Transformational adaptation of key root and tuber crops in Asia:

Assessing crop suitability amidst climate change by species distribution modelling

OCTOBER
2019

Food Resilience Through Root and Tuber Crops in Upland and Coastal Communities of the Asia-Pacific (FoodSTART+)

With funding by

IFAD Investing in rural people

CIP INTERNATIONAL POTATO CENTER

CGIAR RESEARCH PROGRAM ON Roots, Tubers and Bananas

CIAT International Center for Tropical Agriculture Since 1967 / Science to cultivate change

Transformational adaptation of key root and tuber crops in Asia:

Assessing crop suitability amidst climate change by species distribution modelling

October 2019

Transformational adaptation of key root and tuber crops in Asia:
Assessing crop suitability amidst climate change by species distribution modelling

ISBN: 978-92-9060-530-0
DOI: 10.4160/9789290605300

Please send a copy to the Communications Department at the address below.
International Potato Center
P.O. Box 1558, Lima 12, Peru
cip@cgiar.org • www.cipotato.org

Correct citation:
Palao, L.K.; Naziri, D.; Balanza, J.G.; Campilan, D.M. 2019. Transformational adaptation of key root and tuber crops in Asia: Species distribution modelling for assessing crop suitability in response to climate change. Final Report. Food Resilience Through Root and Tuber Crops in Upland and Coastal Communities of the Asia-Pacific (FOODSTART+) Project. Lima (Peru). International Potato Center. 34 p.

Authors:
Leo Kris M. Palao (CIAT)
Diego Naziri (CIP)
Jane Girly C. Balanza (CIAT)
Dindo M. Campilan (CIAT)

Contact
CIP Philippines, PCAARRD, Los Baños, Laguna
4030 Philippines
Tel +63 49 536 8185 | Fax + 63 49 536 1662
E-mail: cip-manila@cgiar.org | Website: www.rtb.cgiar.org/foodstartplus/

Production Coordinator
Leo Kris M. Palao (CIAT)
Diego Naziri (CIP)

Design and Layout
Communications Department

October 2019

CIP thanks all donors and organizations which globally support its work through their contributions to the CGIAR Trust Fund. https://www.cgiar.org/funders/

Acknowledgements

This publication was made possible through the financial support of the International Fund for Agricultural Development (IFAD) and the European Union through the project ‘Food Resilience Through Root and Tuber Crops in Upland and Coastal Communities of the Asia-Pacific’ (FoodSTART+). FoodSTART+ is implemented by the International Potato Center (CIP) in collaboration with the International Center for Tropical Agriculture (CIAT) in the framework of the CGIAR Research Program on Roots, Tubers and Bananas (RTB).

Contents

Summary

Widespread negative impacts of climate change include limited plant growth, decreased soil fertility and ultimately limited food production (Dhankher et al., 2018). Roots, tubers and bananas (RTB) are key commodities for food security, nutrition and livelihoods especially among smallholder farmers. Furthermore, roots and tubers, being resilient crops, can help farmers adapt to climate change and variability. Nevertheless, food security and livelihood agenda mostly emphasize on grain crops (such as rice, maize, and wheat), and very few studies have looked into the future potential of RTB crops and their likely increasing importance in the face of climate change (Atakos, 2018). This study attempts to identify areas in the Asia Pacific region where considerable climate impacts that threaten agricultural viability of major crops are expected. The study used climate projections and species distribution modeling approach for eight key crops in the region. In areas where impacts are very high, it is assumed that the currently cultivated crops may need to be substituted with more resilient crops. Key findings of this study include:

- Countries, such as India, China and Myanmar will experience high impacts of climate change on land suitability for maize.
- Although there is a general decrease of climatic suitability for rice, the viability threshold was not crossed across time periods. However, climate change will put increasing pressure on this crop, particularly in India that will likely experience considerable losses of land suitability for rice.
- Among RTB crops, cassava and sweetpotato can play an important role in terms of food resilience in areas where climate change is likely to trigger transformational changes for non-RTB (rice and maize) and some RTB crops.
- Some RTB crops, although considered resilient crops, will also undergo considerable transformational change, specifically potato in India.
- In terms of food system resilience, considerations and emphasis on the role of cassava and sweetpotato (and RTB in general) should be integrated in any adaptation initiative, especially in countries where food systems and value chains are particularly threatened by climate change.

1. Introduction

Agriculture is a climate-dependent activity, being highly sensitive to climatic changes and climate variability. As reported by Ray et al. (2015), climate controls 33% of global crop yield variation. For instance, in some areas in the Philippines, it has been predicted that yield for maize can decrease by 35% and 44%, by 2020 and 2050, respectively (Balderama et. al., 2016). Climate models provide insights into future climatology (hotter, drier, wetter, cooler, etc.) and allow us to understand the heterogeneity of future climates as well as the average climatology expected in any particular region over time. Combined with crop models and climate downscaling approaches, it is also possible to model and estimate long term shocks associated with changing climate conditions. Understanding future climate also facilitates prediction of how climate conditions (temperature and precipitation) may affect the niches of crops, pests and diseases. With this understanding, it is possible to estimate whether or not the landscape will remain suitable for a particular crop. The EcoCrop model was used for producing spatially-explicit suitability simulations of key crops (rice and maize), banana, and main root and tuber crops (cassava, sweetpotato, potato, yam, taro) in Asia covering India, Myanmar, Vietnam, China, Indonesia, and the Philippines. EcoCrop was chosen over more complex process-based models because of the spatial coverage, limited models and calibrated varieties (genetic coefficients) that are available. For instance, the Cassava model (YUCA - https://dssat.net/manihot-cassava) is currently undergoing intensive testing for different environments. Also, there are limited development of process-based crop models for roots, tubers, and banana (RTB) crops (https://dssat.net/models-and-applications/components). For RTB where crop models are developed, there are limited calibrated varieties available for countries targeted by this study.

There is general consensus that root and tuber crops (RTC) are resilient to climate change. However, less is known about where they can have a comparative advantage over known key crops (i.e., maize and rice) in the future. This research focused on trying to spatially determine the likely impacts of climate change on key selected crops, and identify where RTC are likely to replace or complement existing key crops to sustain food security and livelihoods. This study has been conducted by CIAT in the framework of the IFAD and EU-funded FoodSTART+ project to support IFAD investment projects on promoting RTC's contribution to future food security and agricultural livelihoods across Asia, amidst climate change and vulnerability of major crops.

1.1. Contextual background of transformational change

As suggested, climate-resilient pathways can involve two phases – incremental and transformational change – which can be categorized into intentional and proactive adaptation practices (Denton et. al., 2014) and can occur in human, institutional, technological, and biological systems (Smit and Wandel, 2006; Stringer et al., 2009; National Research Council, 2010a; Pelling, 2010; IPCC, 2012). The recent trends in greenhouse gas (GHG) emissions suggest that climate change impacts will be widespread. Impacts also vary spatially and temporally, and those areas where agricultural systems are already under pressure will be severely affected and will have to undergo fundamental changes in pattern, functions, form, dynamics, and locations (Schipper, 2007; Kates et al., 2012; Marshall et al., 2012; Park et al., 2012). The affected systems will have to face transformative changes to reduce the risks and vulnerabilities (Kates et al. 2012). Rockstrom et al. (2009) stated that, "if the magnitude of climate change impacts on various systems is high enough that resilience cannot be expected to cope, then drastic changes should be introduced or implemented". Rippke et al. (2016) also stated that, in those existing systems where drastic change in climate renders the systems less viable, then options should be considered to introduce crops with higher suitability or redefine livelihoods. In this study, we are interested on the transformational adaptation phase of different commodity systems in Asia in relation to expected change in agricultural suitability of crops in face of climate change.

2. Methodology

Figure 1 describes the data requirements, information flow using species distribution modeling (SDM) for the climate-based suitability assessment of the target crops. The analysis estimates where crops will lose their climate viability and identify areas where negative impacts are very high that a shift to new crops or livelihood should be considered. Transformational change implies shifts in locations for production of specific crops, or shifting to farming systems new to a region or resources system. The emphasis of these analyses is to identify the transformational phase wherein a crop may no longer be agriculturally viable (suitability is low) and might be substituted by another climatically resilient crop.

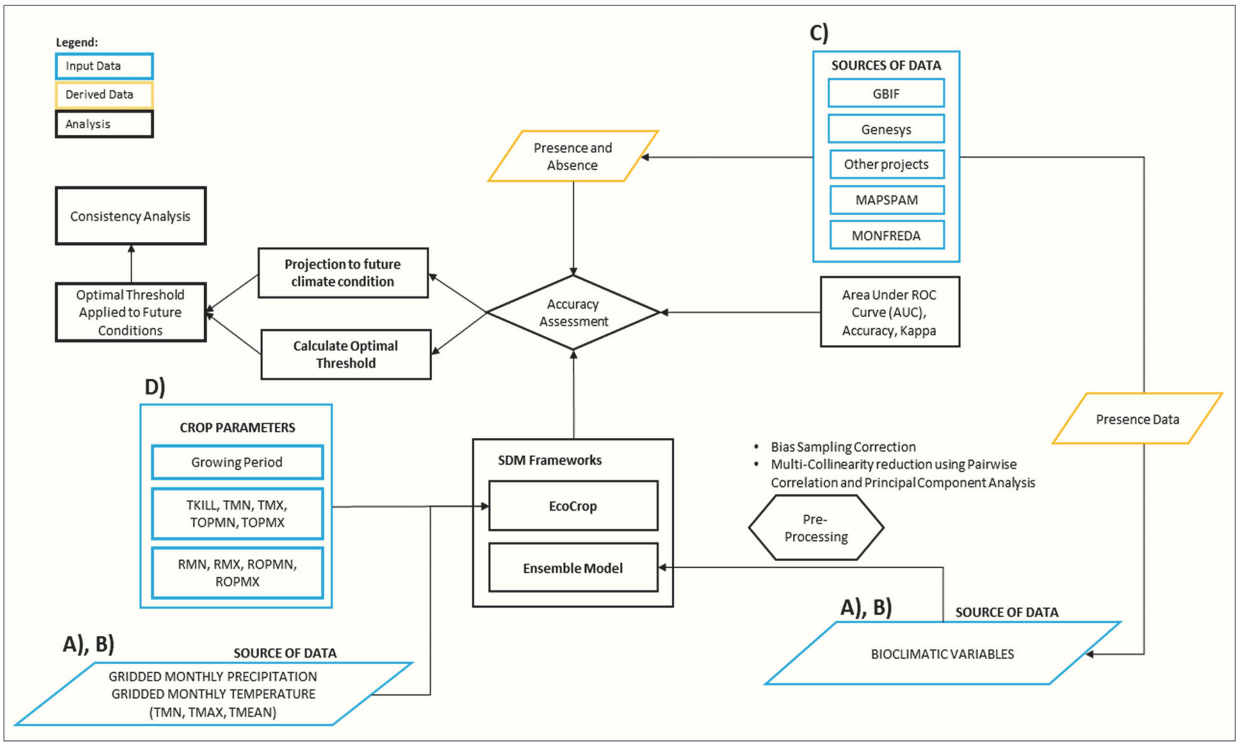


Figure 1. Processing flow for assessing climate change impacts and identification of areas of transformational change. For crop parameters see table 2.

The study focuses on spatial analysis of climate suitability of various crops (rice, maize, cassava, sweetpotato, potato, yam, taro, and banana) and the impacts of climate change (precipitation and temperature) to future suitability of these crops. Appendix 1 summarizes the data used for this assessment. Most of these datasets are global in scale, open-sourced, and can be easily accessible. Hence, assessment can be replicated elsewhere. Most of the analyses were implemented in the R programming language.

Scripts used in the analysis can be accessed thru this link:

- EcoCrop Suitability Modelling - https://github.com/CIAT-DAPA/dapa-climate-change/blob/master/PhD/0007-crop-modelling/scripts/ecocrop/EcoCrop-gnut.R
- EcoCrop calibration - https://github.com/CIAT-DAPA/dapa-climate-change/blob/master/EcoCrop/src/calibrationParameters.R
- Calculation of optimal threshold - https://pastebin.com/fV68gnWW
- Ensemble modeling - https://pastebin.com/FFkVgmzD

Data set A. For baseline climate scenarios, global open-sourced Worldclim version 2 (Fick and Hijman, 2017) climate data was used to generate baseline suitability of crops across Asia. Worldclim database contains a set of high resolution (1 km^2 or 30 arc-seconds) global climate layers generated for time period 1970-2000 that can be used for crop suitability modelling.

Data set B. To simulate climate risk in the future, we used 33 global circulation models (GCMs) simulations (Appendix 1) from the IPCC firth assessment report (IPCC, 2013) for four (4) time periods (the 2030s, 2050s, 2070s, and 2090s), representing short-term and long-term climate risks that can help formulate adaptation strategies. Downscaling procedure using the method of Ramirez-Villegas and Jarvis (2010) yields a 1-km^2 gridded climate aligned with Worldclim grid. We considered only one scenario pathway, RCP 8.5 to assess climate change impacts. The RCP8.5 assumes a high population and relatively slow income growth with modest rates of technological change and energy intensive improvements. This leads to high energy and greenhouse gas emissions (Riahi, et al., 2011). A total of 48 climate gridded layers of monthly precipitation (mm/month), monthly minimum temperature (°C), monthly maximum temperature (°C), and monthly average temperature (°C) were used for each time period to model climatic suitability using EcoCrop. For ensemble model, a set of 19 bioclimatic (Appendix 2) variables were used to predict and forecast suitability.

