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Global climate change impacts on cocoa

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Abstract

Global climate models project a continued increase of temperatures and changes in the spatial and temporal distribution of precipitation. These developments have been shown to potentially impact cocoa production at its most important origins. The prospect of reduced cocoa yields on existing plantations renewed concerns that prevailing cocoa demand could drive producers even deeper into forests in other regions. Thus, prioritization of adaptation strategies for cocoa production and ecosystem conservation efforts will benefit from a global intercomparison of climate change impacts.

We modeled the global distribution of suitable climates for cocoa production under historic and future conditions. A database of cocoa occurrence locations and historic climate data was used to train the Random Forest classification algorithm. Model evaluation on historic data showed a high ability to correctly identify current production regions. The classifier was extrapolated on climate data from multiple global climate models for low, intermediate and high radiative forcing scenarios for mid and end of century projections.

Across all cocoa origins decreases of climatic suitability were projected. We find that available area of high suitability will be diminished while area with low suitability scores may be increasingly available. Furthermore, we find that projected impacts will be unlikely to make major cocoa producing regions unsuitable altogether. These findings could be partially explained with the high uncertainty of precipitation projections of global climate models. Temperatures were found to rise beyond historically experienced levels with high certainty. Areas most likely to retain high suitability were found in proximity of forest reserves where precipitation is most likely to remain sufficiently high. Climate change is thus likely to cause additional challenges to the sector at global scale. Research should focus on the impacts of high temperatures on quality and vitality of the plant, and the management of increased drought risk. Furthermore, the implications of changed climate conditions for regional pest and disease patterns remain largely uncertain.

We conclude that cocoa production will continue to threaten biodiverse forests across tropical countries. Cocoa production is a primary beneficiary of ecosystem services provided by resilient landscapes. Deforestation will exacerbate the effects of climate change by resulting in locally reduced precipitation, addition to emissions from land use change, and diminished barriers to pest and disease spread. Efforts to make cocoa deforestation free are therefore in the self-interest of the cocoa sector.

Introduction

It is virtually certain that global temperatures have increased by about 0.85°C during the period 1880–2012. Global circulation models (GCMs) have projected the effects of continued emissions on the global climate, and an additional increase of 1.4–3.1°C by the end of this century was found to be likely (Stocker et al. 2013). There is increasing consensus that the risk of drought has increased over the past decades. GCMs were found to reproduce these trends and projected additional drought risk for the coming decades, either through decreased precipitation or increased evaporation (Dai 2013).

The cocoa tree, Theobroma cacao L., originated from the wet forests of South America, very close to the equator. In its natural habitat, rainfall is heavy and the temperature is relatively uniform. High precipitation of about 1500 – 2000 mm well distributed throughout the entire year is considered optimal for the cocoa crop. However, in the major production regions in West Africa, production systems have been adapted to a weather pattern with one or two dry seasons per year. Months with less than 100 mm are considered dry months (Lass and Wood 1985), as little as 60 mm is tolerated. While a dry season induces uniform flowering, overall yields are higher without such a period (Zuidema et al. 2005). This may be associated with low assimilation rates caused by vapour pressure deficit in the dry season (Acheampong et al. 2013). In general, for optimal conditions, temperatures should be within 18°C and 32°C for high assimilation rates (Almeida and Valle 2007). Temperatures below 10°C can be lethal (FAO 2007). For maladapted genotypes, fruit size and bean quality may be affected by excessive growing season temperatures (Daymond and Hadley 2008). Heat has been shown to induce unfavourable root development (Sena Gomes and Kozlowski 1987).

Some authors have specifically researched putative impacts of climate change in West Africa and concluded that negative impacts may be related to dry season precipitation (Schroth et al. 2016) and temperatures (Anim-Kwapong and Frimpong 2008; Schroth et al. 2016), or growing season evapotranspiration (Läderach et al. 2013). The extent of suitable climates for cocoa production (Läderach et al. 2013; Schroth et al. 2016) and yields (Anim-Kwapong and Frimpong 2008) were found to be reduced as a result of projected future conditions in these studies.
It is thus likely that climate change will shape the future production of cocoa. The prospect of negative impacts on production in the main production regions has renewed concerns about cocoa production as a driver of deforestation (Ruf et al. 2015). The objective of this study is to compare the degree of climatic changes at potential cocoa growing locations to understand future deforestation threats.

Data and Methods

We modeled the global distribution of suitable climates for cocoa production under historic and future conditions. A database of cocoa occurrence locations and historic climate data was used to train the Random Forest classification algorithm. The classifier was extrapolated on climate data from multiple global climate models for low, intermediate and high radiative forcing scenarios for mid and end of century projections.

