In February 2018, the disease was present in 174 of the 417 municipalities in Bahia, with transmission classified as intense in 17 areas, moderate in 26 and sporadic in 131 (Secretaria de Saúde do Estado da Bahia, 2018). In Sao Paulo State, VL has spread geographically along a major axis extending from the Northwest to the Southeast towards the Bauru Region, following the Bolivia-Brazil gas pipeline and the Marechal Rondon Highway (Cardim *et al*., 2016; Seva *et al*., 2017). The vector has been reported in 193 out of 645 municipalities, with the western region of the state experiencing rapid spread of the disease (Prestes-Carneiro *et al*., 2019).

We evaluate here use of data from the soil moisture active passive (SMAP) satellite, a National Aeronautics and Space Administration (NASA) mission in 2015 that combines L-band radar (15-30 cm) and a radiometer to directly measure volumetric soil moisture in the top 5cm of soil around the world. This corresponds to the known microhabitat of *Lu. longipalpis*, which is reported from peridomicile of households in endemic areas (Casanova *et al*., 2017). Geospatial distribution of VL and risk models based on classical climate station data have been described previously in Brazil based on thermal and hydrological drivers and limiting factors on life cycle development (Nieto *et al*., 2009). In Bahia and Sao Paulo, as in other regions countrywide, despite all the measures taken by Brazilian public health agencies, VL has expanded geographically. There is a clear need for innovative alternative control measures.

In this study, we aimed to map and model potential risk areas for VL and *Lu. longipalpis* in two Brazilian states (Bahia and Sao Paulo) using the computer algorithm of maximum entropy (Maxent) (Phillips *et al*., 2006) and long-term normal temperature and precipitation records from WorldClim 2.0 (Fick and Hijmans, 2017) as compared to monthly soil moisture data from SMAP to identify patterns or similarities with environmental risk factors in both states that can promote transmission and dispersal of VL. The specific objectives of the present report were to: i) map and model potential risk areas for VL and *Lu. longipalpis* using Maxent ecological niche modelling software and classical long term normal monthly temperature and precipitation records from WorldClim 2.0 and 19 derived bioclimatic factors; and ii) compare and contrast models based on WorldClim 2.0 to Maxent-generated potential risk surfaces for VL and *Lu. longipalpis* based on monthly soil moisture data from SMAP to identify geospatial patterns of environmental risk factors that promote transmission and dispersal of VL.

Materials and methods

Study areas

Bahia state is located on the north-eastern Atlantic coast of Brazil, latitude 19°57’00”S and longitude 44°31’00”W. The state has an area of 567,295 km^2 composed by 417 municipalities. According to the Brazilian Institute of Geography and Statistics (IBGE) the population amounts to 14.5 million inhabitants (IBGE 2010). The climate in the state goes from tropical in coastal areas to semi-arid inland and annual average temperatures vary between 19.2° and 26.6°C. Rainfall ranges from 360 to 2000 mm. The dominant vegetation is tropical forest, mangrove, cerrado and caatinga (Bavia, 1996).

São Paulo State is located in the Southwest of the south-eastern part of Brazil, latitude 23°33’1.87”S and longitude 46°37’59.91”W. The state has an area of 248,219,481 km² composed by 645 municipalities with a population of 45,919,049 inhabitants (IBGE, 2010). The state territory covers seven distinct climatic types considering temperature and rainfall. The climate varies from subtropical and tropical savannah to tropical climate of altitude. The predominant weather is characterized by a summer rainy season and a dry season in winter, with temperatures above 22°C in the hottest month of the year (Miranda *et al*., 2014).

Presence data

VL data was derived from the SINAN (http://portalsinan.saude.gov.br/). Human incidence records of VL are reported by municipality and geographic coordinates for the municipality was obtained through IBGE (2010). A retrospective study was carried out that included all the reported cases of VL from 1998-2018 (20 years) in São Paulo collected from the website for the Zoonosis Division of the Epidemiological Surveillance Center of the Disease Control Office, São Paulo State Secretary of Health (CVE). In Bahia State, we obtained data for over 13 years from SINAN (http://tabnet.datasus.gov.br/cgi/deftohtm.exe?sinannet/cnv/leishvba.def).

Occurrence information for *Lu. longipalpis* in Bahia was obtained from entomological monitoring surveys of sand flies carried out by the Entomology Sector of the Central Laboratory, Ministry of Health (LACEN) (Rodgers *et al*., 2019). For Sao Paulo, data on sand fly vectors were recorded during entomological collection protocols used in the surveillance activities by the Superintendence in Control of Endemics (SUCEN) in which presence/absence of the vector were recorded from 1985 to 2015. The maps were prepared for all municipalities in the states: 645 in Sao Paulo and 416 in Bahia.