Data set C. Presence and absence data was acquired from four (4) online databases and primary data from other projects where species location (e.g., longitude and latitude) attributes are included in the records. The data are used to validate the model and calculation of optimal thresholds as shown in Figure 2. These datasets were complemented by harvested area from MAPSPAM. Records of species from online databases and harvested areas from MAPSPAM were compiled for use as presence data for the model. On the other hand, absence data was generated where harvested area from MAPSPAM is equal to 0. A total of 1,000 random points where generated for presence and absence data.

To run Biomod2 for rice, we extracted presence records from GBIF and Genesys and then applied a filter of 5km as a distance threshold in between points. In total, 80,886 presence records were used to run suitability model for rice. To avoid bias, the presence and absence data derived from MAPSPAM were kept and used to calculate the optimal threshold.

Data Set D. This study builds on the previous research of Rippke et al. (2016). Most of the parameters (Table 1) used to run the EcoCrop and Biomod2 model have been validated by crop experts from the CGIAR centers, while some parameters where adjusted based on availability of literatures in the target countries and other available materials online. For instance, to get acceptable results for taro, we modified the EcoCrop parameters provided by the study of Jianchu et al. (2001) in China which characterizes climate parameters for various agro-ecological environments of taro. EcoCrop evaluates the adequate climatic conditions for temperature and precipitation on a monthly basis and then calculates the climatic suitability of the resulting interaction between rainfall and temperature (description of the model is elaborated in the next section). Crop suitability simulation was carried out for the historical period (1970-2000) as the baseline, and 90 years after the baseline.

Table 1: Parameters used to run the EcoCrop model

Crop	GMN[1]	GMX[2]	TKILL[3]	TMN[4]	TOPMN[5]	TOPMX[6]	TMX[7]	RMN[8]	ROPMN[9]	ROPMX[10]	RMX[11]
RTB											
Cassava	240	240	0	15	22	32	45	300	800	2200	2800
Sweetpotato	80	170	-4	15.5	20	32	35	100	355	406	1500
Potato	120	120	-8	3.75	12.4	19.8	24	150	215	326	785.5
Banana	365	365	10	15	24	27	35	700	1000	1300	5000
Yam	210	210	12	20	25	34	40	750	1100	1400	2000
Taro	210	365	0	10	20	25	32	1000	2000	2500	2500
Grain											
Maize	120	120	8	5	22	28.6	30	70	215	650	935

2.1. Modeling frameworks

Two modeling frameworks were used to generate climate suitability scenarios, namely EcoCrop and Ensemble models. The EcoCrop model was used to generate climate suitability scenarios for crops that are less reliant to irrigation, such as maize, cassava, sweetpotato, potato, banana and yam. For rice, which is an irrigation-dependent crop, an empirical model using an ensemble of Random forests (RF), generalized linear model (GLM), and flexible discriminant analysis (FDA) provided by Biomod2 (Thuiller et al., 2016) was used to generate the climate suitability scenarios. The description of the two modeling approaches used to generate the suitability predictions in the future are given below.

EcoCrop is a basic mechanistic model that uses environmental ranges to determine the niche and distribution of a crop and produce a suitability index based on the interaction of the environmental variables (Ramirez-Villegas, et al., 2013). The model was adapted by CIAT based on the original EcoCrop model developed by Hijman et al. (2001). In the model, there are two ecological ranges for a given crop, each one defined by a pair of parameters for each variable for temperature and rainfall. When the conditions over the growing seasons in a particular location are beyond the absolute thresholds, there are no suitable conditions for the crop; when they are between absolute and optimum thresholds there are ranges of suitability conditions (1 to 99), and whenever they are within the optimum conditions there are highly suitable conditions and the suitability score is 100%. The values are shown as an index where values closer to 100 are the areas where the climate is very suitable for a crop and entails no or minimum intervention to optimize production. The level of crop suitability can be classified as follows (Table 2):

Table 2. Different classes of suitability produced using the EcoCrop model

Index range	Description
0-20	Very Marginal
20-40	Marginal
40-60	Suitable
60-80	Very Suitable
80-100	Excellent

[1] GMN: Minimum length of the growing season (days)
[2] GMX: Maximum length of the growing season (days)
[3] TKILL: absolute temperature that will kill the plant (◦C)
[4] TMN: minimum average temperature at which the plant will grow (◦C)
[5] TOPMN: minimum average temperature at which the plant will grow optimally (◦C)
[6] TOPMX: maximum average temperature at which the plant will grow optimally (◦C)
[7] TMX: maximum average temperature at which the plant will cease to grow (◦C)
[8] RMN: minimum rainfall (mm) during the growing season
[9] ROPMN: optimal minimum rainfall (mm) during the growing season
[10] ROPMX: optimal maximum rainfall (mm) during the growing season
[11] RMX: maximum rainfall (mm) during the growing season

Ensemble the Biomod2 species distribution model (SDM) was used to map climate suitability of rice and potato. Biomod2 has the ability to run 10 state-of-the-art modeling techniques to describe and model the relationships between a given species and its environment. It attempts to define the ecological niche of a species using a set of environmental variables (precipitation and temperature). It fits an ensemble of forecasts by simulating across more than one set of initial conditions, model classes, model parameters, and boundary conditions (Thuiller et al., 2009). However, SDM models are prone to biases and overfitting where multi-collinearity and high-dimensional spaces of data are present. Therefore, it is necessary to run statistical tests, such as principal component analysis (PCA) and correlation analysis to determine appropriate number of environmental variables that should be retained and used for modeling. Table 3 shows the parameters used to map the climatic suitability of rice and maize.

Table 3. Parameters used for the ensemble model

Crop	Bioclimatic variables used
Rice	Annual Mean Temperature (Bio 1), Isothermality (Bio 3), Temperature Seasonality (Bio 4), Maximum Temperature of Warmest Month (Bio 5), Minimum Temperature of Coldest Month (Bio 6), Temperature Annual Range (Bio 7), Mean Temperature of Wettest Quarter (Bio 8), Mean Temperature of Driest Quarter (Bio 9), Mean Temperature of Warmest Quarter (Bio 10), Annual Precipitation (Bio 12), Precipitation Seasonality (Bio 15), Precipitation of Driest Quarter (Bio 17), and Number of Consecutive Dry Months (Bio 20)
Potato	Annual Mean Temperature (Bio 1), Mean Diurnal Range (Bio 2), Isothermality (Bio 3), Maximum Temperature of Warmest Month (Bio 5), Precipitation Seasonality (Bio 15), Precipitation of Wettest Quarter (Bio 16), Precipitation of Coldest Quarter (Bio 19)

2.2. Model validation

To analyze the performance of the model, the Area under the Receiving Operating Characteristic (ROC) Curve (AUC) was used for validation. This is an indication of an agreement between presence and suitability results from the model. To assess the AUC, the MAPSPAM data were used as a reference for crop presence. Random points were generated per crop in those pixels where a crop harvest is greater than zero (0), and these were labeled as presence data. Another set of random points was generated where harvest is equal to zero (0), and these were labeled as absence data. Other data sources to collect presence data came from potatopro (https://www.potatopro.com), GBIF (Global Biodiversity Information Facility), EarthStat (http://www.earthstat.org), and primary data from other projects in Asia. Most of the maps came from Monfreda et al. (2008), official data whenever available (e.g. for Vietnam) and other secondary dataset from projects in the Philippines. Presence-absence package in R was used to generate the AUC. The AUC is a threshold independent measure of model quality (Hanley and McNeil, 1982; Swets, 1988). A poor model (i.e., a model that is no better than random assignment) will have a ROC plot lying along the diagonal, with an AUC near 0.5 (Freeman and Moisen, 2008).

2.3. Transformational analysis

Analysis of transformation adaptation is determined by a crop-specific threshold, below which the crop is considered not agriculturally viable (Rippke, et al., 2016). The crop suitability dataset from the baseline condition, combined with presence-absence data generated from MapSPAM, GBIF, was used to determine the optimal threshold. Presence-absence modeling in R was used to generate the crop-specific optimal threshold value. The optimal threshold takes the observed presence and absence record of a crop, and then combine with the suitability prediction, and then maximize the percentage of presence correctly predicted (sensitivity[12]) and the percentage of absence correctly predicted (specificity[13]). This method tries to find the threshold minimizing the difference between sensitivity and specificity (VanDerWal et al., 2015). The fraction of true positives (TP), true negatives (TN), and false positives (FP) was calculated. Sensitivity *[SE = TPx(TP+TN)-1]* and specificity *[SP = TNx(TN+FP)-1]* were calculated for all suitability values in the range [0,100]. For each crop, the suitability threshold at which the maximum value of SE+SP (maximum specificity and sensitivity, MSS) was recorded was used as the optimal threshold value for the viability of the crop. The viability threshold is shown in Table 4. Consistency pattern analysis was undertaken to retain only persistent transformation pixels. A pixel is considered a false detection if the transformation threshold is inconsistent across time periods (e.g., 2030-2050-2070-2090 = 0-1-0-1). The conditions for identifying the threshold are as follows: 1) below threshold for four consecutive time periods; 2) below threshold for three consecutive, only if it occurs towards the last three time period. If the threshold was detected for the first three, and the latter time period is above threshold, it is considered a false detection; 3) two consecutive below threshold only if it occurs towards the last two time period. If the threshold was detected for the first two, and the latter two time periods are above threshold, it is considered a false detection.

[12] Sensitivity is the proportion of observed positives (presence) correctly predicted, and reflects a model's ability to predict a presence given that a species actually occurs at a location.

[13] Specificity is the proportion of observed negatives (absences) correctly predicted, and reflects a model's ability to predict an absence given that a species actually does not occur at a location.

3. Results

The result of the climate suitability modeling is shown in Appendix 3-A to H. The modeled distribution of crops in the Asia-Pacific shows an acceptable accuracy (Table 4) with AUC ranging from 0.66 (lowest for taro) to 0.93 (highest for rice and maize). Furthermore, the result of the crop suitability modeling (Appendix 3) shows broader agreement with the harvested area maps developed by Monfreda et al. (2008) and MAPSPAM (2019).

Table 4. Accuracy assessment and transformation threshold of each crop

Crop	AUC [0-1][14]	Optimal Threshold [0-100%]
RTB		
Cassava	0.91	24%
Sweet Potato	0.79	24%
Potato	0.73	59%
Banana	0.75	12.5%
Yam	0.93	49%
Taro	0.65	3%
Key non-RTB Crops		
Maize	0.93	40%
Rice[15]	0.81	19%

3.1. Potential climate change impacts on crops

Potential climate change impact for each crop were represented as the change of suitability values per pixel expressed as percentage change from the baseline conditions. The crops were selected based on the consultation with partners for each country, their importance for food consumption and livelihood, and food security. We then show the areas where crops are predicted to transform due to climate change based on calculating the optimal threshold of suitability.

3.1.1. Climate suitability scenarios for key non-RTB crops

The general trend of projected impact of climate change to key crops shows that all countries will experience different degree of crop suitability losses across all time periods, although losses for maize is much higher than rice (Figure 2A-B). Results for maize should be considered carefully as EcoCrop model has shown poor performance in Central America (Borouncle et al., 2017).

3.1.1.1. **Maize** (Appendix 3-F)

- For maize, widespread and drastic decrease in suitability is expected in all countries. Accordingly, suitability simulation shows higher suitability losses across countries. Consistent losses of suitability from 2030 to 2090. Drastic changes might occur as early as 2030 for China and India.
- China, India, Myanmar, and Indonesia are the countries that will experience the highest negative impact for maize. The model result from EcoCrop broadly agrees with the change in suitability for maize developed by Ramirez-Cabral et al. (2017) using CLIMEX model (http://climatemodel.net/climex.htm).

[14] Poor model performance is indicate by an AUC ≤ 0.5
[15] Biomod2 model with RF, FDA, and GLM models used to assess climatic suitability.

- In China, seven (7) provinces along the eastern and northeastern part will experience over 50% reduction in suitability by 2030, e.g., Hubei (-50%), Hunan (-50%), Zhejiang (-54%), Jiangxi (-70%), Anhui (-81%), Jiangsu (-50%), Shanghai (-66%).
- In India, northern states (Bihar and Uttar Pradesh) will experience as much as 70% reduction in suitability as early as 2030. In Gujarat (eastern India), around 61% loss of suitability is expected by 2030, and will continue to increase as much as 90% by 2050.
- Philippines, Indonesia, and Vietnam will have minimal losses of suitability by 2030. However, this is followed by higher losses of suitability on a later time period.
- Suitability losses are projected to continue in all countries until the end of century.
- Although the general trend shows losses of suitability, there are areas that are predicted to gain suitability for maize in the future. In China, provinces of Liaoning and Shaanxi will increase suitability by two folds, and Liaoning by five folds from the very low suitability value in the baseline conditions. This can be attributed to decrease incidence of cold stress leading to an increase in growing season and yields (Wei et al., 2016).

3.1.1.2. Rice (Appendix 3-G)

- Large rice producing states in India are projected to lose suitability over time. As much as 40% reduction in suitability as early as 2050 in West Bengal and Bihar (covering rice area of 5.46 and 3.21 million hectares, respectively).
- Although the general trend shows losses of suitability, there are areas that are predicted to gain suitability for rice in the future. For instance, some provinces in Indonesia, Bengkulu, Gorontalo, and Papua Barat -- which currently have small rice area – will experience increase in suitability by almost 30%.
- Minimal decrease in suitability is expected in Indonesia by 2030. However, this is followed by drastic suitability reduction by as much as 25% at the end of century (2090).
- In Myanmar, rice suitability continues to decrease by more than 25%, especially in the central dry zone of the Ayeyarwady region.

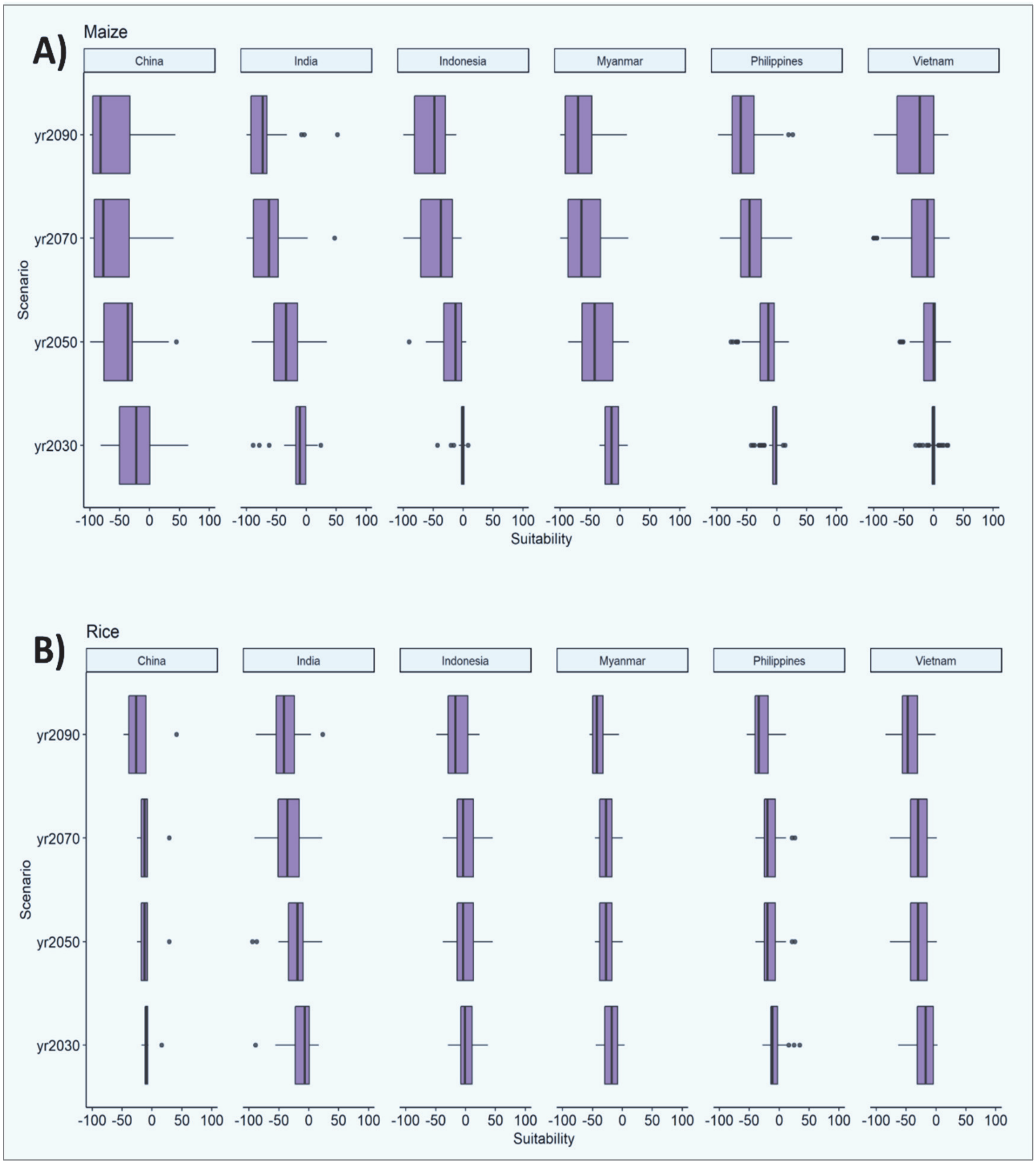


Figure 2. Climate suitability change for key crops in Asia: **A)** Maize, and **B)** Rice.

3.1.2. Climate suitability scenarios for root, tuber and banana (RTB)

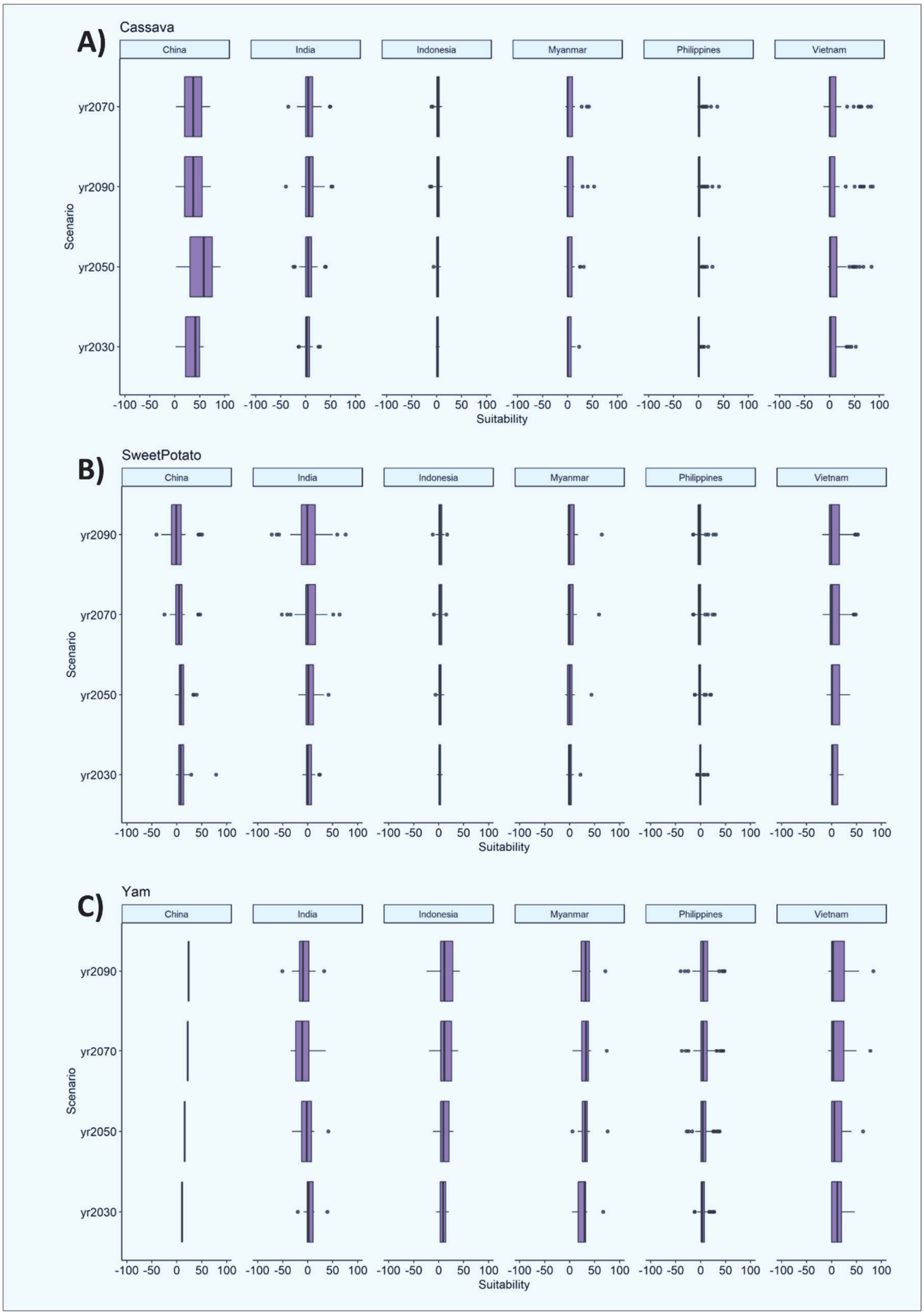
Based on simulations, the general trend for RTB suitability shows a wide variation across Asia (Figure 3A-F). According to model results, trends of suitability changes are discussed in the following sections.

3.1.2.1. Root and tuber crops

- Predictions show an increase in suitability for cassava and sweetpotato across countries.
- For cassava, sweetpotato, and yam, large portions of suitable area are projected to stay suitable in the future.
- Expansion of suitability is expected for sweetpotato and cassava in China. For instance, considerable increase in suitability of cassava in the eastern part of China where maize will undergo dramatic decrease in suitability. This means, cassava will have a comparative advantage in these geographic areas.
- For sweetpotato, a considerable increase in suitability (from very marginal to suitable) is expected for Jilin and Heilongjang provinces in the northeastern part of China.
- Decrease in suitability for yam from 2050 to 2090 is expected in China, although the decrease in suitability is still within a positive range as compared to the baseline suitability values.
- Consistent losses are predicted for potato and taro across countries and time periods. For potato, suitable areas will recede to higher elevation as shown in countries like Myanmar and Philippines (Appendix 3-D). Large suitable areas are still in China. The same case with taro, where a drastic decrease in suitability (from very suitable to very marginal) is expected to occur in lowlands of Indonesia and in the Philippines towards the end of the century.

3.1.2.2. Banana

- For banana, most of areas will decrease in suitability (from suitable to marginal), especially in the lowlands of Indonesia, Vietnam, Philippines, and eastern India. On the other hand, suitability is projected to expand in Northern Vietnam (Appendix 3-E) and in areas that are classified as with marginal suitability that will shift to suitable conditions in Central Vietnam. In Kon Tum, suitability will increase threefold from very marginal to suitable conditions at a later time period.
- In China, banana is predicted to gain suitability by as much as 50% by 2050. This is followed by a decrease in suitability until the end of century but still within the positive suitability change as compared to baseline conditions. Moreover, in Vietnam, suitability change remains stable. Suitability losses are indicated for India, Indonesia, Myanmar, and Philippines, although higher losses are expected in India.
- In Myanmar, banana is predicted to gain suitability as much as 50% by 2050 along the eastern and north eastern regions of the country.


A)
Cassava
China
India
Indonesia
Myanmar
Philippines
Vietnam
yr2070
yr2090
yr2050
yr2030
Scenario
-100 -50 0 50 100
Suitability
B)
SweetPotato
China
India
Indonesia
Myanmar
Philippines
Vietnam
yr2090
yr2070
yr2050
yr2030
Scenario
-100 -50 0 50 100
Suitability
C)
Yam
China
India
Indonesia
Myanmar
Philippines
Vietnam
yr2090
yr2070
yr2050
yr2030
Scenario
-100 -50 0 50 100
Suitability

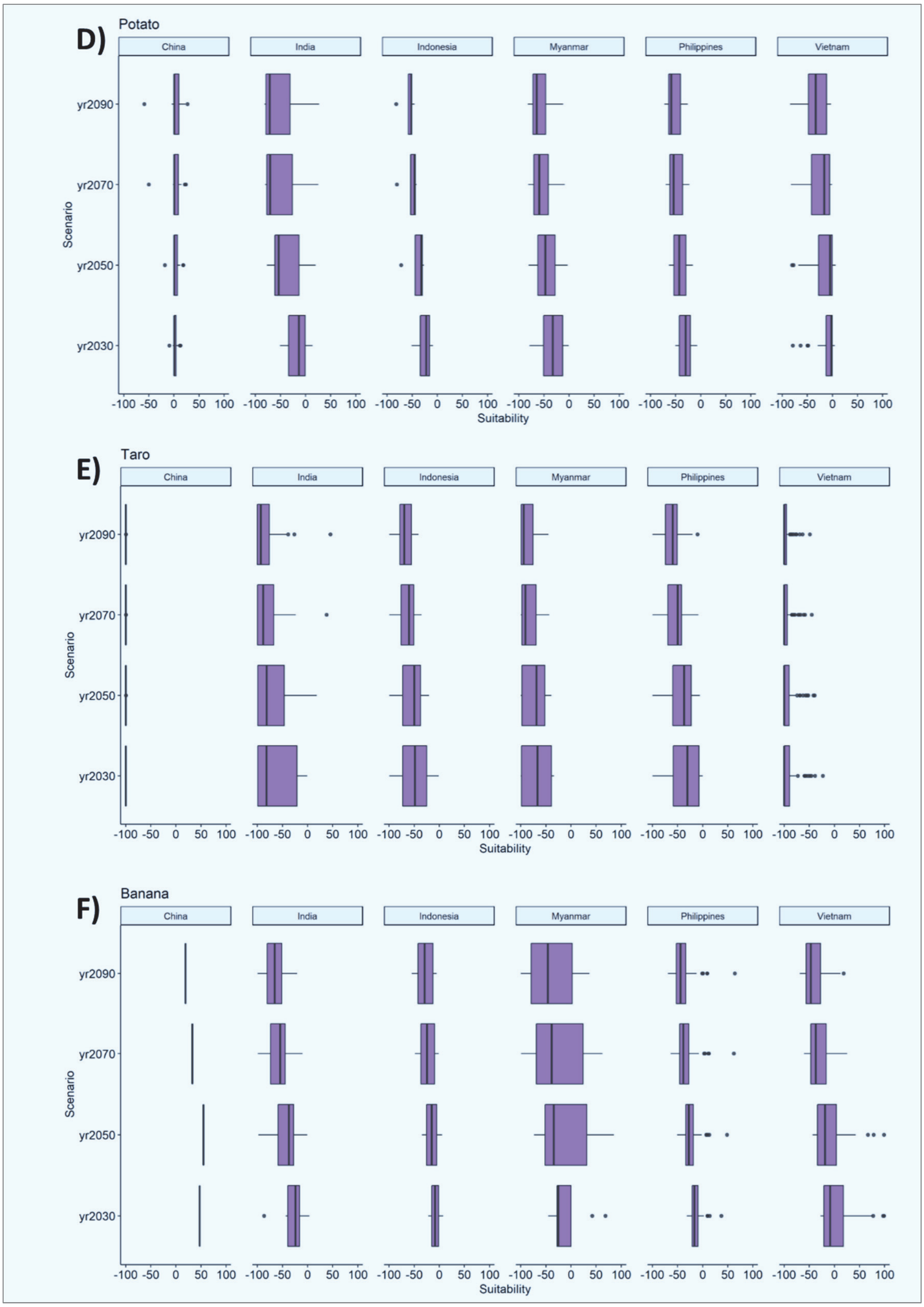


Figure 3. Climate suitability change for root, tubers, and banana (RTB) across Asia: **A)** Cassava, **B)** Sweetpotato, **C)** Yam, **D)** Potato, **E)** Taro, and **F)** Banana

3.2. Crops transformational change

Transformational change implies shifts in locations for production of specific crops, or shifting to farming systems new to a region or resource system (Rippke, et al., 2016). In this study, we identified where major crop transformations are most likely to occur in the Asia-Pacific. In geographic areas where transformation is required farmers, policy makers, and development institutions need to rethink the agricultural land use and, whenever necessary, options should be explored such as an alternative cropping system or move out from crop-based livelihoods in cases where no viable alternative exists. Steffens (2018) revealed that farmers in Guatemala are forced to migrate due to erratic weather patterns that continue to cause failed harvest of crops.