Environmental data sources and models

Monthly SMAP L4 soil moisture data was obtained from NASA’s Earth Data site (https://search.earthdata.nasa.gov/search). SMAP L4 Global 3-hourly 9 km EASE-Grid Surface and Root Zone Soil Moisture Geophysical Data V004 were downloaded for the first image of day 1 and day 15 (0:00-3:00 hour) of each month. WorldClim 2.0 data (30-year climate normal, -km spatial resolution, 1970-2000) were obtained from the WorldClim 2.0 Internet site (www.worldlim.org/). We constructed separate ENMs for VL and *Lu. longipalpis* using occurrence data records. The distribution of VL cases was analysed considering the entire transmission cycle and its ecological relationships (Nieto *et al*., 2006; Sami *et al*., 2016). Environmental suitability models for VL and its *Lu longipalpis* vector in Bahia and Sao Paulo were generated using WorldClim 2.0 data and the monthly SMAP data using the computer algorithm of maximum entropy (Maxent). Human VL case records were reported by municipality using geographic coordinates for the municipality obtained through IBGE (2010). *Lu. longipalpis* occurrence in Bahia was obtained from entomological monitoring surveys of sand flies carried out by LACEN. WorldClim 2.0 data (30-year climate normal, 1-km) and monthly soil moisture data for the years 2015-2018 (SMAP L4, 10-km) were used to model suitability. SMAP layers were then resampled at 30 arc-seconds using the nearest neighbour joining method in ArcGIS10.7 (ESRI; Redlands, CA, USA). Models for each year for VL and *Lu. longipalpis* were developed using environmental data layers derived from SMAP as compared to WorldClim 2.0. data. Potential distribution maps for visceral leishmaniasis and *Lu. longipalpis* were prepared using Maxent software to enable a comparison of map distribution patterns generated using SMAP monthly average data as compared to maps generated using WorldClim 2.0 bioclimatic monthly data.

Statistics

Similar methods were used to generate VL and *Lu. lutzomyia* risk maps in Sao Paulo and Bahia. Initial models were run in Maxent, while the jack-knife (Phillips *et al.*, 2006) procedure was used to identify the value of each variable to model performance so that the most meaningful variables generated the potential distribution. The models were built with 75% of the occurrence data for model calibration/training data and 25% of the occurrence data for model evaluation/test data, with ten replicate models based on bootstrapping and a random seed. Model validation was done by calculating the area under the receiver operating characteristic (ROC) curve (AUC), which reflects the model's ability to distinguish between presence records and random background points. The jack-knife test was used to evaluate the relative importance of the variables, considering the increase and decrease in model gain.

ENMTools.v. 1.3 (http://enmtools.blogspot.com) was then employed to quantitatively compare the models by first calculating the niche overlap between the vector distribution with the VL case distribution. This tool calculated two indices for niche identity, Schoener's D (Schoener, 1968; Warren *et al.*, 2008) and Hellinger's-based I (Schoener, 1968; Hosseinian *et al.*, 2016) based on the probability distribution of a given species for inhabiting particular regions. Both indices range from 0 to 1 (complete divergence to high similarity, respectively). The best model for SMAP and WorldClim2.0 was then selected based on sample size corrected Akaike information criteria (AIC_c) for Maxent ENMs (Warren *et al.*, 2010; Warren and Seifert, 2011). Data preparation and distribution maps for visualization were created in ArcMap 10.7.

Results

The occurrence database was constructed using the human cases for VL and *Lu. lutzomyia* captures in Bahia and Sao Paulo from incidence records of SINAN and LACEN (for Bahia) and SUCAN (for Sao Paulo) for the years 2015 to 2018. A map showing the spatial distribution of both during the study period is shown in Figure 1. A total of 202 locations in Bahia State had reported the presence of VL cases, while only 76 municipalities had reported