Based on simulations, widespread transformational changes are expected for maize (49% of the total area of maize), rice (8%), and potato (18%). Transformational adaptation suggests that particular attention has to be paid to the cropping systems based on these crops (Figure 4). We did not compute the transformation losses for taro because of limited production area records from open-sourced databases.

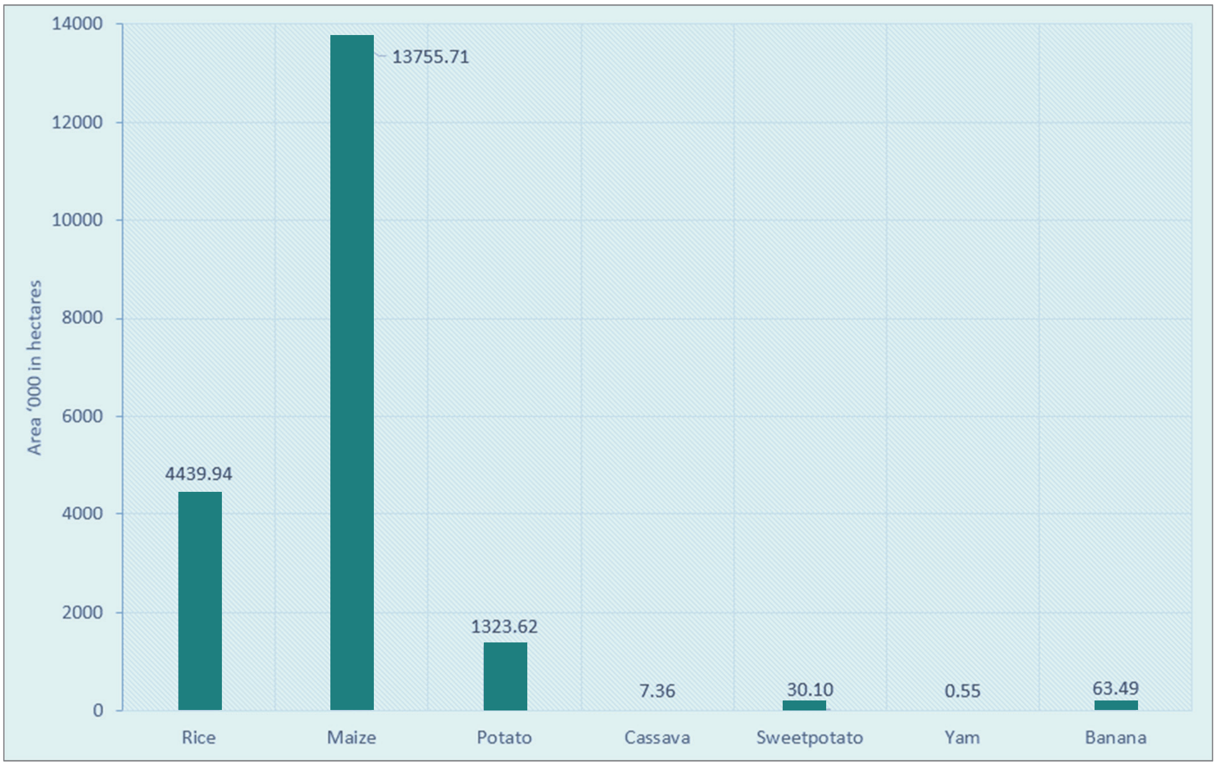


Figure 4. Areas that are projected to require transformation (area '000 of hectares). Area for each crop was acquired from MAPSPAM (You et al., 2014)

Large scale change for maize (see Figure 6). For maize, highest change is projected in China (40% of its present suitable area), particularly in the northeastern part encompassing the provinces of Anhui (93%), Jiangxi (88%), Henan (79%), Hunan (73%), and Anhui (69%). In total, this accounts for 13.8 million hectares out of the 34 million hectares of maize presently cultivated in the country (FAO, 2012 cited in Ely et al., 2016). In India large areas (39%) which accounts for 3.5 million hectares (FAO, 2019) are projected to undergo transformational change in regions above 15° latitude including the States of Uttar Pradesh (95%), Bihar (94%), Gujarat (92%), Rajasthan (14%), West Bengal (85%), Rajasthan (76%), Telangana (37%), Odisha (36%), and Andra Pradesh (36%). In Indonesia (25% equivalent to 1.3 million hectares), the highest changes are expected in Sumatra Selatan (61%), Kalimantan Tengah (55%) and Barat (50%), Riau (38%), and Papua (27%). In Myanmar (24% equivalent to 120,000 hectares) transformation stretches from the dry zone down to the Ayeyarwady region. More limited transformation is expected for Philippines (14%), and Vietnam (2%).

For rice, the highest transformational changes are predicted for India (8% of total suitable area, equivalent to 7.1 million hectares of rice), followed by China (4%, equivalent to 1.2 million ha), and Myanmar (2%, equivalent to 134,000 ha). Sub-national assessment shows that mostly impacted Indian States are along the eastern coast from Odisha (4% of the total suitable area) to Tamil Nadu (17%). Highest change is predicted in Andra Pradesh with an estimate of about 37% loss of suitable areas (~734,400). Transformational changes are also expected in Rajasthan covering an area of 30,928 hectares (14%). Pandya and Prem Meena (n.d) reported that in the Rajastan, rice yields are low because of poor soil fertility and heat stress (hot days and nights), and that productivity is very much dependent on timing of rainfall especially in rain-fed areas. In China, the highest transformational change is expected in Guangxi Province (16%), followed by Jiangxi (12%), and then Gansu (9%).

In the case of potato, large scale transformation (46%, equivalent to 1 million ha) is expected in India along the Indo-Gangetic region (Uttar and Madya Pradesh, Gujarat, Rajasthan, and Chhattisgarh), eastern seaboard (Odisha and West Bengal), and the states of Maharashtra and Telangana. In Myanmar, transformation areas (23%, equivalent to 7,500 ha) are simulated along the dry zone down (Magway and Mandalay) to the Ayeyarwady Region, and the mountainous region in Tanintharyi. Limited transformation areas are also simulated in Vietnam which only account for about 11% (equivalent to 2,252 ha). In the Philippines, it is expected that 55% (4,285 ha) of the limited area planted to potato will undergo transformational change.

Based on simulations, the crops that will require limited or no transformation in the future are sweetpotato and cassava (Figure 5), which are likely to represent viable alternatives in the future to either substitute or complement (mixed cropping system) present crops and increase their contribution to livelihood, food security, and nutrition in areas where key crops, and other RTC crops can potentially become marginalized in the future.

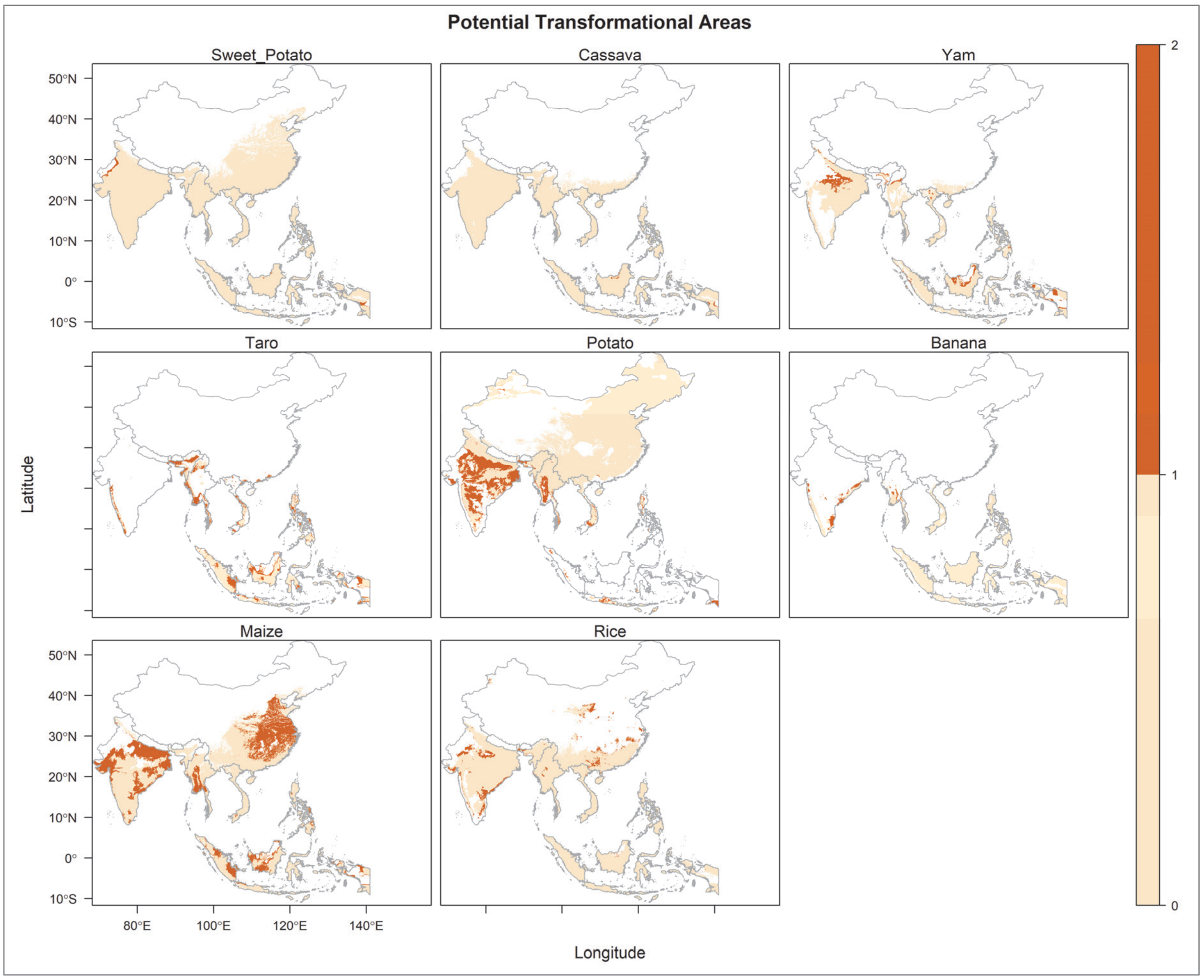


Figure 5. Map showing areas where transformational changes (red color) of each crop are expected in the Asia-Pacific.

Figure 6 below shows where RTB crops can be potentially considered as a future substitute crop for the most important current crops, namely maize and rice. Several root and tuber crops can potentially substitute maize in the lowland of Indonesia and Myanmar, while fewer RTB options (i.e. cassava and sweetpotato, and some yams) are predicted to be available for substitution of maize along the eastern and western seaboard of India, including the Indo-Gangetic plains. For rice, root and tuber crops can have comparative advantage in Guangxi and the narrow stretch of the eastern seaboard in India. Limited rice areas in Uttar and Madhya Pradesh can only be substituted by cassava and sweetpotato.

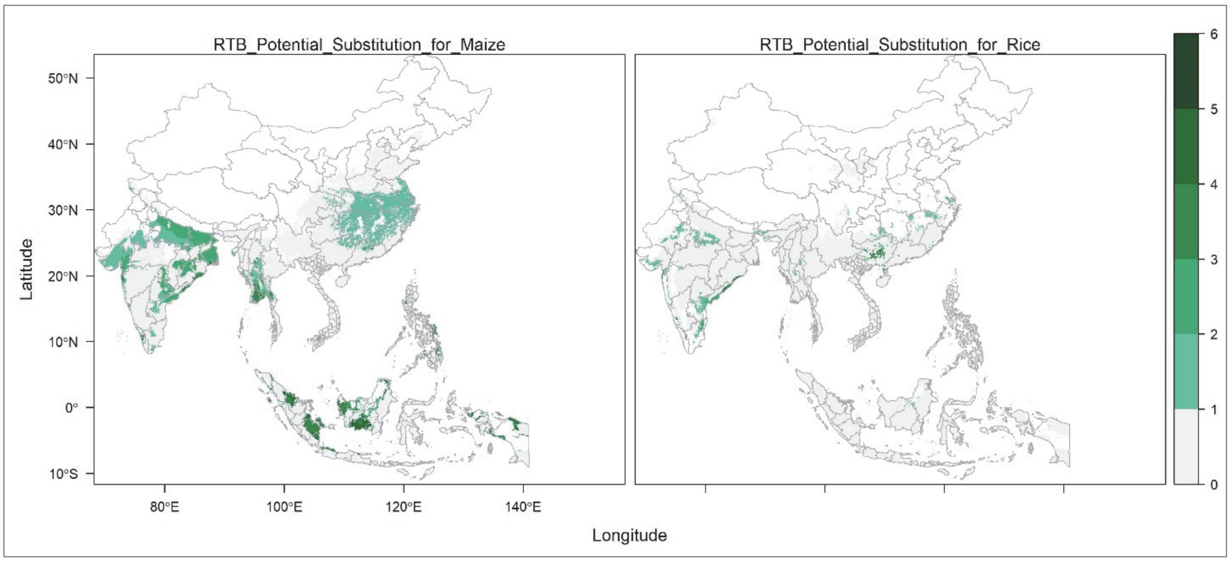


Figure 6. Number of root, tuber, and banana crops that can be used as substitute for key crops (maize and rice) in areas where climate change impact is high.

4. Limitations

This study aimed at assessing impact of climate change on crops and did not consider other factors affecting crop performance in the future, such as the CO_2 fertilization. Several studies synthesized by FAO confirms that the rise in CO_2 concentration has an effect on fertilization (Allen and Boote, accessible online: http://www.fao.org/docrep/w5183e/w5183e06.htm). This was not accounted in the model to predict crop suitability in the future. The prediction was solely based on precipitation and temperature. Moreover, we know that suitability can be determined by several factors, such as soil and terrain (while some aspects of topography are already captured by the climate data, i.e., inverse relationship between altitude and temperature). Moreover, we did not explore the relationship between suitability and yield in this study. As reported by Ramirez-Villegas et al. (2013), there is no clear linear relationship between the two parameters - there are insights that link high value of yield with high suitability values. We have not taken this into account because of limited validation information of yield for some of the crops. Although, based on model prediction, root and tuber crops will increase in suitability, the associated pest and disease (P&D) of each crop was not taken into account on the basis that, the future P&D incidence still remains uncertain.

The study can be further improved by incorporating the various hazards, such as drought (Figure 7), typhoons, and floods, as an additional layer to represent climate-related extreme weather events. The analysis can focus on historical baseline conditions because many climate hazards can be large scale singular events and projections of climate hazards would add further layers of uncertainty. However, while it is not possible to attribute singular extreme events to progressing climate change, it is agreed that the likelihood of most extreme events is increasing under progressing climate change (IPCC 2012).

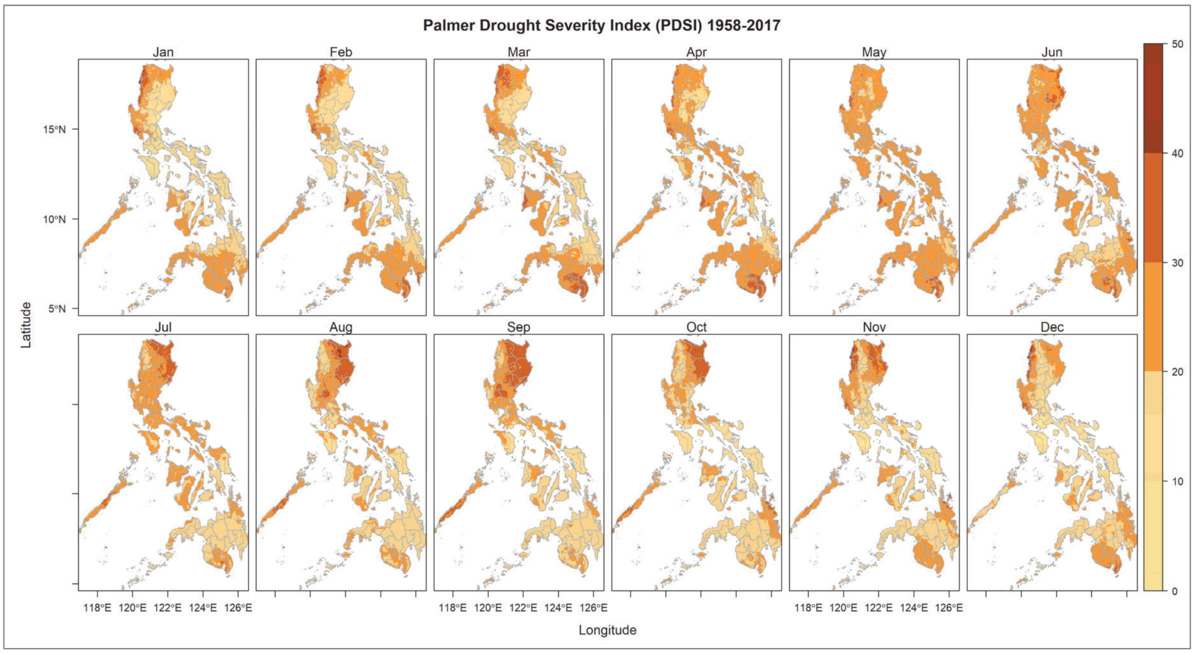


Figure 7. Drought risk in Asia based from 60 years of Palmer Drought Severity Index (PDSI) dataset.

The EcoCrop model did not capture enough growing areas of potato in India for the baseline conditions. Calibration of the model was undertaken using the procedure suggested by Ramirez-Villegas et al (2013) but result overestimated or underestimated the growing areas for potato. Ensemble model (Figure 8) was used to capture suitable growing conditions of potato in India.

5. References

Atakos, V. 2018. Next generation technologies: Tackling climate change in agriculture. Retrieved from: https://cipotato.org/blog/next-generation-technologies-tackling-climate-change-in-agriculture/

Bouroncle, C., Imbach, P., Rodríguez-Sánchez, B., Medellín, C., Martínez-Valle, A., Läderach, P., 2017. Mapping climate change adaptive capacity and vulnerability of smallholder agricultural livelihoods in Central America: ranking and descriptive approaches to support adaptation strategies. Clim. Chang. 141, 123–137.

Balderama, O. F., Alejo, L. A., and Tongson, E. E. 2016. Calibration, validation and application of CERES-Maize model for climate change impact assessment in Abuan Watershed, Isabela, Philippines. Climate, Disaster and Development Journal. DOI: https://doi.org/10.18783/cddj.v002.i01.a02

Denton, F., T.J.Wilbanks, A.C. Abeysinghe, I. Burton, Q. Gao, M.C. Lemos, T. Masui, K.L. O'Brien, and K.Warner, 2014. Climate-resilient pathways: adaptation, mitigation, and sustainable development. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L.White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1101-1131.

Dhankher, Om Parkash and Foyer, Christine H. 2018. Climate resilient crops for improving global food security and safety. Plant, Cell and Environment. Wiley Online Library. Accessible online: https://onlinelibrary.wiley.com/doi/epdf/10.1111/pce.13207. DOI: https://doi.org/10.1111/pce.13207

EarthStat. 2018. EarthStat shares cutting-edge on the global food system to help others make science-based decisions. Accessible online: http://www.earthstat.org/

Ely A., Geall, S., and Song, Y. 2016. Sustainable maize production and consumption in China: practices and politics in transition. Journal of Cleaner Production, Volume 134, Part A. https://doi.org/10.1016/j.jclepro.2015.12.001. Retrieved online: https://www.sciencedirect.com/science/article/pii/S0959652615018120

FAO, 2012. FAOSTAT Maize production Data. Retrieved online: http://faostat3.fao.org/

FAO, 2019. FAOSTAT Maize area, production, and yield. Retrieved online: http://www.fao.org/faostat

Fick and Hijman, 2017. WorldClim 2: New 1-km spatial resolution climate surfaces for global land areas. International Journal of Climatology. DOI: 10.1002/joc.5086

Hanley, J.A., and McNeil, B.J. 1982. The meaning and use of the Area Under a ROC Curve. Radiology, 143, 29-36

Hijman R. J., Guarino, L., Cruz, M., and Rojas, E. 2001. Computer tools for spatial analysis of plant genetics resources data: 1. DIVA-GIS. Plant Genetic Resources Newsletter, 127: 15-19

Intergovernmental Panel on Climate Change (IPCC) (2012). Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 582 pp.

Jianchu X., Yongping, Y., Yingdong, P., Ayad, W. G., and Eyzaguirre, P. B. 2001. Genetic Diversity in Taro (*Colocasia esculenta* Schott, Araceae) in China: An Ethnobotanical and Genetic Approach. Economy Botany, Vol. 55, No. 1 (Jan. - Mar., 2001), pp 14-31. Springer on behalf of New York Botanical Garden Press

MapSPAM [Spatial Production Allocation Model], 2019. Spatial Production Allocation model. Retrieved on: June 2018. Accessible online: http://mapspam.info/

Monfreda, C., Ramankutty, N., and Foley, J. A. 2008. Farming the planet: 2. Geographical distribution of crop areas, yields, physiological types, and net primary production in the year 2000. Global Biogeochemical Cycles, Vol. 22, GB1022. Doi: 10.1029/2007GB002947

Pandya R., and Prem Meena, P. K. n.d. Status report on rice in Rajasthan. Retrieved online: http://www.rkmp.co.in/sites/default/files/ris/rice-state-wise/Status%20Paper%20on%20Rice%20in%20Rajasthan.pdf

Thuiller, W., Lafourcade, B., Engler, R., & Araújo, M. B. (2009). BIOMOD - A platform for ensemble forecasting of species distributions. Ecography, 32(3), 369–373. https://doi.org/10.1111/j.1600-0587.2008.05742.x

Thuiller, W., Georges, D., Engler R., and Breiner, F. 2016. Package 'biomod2': Ensemble platform for species distribution modeling. Available on line: https://cran.r-project.org/web/packages/biomod2/biomod2.pdf

Ramirez-Cabral, N. Y. Z., Kumar, L., and Shabani, F. 2017. Global alterations in areas of suitability for maize production from climate change and using a mechanistic species distribution model (CLIMEX). Nature Scientific Reports. Available on line: https://www.nature.com/articles/s41598-017-05804-0. DOI: https://doi.org/10.1038/s41598-017-05804-0

Ramirez-Villegas, J., Jarvis, A., and Laderach, P. 2013. Empirical approaches for assessing impacts of climate change on agriculture: The EcoCrop Model and a case study with Grain Sorghum. Agriculture and Forest Meteorology 170:67-78. DOI: https://dx.doi.org/10.1016/j.agrformet.2011.09.005. Available on line: http://hdl.handle.net/10568/42056

Ray, D.K., Gerber, J.S., MacDonald, G.K., and West, P.C. 2015. Climate variation explains a third of global crop yield variability. Nature Communications 6, Article number: 5989 (2015). Available on line: https://www.nature.com/articles/ncomms6989

Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., … Rafaj, P. (2011). RCP 8.5-A scenario of comparatively high greenhouse gas emissions. Climatic Change, 109(1), 33–57. https://doi.org/10.1007/s10584-011-0149-y

Rippke, U., Ramirez-Villegas, J., Jarvis, A., Vermeulen S. J., Parker, L., Mer, F., Diekkrüger, B., Challinor, A. J., and Howden, M. 2016. Timescales of transformational climate change adaptation in sub-Saharan African agriculture. Nature Climate Change Letters. DOI: 10.1038/NCLIMATE2947. Available on line: https://www.nature.com/articles/nclimate2947

Smit B., and Wandel, J. 2006. Adaptation, Adaptive Capacity, and Vulnerability. Global Environmental Change 16(3):282-292. DOI: 10.1016/j.gloenvcha.2006.03.008

Steffens, G. 2018. Changing climate forces desperate Guatemalans to Migrate (National Geographic Article). Retrieved online: https://www.nationalgeographic.com/environment/2018/10/drought-climate-change-force-guatemalans-migrate-to-us/

Swets, J.A. 1988. Measuring the accuracy of diagnostic systems. Science, 240, 1285-1293

VanDerWal, J., Falconi, L., Januchowski, S., Shoo, L., and Storlie, C. 2015. Species Distribution Modelling Tools: Tools for processing data associated with species distribution modelling exercises. Available online: http://www.rforge.net/SDMTools/

Wei, T., Zhang, T., de Bruin, K., Glomrød, S., & Shi, Q. (2017). Extreme weather impacts on maize yield: The case of Shanxi Province in China. *Sustainability (Switzerland)*, *9*(1), 1–12. https://doi.org/10.3390/su9010041

You, L., U. Wood-Sichra, S. Fritz, Z. Guo, L. See, and J. Koo. 2014. Spatial Production Allocation Model (SPAM) 2005 v3.2. [October 12, 2017]. Available from http://mapspam.info.