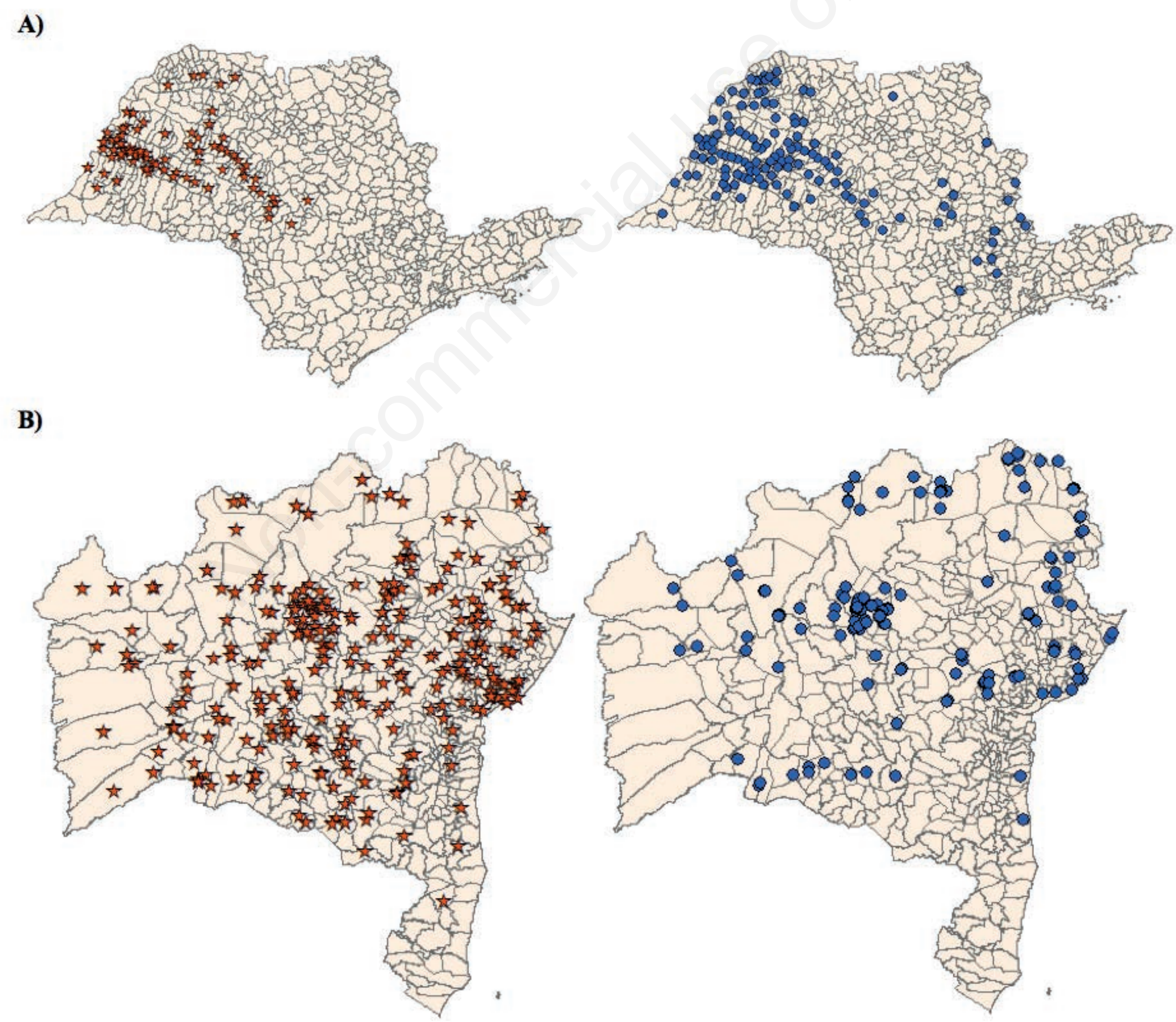

Figure 1. Municipalities with human visceral leishmaniasis case records from 2015-2018 (red) and *Lu. longipalpis* official presence records (blue) in two Brazilian states. A) Sao Paolo State; B) Bahia State.

presence of the vector. For Sao Paulo, the relationship between VL and the vector was the opposite: 62 municipalities with VL cases and 123 with the vector.

The contribution of each environmental variable to the model was determined by its percentage contribution and the jack-knife test of variable importance. Thus, the variable with the highest percent contribution, *i.e.* the variable that increases model gain the most when used in isolation and the variable that decreases the gain the most when excluded, were selected as the top three contributing variables to the ENM for Bahia state (Table 1) and Sao Paulo state (Table 2).

All of the years modelled for both states produced AUC values above 0.76 with the models for Sao Paulo yielding significantly higher AUC values than Bahia for VL (P=0.014 and P=0.0018 for SMAP and WorldClim 2.0, respectively). No significant difference between AUC values for sand fly models for Bahia and Sao Paulo was observed.

Table 1. Maxent results comparing the predictive value of soil moisture active passive instrument *vs* WorldClim 2.0 data on risk of visceral leishmaniasis in Bahia State.