Appendices

Appendix 1: Overview of the used CMIP5 models for RCP 8.5 and the corresponding modelling center and institution

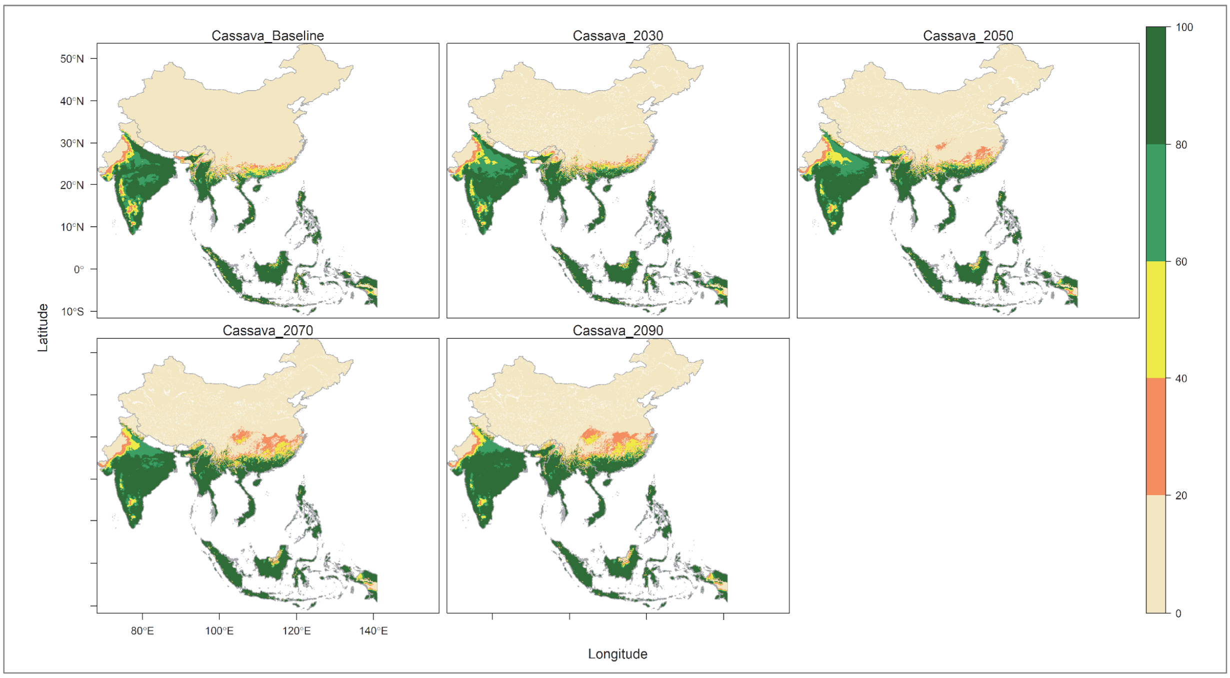
Model	Modeling Center	Institution
bcc_csm1_1	BCC	Beijing Climate Center, China Meteorological Administration
bcc_csm1_1_m	BCC	Beijing Climate Center, China Meteorological Administration
bnu_esm	GCESS	College of Global Change and Earth System Science, Beijing Normal University
cccma_canesm2	CCCMA	Canadian Centre for Climate Modelling and Analysis
cesm1_bgc	NSF-DOE-NCAR	National Science Foundation, Department of Energy, National Center for Atmospheric Research
cesm1_cam5	NCAR	National Center for Atmospheric Research
cnrm_cm5	CNRM-CERFACS	Centre National de Recherches Meteorologiques / Centre Europeen de Recherche et Formation Avancees en Calcul Scientifique
csiro_access1_0	CSIRO-BOM	CSIRO (Commonwealth Scientific and Industrial Research Organisation, Australia), and BOM (Bureau of Meteorology, Australia)
csiro_access1_3	CSIRO-BOM	CSIRO (Commonwealth Scientific and Industrial Research Organisation, Australia), and BOM (Bureau of Meteorology, Australia)
csiro_mk3_6_0	CSIRO-QCCCE	Commonwealth Scientific and Industrial Research Organization in Collaboration with the Queensland Climate Change Centre of Excellence
ec_earth	EC-EARTH	EC-EARTH Consortium
fio_esm	FIO	The First Institute of Oceanography, SOA, China
gfdl_cm3	NOAA GFDL	Geophysical Fluid Dynamics Laboratory
gfdl_esm2g	NOAA GFDL	Geophysical Fluid Dynamics Laboratory
gfdl_esm2m	NOAA GFDL	Geophysical Fluid Dynamics Laboratory
giss_e2_h	NASA GISS	NASA Goddard Institute for Space Studies
giss_e2_r	NASA GISS	NASA Goddard Institute for Space Studies
inm_cm4	INM	Institute for Numerical Mathematics
ipsl_cm5a_lr	IPSL	Institut Pierre-Simon Laplace
ipsl_cm5a_mr	IPSL	Institut Pierre-Simon Laplace
ipsl_cm5b_lr	IPSL	Institut Pierre-Simon Laplace
lasg_fgoals_g2	LASG-CESS	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences; and CESS, Tsinghua University
miroc_esm	MIROC	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
miroc_esm_chem	MIROC	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies
miroc_miroc5	MIROC	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
mohc_hadgem2_cc	MOHC (additional realizations by INPE)	Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)
mohc_hadgem2_es	MOHC (additional realizations by INPE)	Met Office Hadley Centre (additional HadGEM2-ES realizations contributed by Instituto Nacional de Pesquisas Espaciais)
mpi_esm_lr	MPI-M	Max Planck Institute for Meteorology (MPI-M)
mpi_esm_mr	MPI-M	Max Planck Institute for Meteorology (MPI-M)
mri_cgcm3	MRI	Meteorological Research Institute
ncar_ccsm4	NCAR	National Center for Atmospheric Research
ncc_noresm1_m	NCC	Norwegian Climate Centre
nimr_hadgem2_ao	NIMR/KMA	National Institute of Meteorological Research/Korea Meteorological Administration

Appendix 2: Bioclimatic variables used in crop distribution modelling

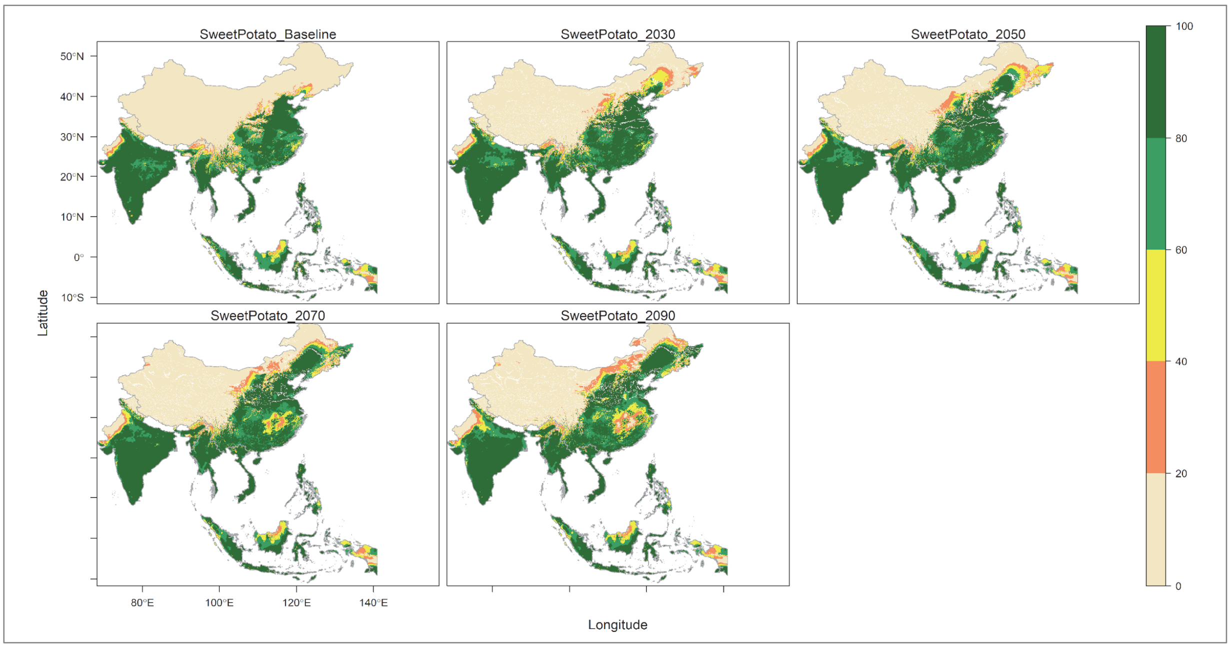
Parameters	Description (O'Donnell, M and Ignizio, D., 2012)
Temperature Related	
Bio_1 - Annual mean temperature	Annual mean temperature derived from the average monthly temperature.
Bio_2 - Mean diurnal range	The mean of the monthly temperature ranges (monthly maximum minus monthly minimum).
Bio_3 - Isothermality	Oscillation in day-to-night temperatures.
Bio_4 - Temperature seasonality	The amount of temperature variation over a given year based on standard deviation of monthly temperature averages.
Bio_5 - Maximum temperature of warmest month	The maximum monthly temperature occurrence over a given year (time-series) or averaged span of years (normal).
Bio_6 - Minimum temperature of coldest month	The minimum monthly temperature occurrence over a given year (time-series) or averaged span of years (normal).
Bio_7 - Temperature annual range	A measure of temperature variation over a given period.
Bio_8 - Mean temperature of wettest quarter	This quarterly index approximates mean temperatures that prevail during the wettest season.
Bio_9 - Mean temperature of driest quarter	This quarterly index approximates mean temperatures that prevail during the driest quarter.
Bio_10 - Mean temperature of warmest quarter	This quarterly index approximates mean temperatures that prevail during the warmest quarter.
Bio_11 - Mean temperature of coldest quarter	This quarterly index approximates mean temperatures that prevail during the coldest quarter.
Precipitation Related	
Bio_12 - Annual precipitation	This is the sum of all total monthly precipitation values.
Bio_13 - Precipitation of wettest month	This index identifies the total precipitation that prevails during the wettest month.
Bio_14 - Precipitation of driest month	This index identifies the total precipitation that prevails during the driest month.
Bio_15 - Precipitation seasonality	This is a measure of the variation in monthly precipitation totals over the course of the year. This index is the ratio of the standard deviation of the monthly total precipitation to the mean monthly total precipitation and is expressed as percentage.
Bio_16 - Precipitation of wettest quarter	This quarterly index approximates total precipitation that prevails during the wettest quarter.
Bio_17 - Precipitation of driest quarter	This quarterly index approximates total precipitation that prevails during the driest quarter.
Bio_18 - Precipitation of warmest quarter	This quarterly index approximates total precipitation that prevails during the warmest quarter.
Bio_19 - Precipitation of coldest quarter	This quarterly index approximates total precipitation that prevails during the coldest quarter.
Bio_20 - Number of consecutive dry days	Consistent number considered as dry days.

Appendix 3: Maps of climate suitability of key and RTC crops in Asia

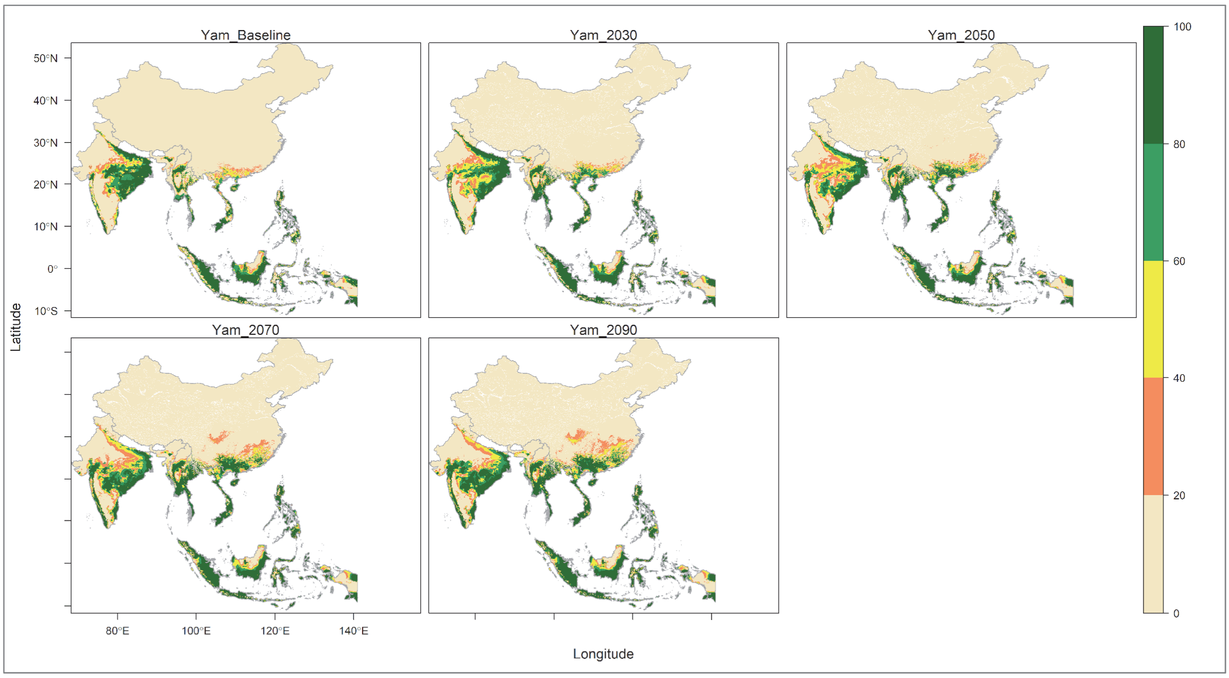
Appendix 3-A: Climate suitability scenarios for cassava in the Asia-Pacific



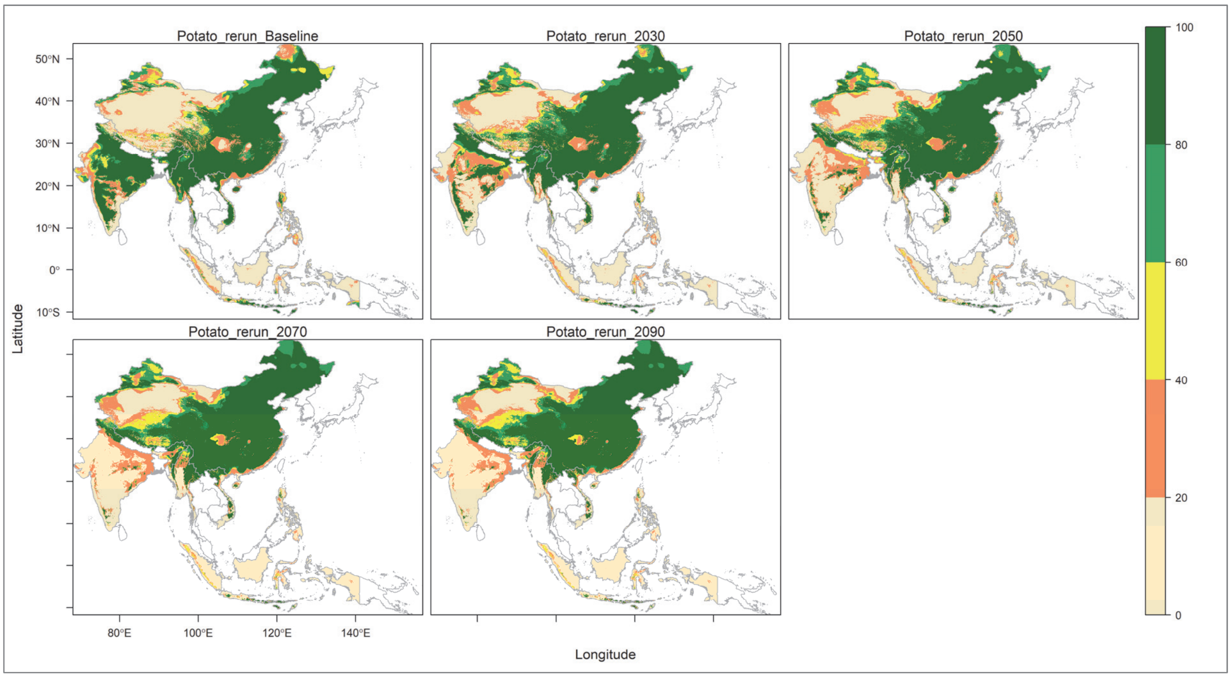
Appendix 3-B: Climate suitability scenarios for sweetpotato in the Asia-Pacific



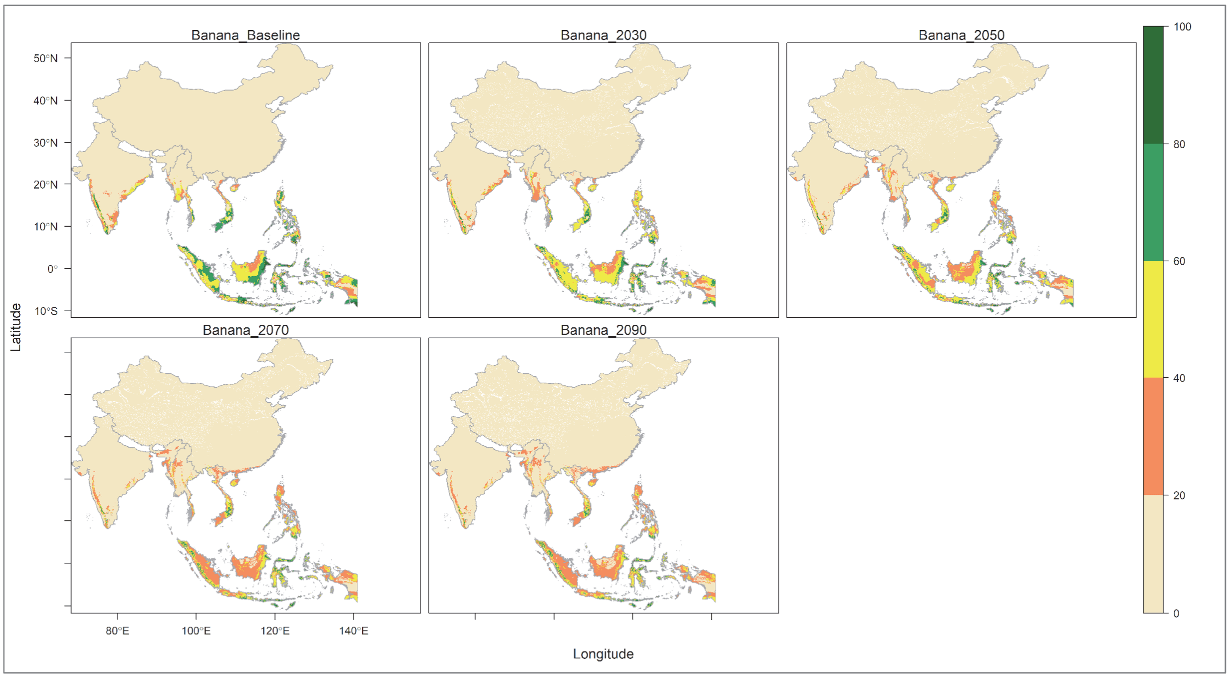
Appendix 3-C: Climate suitability scenarios for yam in the Asia-Pacific



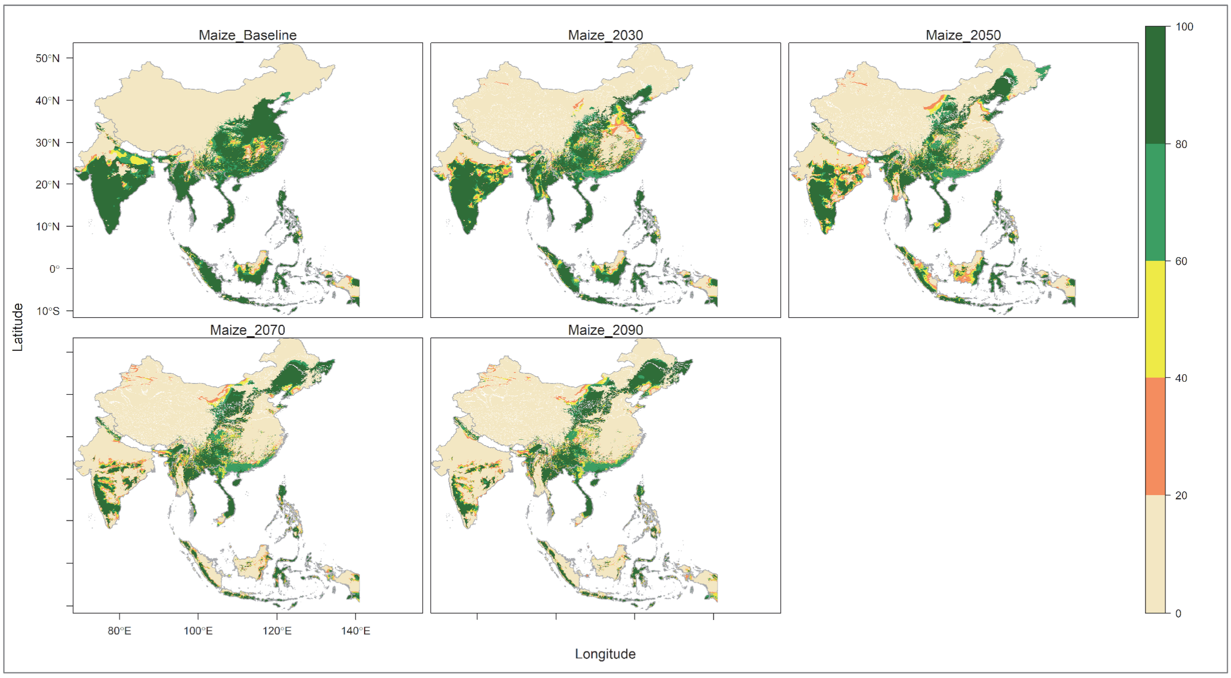
Appendix 3-D: Climate suitability scenarios for potato in the Asia-Pacific



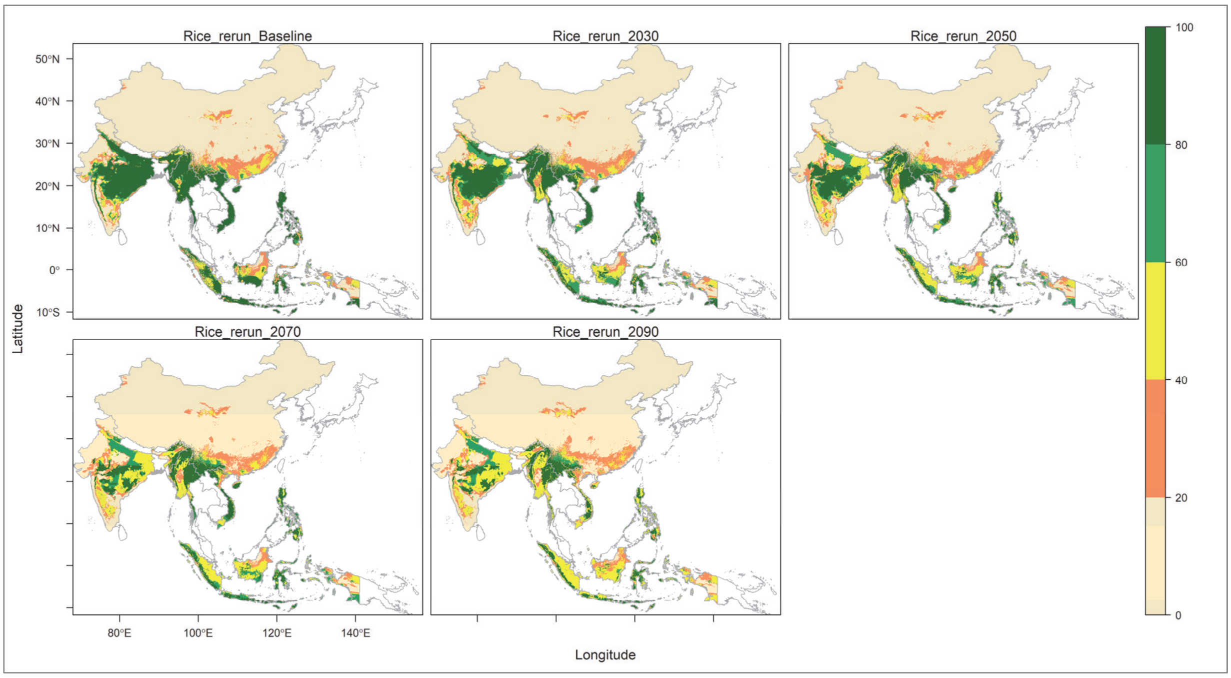
Appendix 3-E: Climate suitability scenarios for banana in the Asia-Pacific



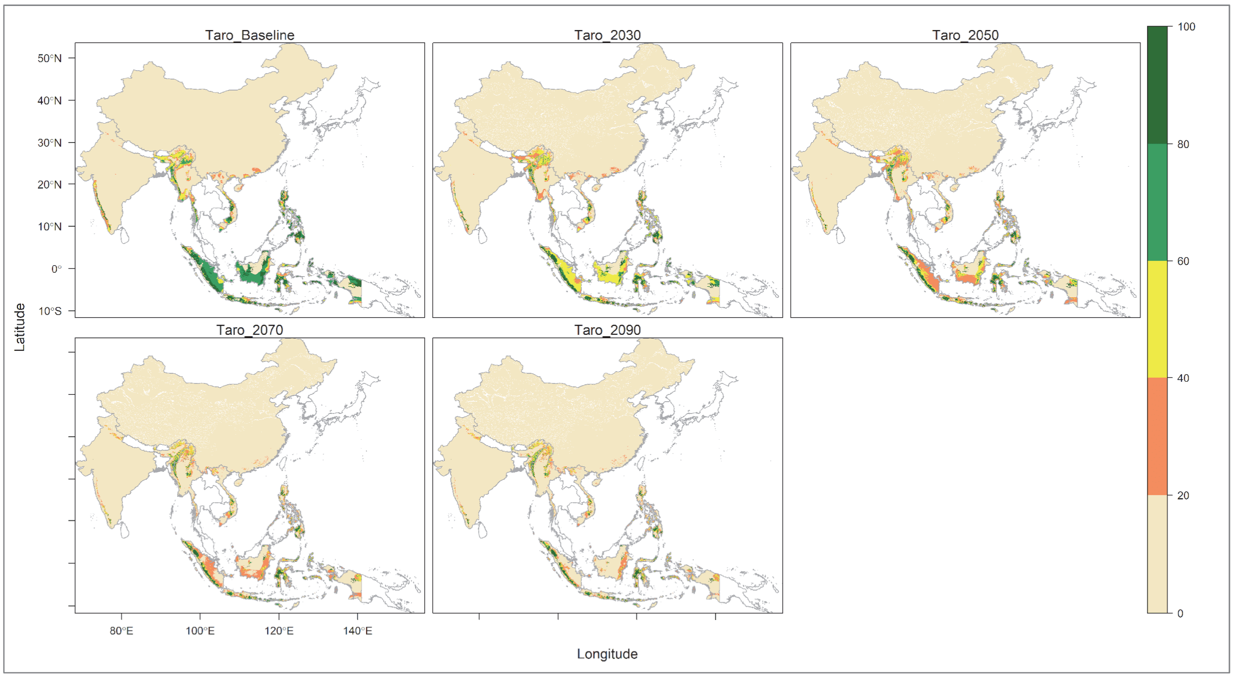
Appendix 3-F: Climate suitability scenarios for maize in the Asia-Pacific