Visceral leishmaniasis	AUC	SMAP Variable contribution (%)	Jack-knife analysis
2015	0.818	SMAP 12 (21.3) SMAP 04 (19.9) SMAP 06 (15)	AP 04 (increases and decreases SM model gain)
2016	0.804	SMAP 01 (28.3) SMAP 08 (13.9) SMAP 04 (12.7)	SMAP 01 (increases and decreases model gain)
2017	0.763	SMAP 09 (34.1) SMAP 06 (19.7) SMAP 01 (14.8)	SMAP 09 (highest gain) SMAP 06 (decreases gain)
2018	0.838	SMAP 01 (27.1) SMAP 05 (11) SMAP 11 (10.9)	SMAP 01 (highest gain) SMAP 05 (decreases gain)
Sand fly	**AUC**	**Variable contribution (%)**	**Jack-knife analysis**
2015	0.85	SMAP 12 (44.2%) SMAP 04 (20.2%) SMAP 08 (7.5%)	SMAP 12 (increases and decreases model gain)
2016	0.859	SMAP 11 (31.9) SMAP 01 (16.8) SMAP 10 (15.1)	SMAP 11 (highest gain) SMAP 01 (decreases gain)
2017	0.828	SMAP 02 (20.8) SMAP 11 (19) SMAP 04 (16)	SMAP 02 (highest gain) SMAP 11 (decreases gain)
2018	0.869	SMAP 01 (32) SMAP 12 (17.5) SMAP 05 (10.4)	SMAP 01 (highest gain) SMAP 12 (decreases gain)
Visceral leishmaniasis	**AUC**	**WorldClim 2.0 Variable contribution (%)**	**Jack-knife analysis**
2015	0.871	Precip 10 (23.6) Precip 02 (11.5) Precip 06 (8.7)	Precip10 (increases and decreases model gain)
2016	0.863	Precip 10 (23.5) Precip 05 (10.1) Precip 02 (7.8)	TMin 01 (highest gain) Precip 10 (decreases gain)
2017	0.852	Precip 10 (41.1) Precip 04 (6.7) Precip 11 (4.4)	Precip 10 (increases and decreases model gain)
2018	0.802	Precip 10 (28.5) Precip 05 (11.1) Precip 02 (7.8)	Precip 10 (increases and decreases model gain)
Sand fly	**AUC**	**Variable contribution (%)**	**Jack-knife analysis**
All years	0.881	Precip 10 (27.4) TMin 05 (15) Precip 03 (6.6)	Precip 10 (highest gain) Precip 03 (decreases gain)

SMAP, soil moisture active passive instrument; AUC, area under the curve; Precip, precipitation; TMax, maximum temperature; Tmin, minimum temperature.

Bahia State model

The Maxent models for VL in Bahia suggest a seasonal high for SMAP in the months of September, November and January and precipitation of the months of April, October and November as the most meaningful variables in the VL prediction model. For the sand fly model, the variables with most importance were maximum temperature of December and November, SMAP for the months of October, November, January and May and precipitation for the months of October and December. The geographic distribution of VL and its vector in Bahia is expanding toward the northern and central regions of the state, with a well-defined small expansion toward the South (Figures 2-4).

ENM Tools was used to select the 'best' model for VL and sand fly suitability in Bahia and Sao Paulo states. According to the AIC model evaluation criteria, the model for VL in 2017 in Bahia state using SMAP data was the best model. For Sao Paulo, the best model was the VL in 2018 using SMAP data. Overall, the SMAP

Table 2. Maxent results comparing the predictive value of soil moisture active passive instrument *vs* WorldClim 2.0 data on risk of visceral leishmaniasis in Sao Paolo State.