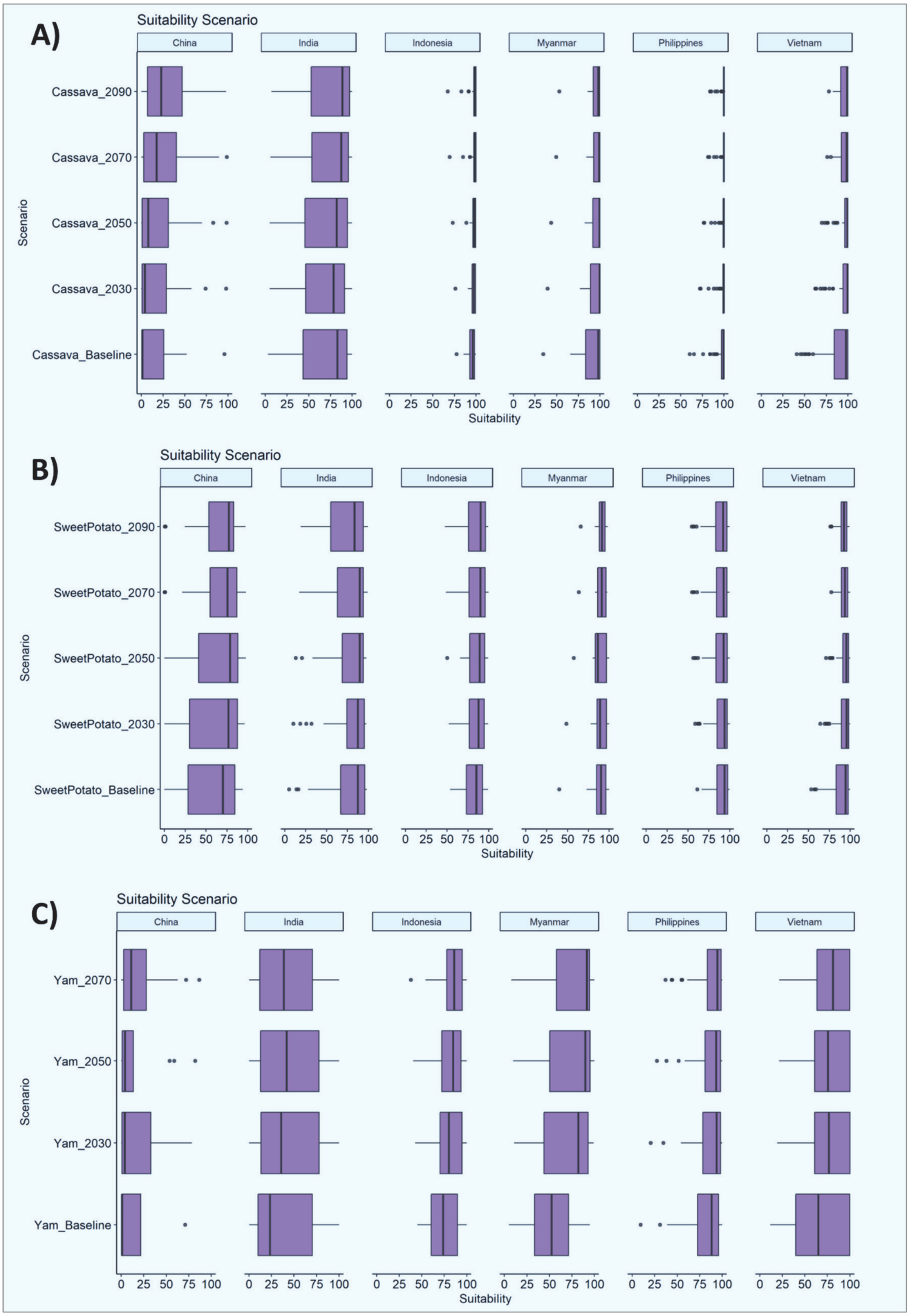
Appendix 3-G: Climate suitability scenarios for rice in the Asia-Pacific

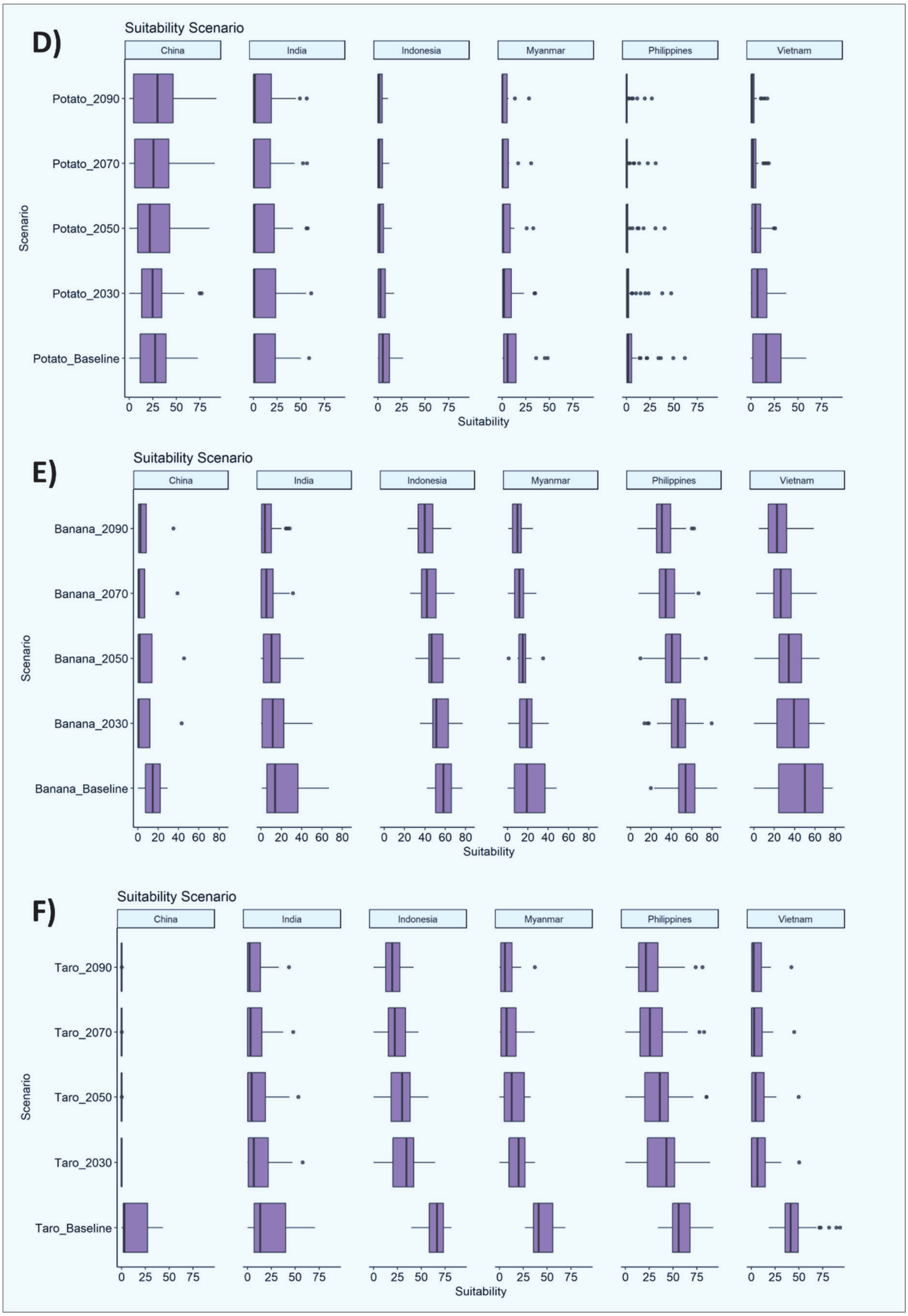


Appendix 3-H: Climate suitability scenarios for taro in the Asia-Pacific

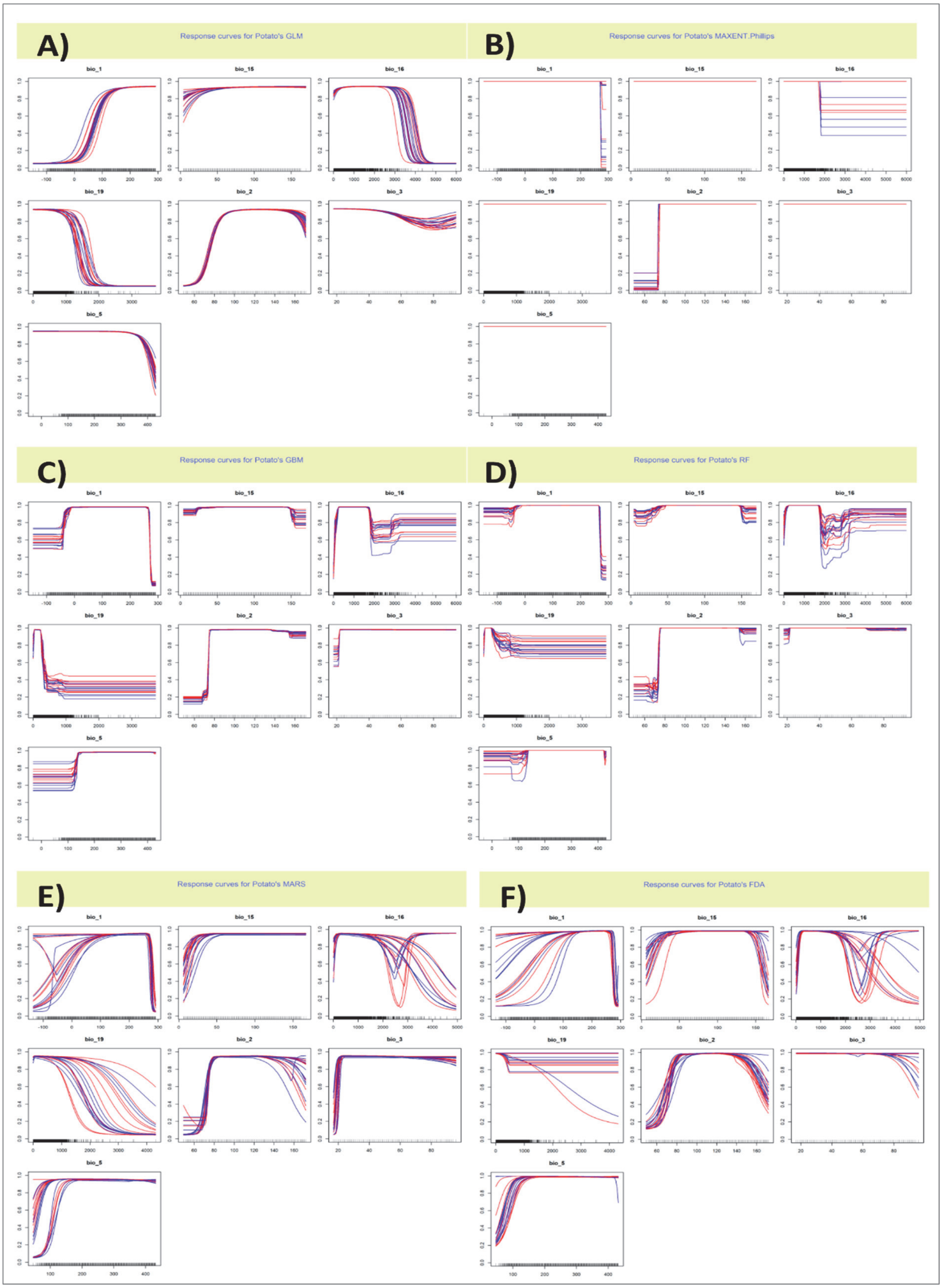


Appendix 4: Climate suitability scenarios




D)
Suitability Scenario
China
India
Indonesia
Myanmar
Philippines
Vietnam
Potato_2090
Potato_2070
Potato_2050
Potato_2030
Potato_Baseline
Scenario
0 25 50 75
Suitability
E)
Suitability Scenario
Banana_2090
Banana_2070
Banana_2050
Banana_2030
Banana_Baseline
0 20 40 60 80
F)
Suitability Scenario
Taro_2090
Taro_2070
Taro_2050
Taro_2030
Taro_Baseline

Appendix 5: Response curves from GLM, MAXENT.Phillips, GBM, and RF for potato



Appendix 6: Overview of external data sets used in the suitability assessment

Parameter	Source	Unit of measurement, spatial and temporal resolution
Data set A.) Baseline climate data	Worldclim version 2 (Fick and Hijman, 2017). Available online: http://worldclim.org/version2	30 arc-seconds monthly climate/bioclimatic data from year 1970-2000
Data set B.) Future climate data	Downscaled climate projections from Climate Change and Food Security (CCAFS) climate portal. Available online: http://www.ccafs-climate.org/	30 arc-seconds monthly climate/bioclimatic data for time period 2030s, 2050s, 2070s, and 2090s
Data set C.) Presence/Absence data	Global Biodiversity Information Facility (GBIF). Available online: https://www.gbif.org/	Global data for species location
	MAP Spatial Production Allocation Model (MAPSPAM). Available online: http://mapspam.info/	10km resolution harvested area globally, year 2005
	EarthStat. Available online: http://www.earthstat.org/	10km resolution harvested area globally, year 2005
	Genesys portal. Available online: https://www.genesys-pgr.org/welcome	Database of plant genetic resources.
	Potatopro. Available online: https://www.potatopro.com/	Crop statistics for Potato for gathering crop presence
	General Statistics Office (GSO), Vietnam	Commune-level crop Area-Production-Yield data of Vietnam
	Department of Agriculture - Adaptation and Mitigation Initiative in Agriculture (AMIA) Project	Crop occurrence data for selected 17 provinces in the Philippines
Data set D.) EcoCrop Parameters	Rippke et al (2016). Available online: https://www.nature.com/articles/nclimate2947	Precipitation and temperature parameters (Table 2) used for crop modeling validated with crop experts from various institutes and CGIAR centers
	EcoCrop database. Available online: http://ecocrop.fao.org/ecocrop/srv/en/home	EcoCrop database developed by the Food and Agriculture Organisation (FAO)

WWW.CIPOTATO.ORG

For more information, please contact CIP Headquarters. Av. La Molina 1895, La Molina. Apartado 1558, Lima 12, Peru.

+51 1 3496017 *cip-cpad@cgiar.org* *www.cipotato.org* | *@cipotato* *@Cipotato* *@cip_cipotato*