Visceral leishmaniasis	AUC	SMAP Variable contribution (%)	Jack-knife analysis
2015	0.869	SMAP 06 (29.3) SMAP 04 (16.5) SMAP 09 (10.2)	SMAP 08 (increases gain) SMAP 07 (decreases gain)
2016	0.959	SMAP 11 (37.1) SMAP 08 (15.7) SMAP 03 (14.1)	SMAP 11 (increases and decreases model gain)
2017	0.945	SMAP 07 (49.1) SMAP 09 (13.9) SMAP 08 (11.8)	SMAP 09 (highest gain) SMAP 07 (decreases gain)
2018	0.928	SMAP 06 (66.1) SMAP 11 (7.2) SMAP 04 (5.1)	SMAP 06 (increases and decreases model gain)
Sand fly	**AUC**	**Variable contribution**	**Jack-knife analysis**
2015	0.869	SMAP 06 (29.3) SMAP 04 (16.5) SMAP 09 (10.2)	SMAP 08 (highest gain) SMAP 07 (decreases gain)
2016	0.874	SMAP 11 (29.6) SMAP 03 (24.3) SMAP 08 (9.9)	SMAP 11 (increases and decreases model gain)
2017	0.878	SMAP 07 (27.2) SMAP 10 (18.6) SMAP 03 (10.9)	SMAP 06 (highest gain) SMAP 07 (decreases gain)
2018	0.878	SMAP 06 (45.5) SMAP 07 (12.4) SMAP 02 (9.5)	SMAP 09 (highest gain) SMAP 02 (decreases gain)
Visceral leishmaniasis	**AUC**	**WorldClim 2.0 Variable contribution (%)**	**Jack-knife analysis**
2015	0.971	TMax 12 (28.5) Precip 07 (10.9) Precip 04 (10)	TMax 12 (highest gain) Precip 04 (decreases gain)
2016	0.977	TMax 12 (23.6) Precip 05 (15.7) Precip 08 (9.8)	TMax 12 (highest gain) Precip 04 (decreases gain)
2017	0.961	TMax 12 (30.1) Precip 08 (9.9) Precip 03 (9.5)	Precip 01 (highest gain) Precip 03 (decreases gain)
2018	0.968	TMax 11 (25.4) Precip 08 (14.1) Tax 12 (9.2)	TMax 12 (highest gain) Precip 08 (decreases gain)
Sand fly	**AUC**	**Variable contribution (%)**	**Jack-knife analysis**
All years	0.883	TMax 12 (25.5) Precip 06 (24.8) Precip 08 (7.5)	Precip 08 (highest gain) Precip 07 (decreases gain)

SMAP, soil moisture active passive instrument; AUC, area under the curve; Precip, precipitation; TMax, maximum temperature; Tmin, minimum temperature.

dataset were better models than the WorldClim 2.0 dataset for VL and sand fly in Bahia and Sao Paulo. The models using disease occurrence data were considered better than when sand fly occurrence data was used when compared in ENM Tools.

ENM Tools was used to calculate niche overlap between the models using Schoener's *D* in ENM Tools (Warren *et al*., 2010). For Bahia state we observed that the models for VL and sand fly have some similar ENMs either using SMAP or WorldClim 2.0 data. None of the models have shown a complete identical niche between disease and vector. For Sao Paulo, the models have shown some niche overlap, except that the pair-wise overlaps for VL in the year of 2017 had shown the least similarity between the niches of each year analysed. In this state, complete identical niches were not observed either.

Discussion

The U.S. National Academies of Sciences decadal survey '*Thriving on our changing planet: a decadal strategy for earth observation from space*' (2018), recommends a renewed assessment of potential public health applications of Earth-observing satellite data systems in light of the more advanced capabilities of the more recently launched satellite missions. A growing number

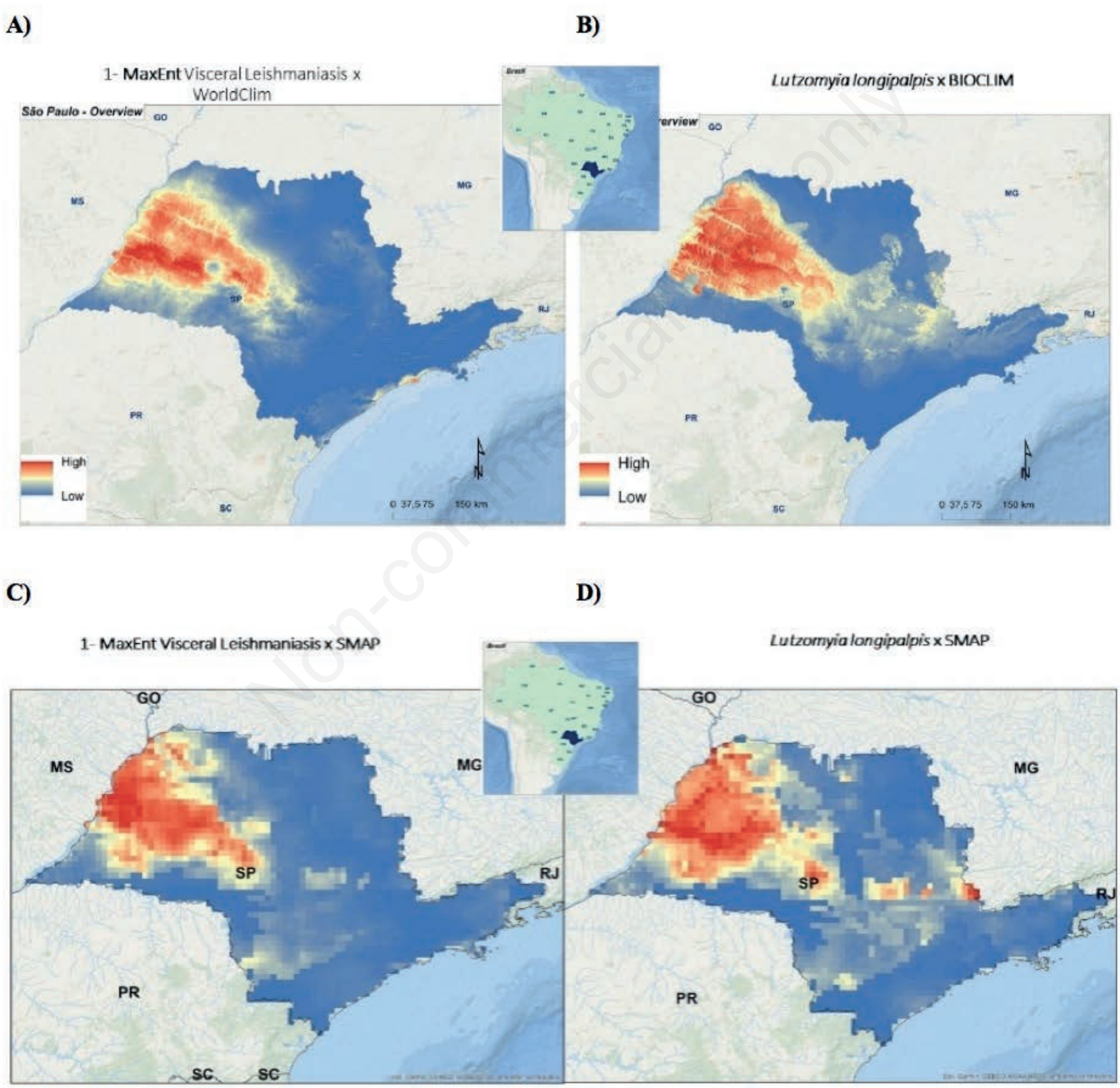

Figure 2. Maxent probability models for visceral leishmaniasis cases and *Lu. longipalpis* presence based on Sao Paolo State health records: comparison between soil moisture active passive instrument (SMAP) and WorldClim 2.0 data. A, C) models generated for VL; B, D) models generated for the *Lu. longipalpis* vector.

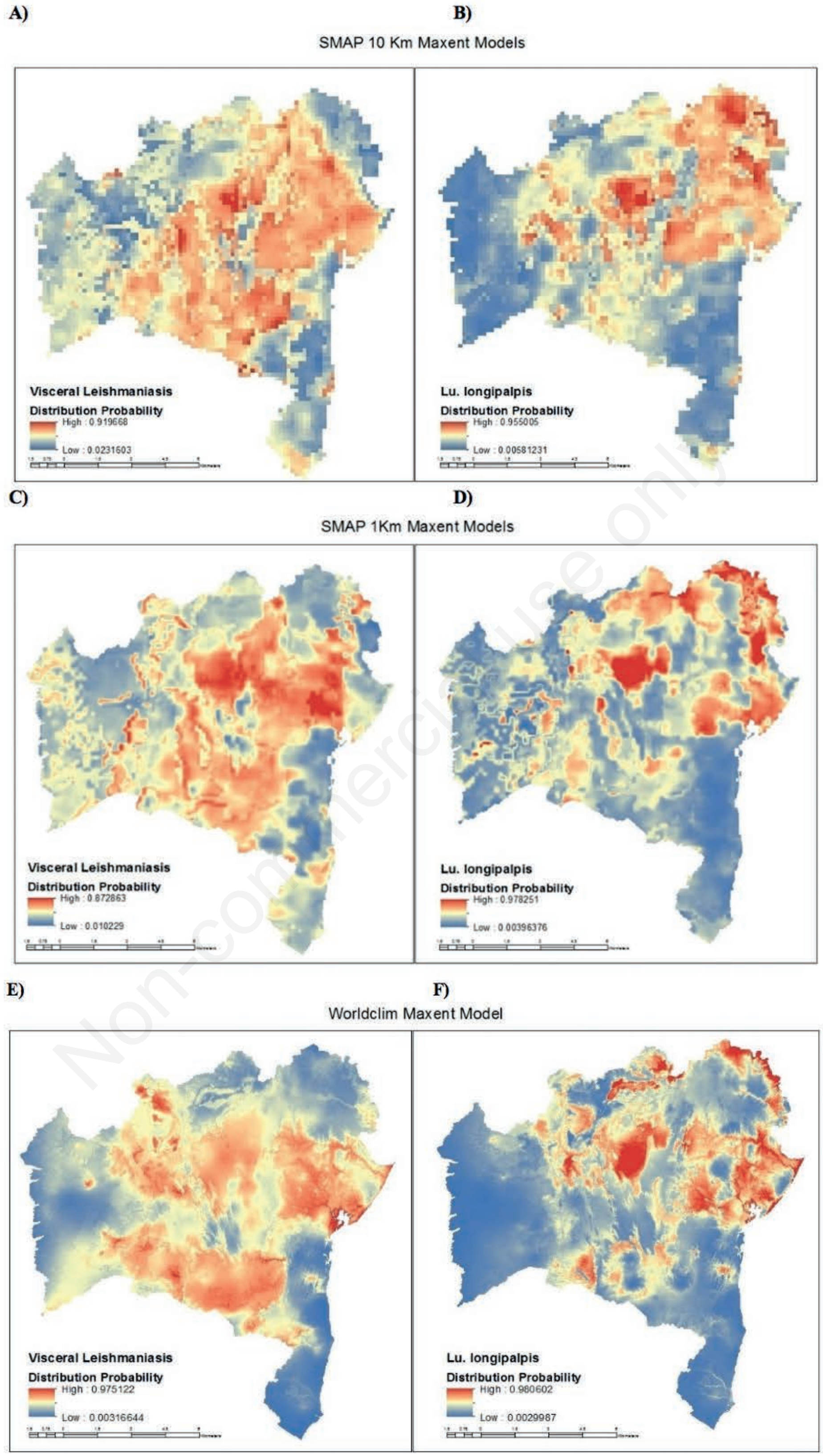

Figure 3. Maxent probability models for visceral leishmaniasis cases and *Lu. longipalpis* based on Bahia State health records: comparison between soil moisture active passive instrument (SMAP) and WorldClim 2.0 data. A, C, E) models generated for VL; B, D, F) models generated for the *Lu. longipalpis* vector.

of published reports suggests that environmental satellite data and ENM can be used to predict risk of vector-borne diseases as it would lead to more effective public health surveillance and response systems (Malone and Bergquist, 2012; Hess *et al*., 2018; Malone *et al*., 2019; Scavuzzo *et al*., 2021).

To provide the U.S. Department of Agriculture (USDA) regional crop analysts with accurate soil moisture information to predict where there could be too little or too much water in the soil to support crops, SMAP data have been incorporated into USDA's Crop Explorer website (https://ipad.fas.usda.gov/cropexplorer/; Colliander *et al*., 2017). By incorporating direct SMAP measurements into Crop Explorer, agriculture analysts can review the gaps in classical climate station data, especially where climate station data coverage are sparse. With three-day global coverage and 3-10 km^2 spatial resolution, SMAP can provide the Crop Explorer tool with timely updates on soil moisture conditions. SMAP and USDA data, along with tools to analyse it, are publicly available on Google Earth Engine (https://earthengine.google.com/) for researchers, non-profits, resource managers, and others who need the information (Gorelick *et al.*, 2017; Anderson, *et al*., 2016).

As has been done for crop prediction models, we propose to use new remote sensing soil moisture tools in public health to model the environmental suitability and geospatial developmental dynamics of the 'visceral leishmaniasis crop' each year. Satellite soil moisture data from SMAP was used to develop ENMs to predict the potential distribution of visceral leishmaniasis and its sand fly vector *Lu. longipalpis* in Brazil based on the ambient thermal-hydrologic regime. Results were compared to ENM risk maps based on global long-term normal climate station data (WorldClim 2.0) in Sao Paulo and Bahia states in Brazil.

Next steps would be to factor in population, land use, poverty, irrigation (by municipality or census tract) to build a comprehensive VL model using satellite-generated data at the household/habitat scale (1-2 m) community/agricultural field scale (30 m) and regional/climatic scale (1 km) in one system (Boser *et al*., 2021). In combination with other eco-epidemiologic factors it may be possible to produce a viable model for use in a spatiotemporal surveillance and response system, each 7-10 days, leading to the long-term goal of VL elimination from the western hemisphere. If successful, ENM models for VL may serve as a prototype for other vector-borne diseases +/or soil transmitted helminths (STHs) that develop in or on surface soils.

Conclusions

This report should be regarded as proof of concept demonstrating validity of direct measurement of surface soil moisture as component of ENM models of vector-borne and other environmentally sensitive diseases using monthly data. Our results indicate *direct* Earth-observing satellite measurements of soil moisture by SMAP can be used *in lieu* of models calculated from standard temperature and precipitation climate station data to assess disease risk and to guide the need for control program interventions. There is a unique match of the VL niche and moisture in the top 5cm surface soil via the geophysical parameter measured by SMAP radar and microwave sensors. However, there may not be a similar correspondence, or as close a match, to microclimate life cycle param-

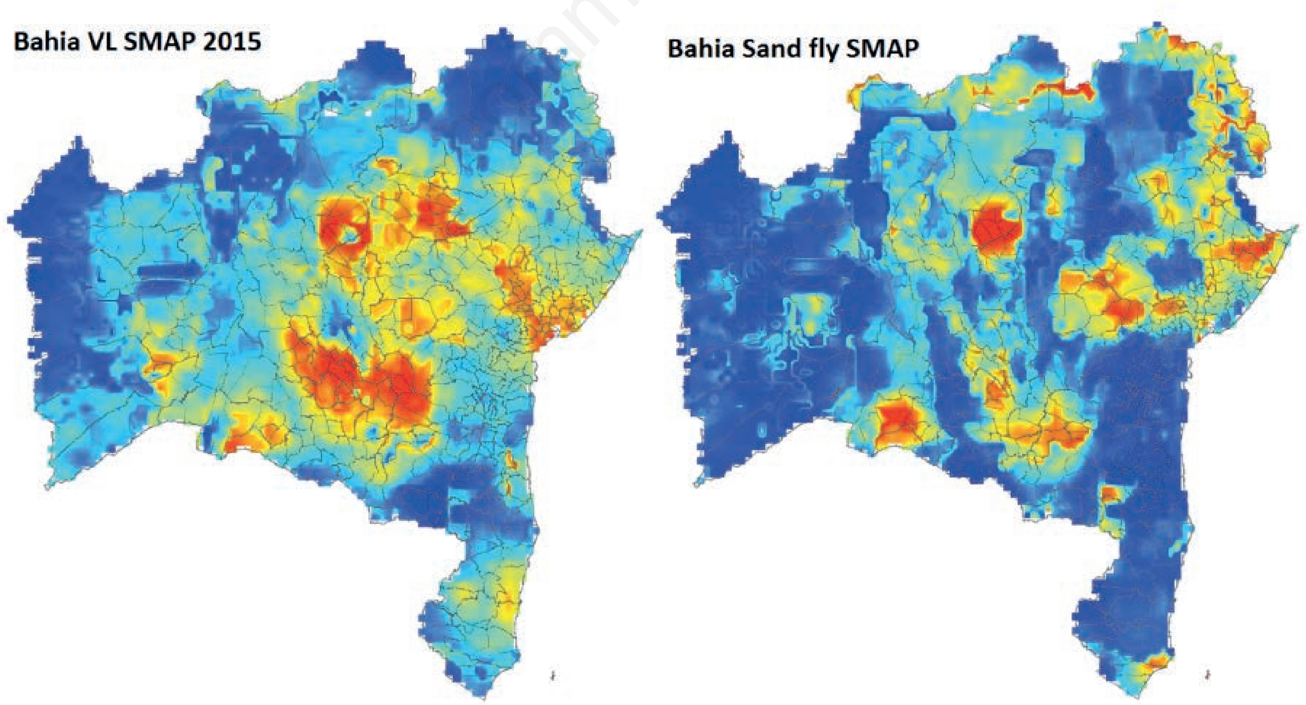

Figure 4. Four-year composite map for VL and *Lu. longipalpis* in Bahia State by county pending availability of more data years to compare long-term with annual incidence data.

eters for other vector-borne diseases, *e.g.*, malaria or *Aedes*-borne arboviruses because of their different microhabitats. Further work is in progress on more comprehensive spatio-temporal developmentrate models using data from SMAP and other satellites at more frequent temporal resolutions at scales needed to capture essential life cycle features of vector-borne diseases. Anticipated 'precision public health' applications by municipality/county health unit surveillance and response systems, with accurate case finding at household-habitat level and sensor data collection frequencies are needed to resolve seasonal and geospatial risk factors and to guide appropriate control program interventions.

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