Cocoa occurrence data

We used data of the current distribution of T. cacao to characterize the climates that are suitable for cultivation. We assembled a global data set of cocoa occurrences with the objective to include all major climatic regions in which cocoa is produced (Figure 1). We reached out to stakeholders in West Africa, Asia, and South and Central America to request data contributions. Stakeholders included private sector actors, research institutions, certification programmes (e.g. Rainforest Alliance) and farmer organizations. We also used data from previous publications on the climate change impacts in West Africa (Läderach et al. 2013; Schroth et al. 2016), GBIF (Global Biodiversity Information Facility) (Global Biodiversity Information Facility 2015) and centroides of census units of the 2012 Censo Nacional Agropecuario, in which relevant cocoa quantities were reported (INEI 2012).

The resulting raw databases included a total of 88857 cocoa occurrence locations. We reduced this initial dataset to unique occurrence pixels at 20 Arcmin (about 40 km at the equator) to eliminate bias from highly clustered occurrences. The final database included 1488 cocoa occurrence locations (Figure 1).

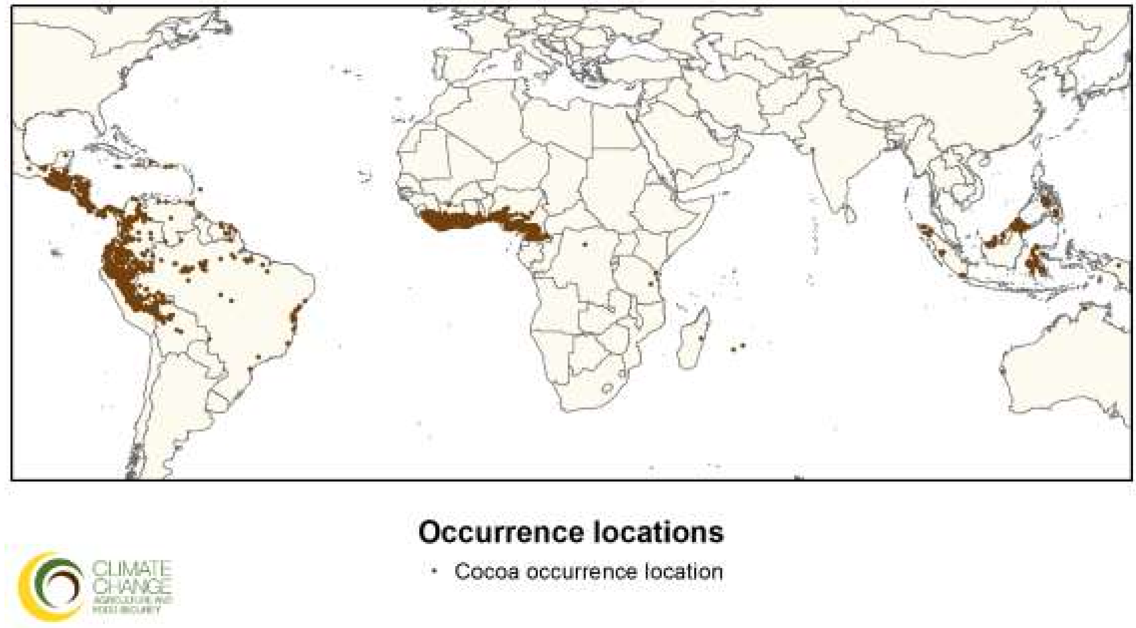

Figure 1 Occurrence locations of cocoa production

Climate data

For the current climate (1950–2000), we used the WorldClim data set (Version 1.4) at 20 arc-minute resolution (Hijmans et al. 2005). Future climate data layers were generated by downscaling the native outputs of 10 GCM's from the 5th assessment report for the representative concentration pathway (RCP) 6.0 (Fujino et al. 2006) using the delta method (Ramirez and Jarvis 2010): The difference between model outputs for current conditions and the average for the period 2040 to –2069 (2050ies) was computed. The resulting layers were smoothed to a 20 ArcMin resolution and applied to the WorldClim layers for current climate. Potential evapotranspiration is considered a good proxy of vapour pressure (Allen et al. 1998) which may have direct effects on the cocoa tree (Mielke et al. 2005). We estimated potential evapotranspiration following Hargreaves and Samani (Hargreaves and Samani 1985) as recommended by the FAO (Allen et al. 1998). We derived 24 bioclimatic variables for current conditions using the WorldClim data and for future conditions using the CMIP5 data.

Random Forest Classification

We used the Random Forest (RF) (Breiman 2001) classifier in two distinct applications. (1) We initially used it to produce a dissimilarity measure to group occurrence locations into suitability clusters with similar climate characteristics in an unsupervised variation. (2) We used the RF classifier to classify climate data of current and future conditions into the resulting suitability types. Random Forests are machine learning classifiers that are formed by ensembles of classification trees. RF are very popular because of their efficiency on large datasets without overfitting. We used the randomForest package (Liaw and Wiener 2002) in the statistical software R (R Core Team 2014) that implements the RF approach.

First, to determine distinct suitability zones for cocoa we used the RF classifier in unsupervised mode (Shi and Horvath 2006) to calculate dissimilarities based on the bioclimatic variables at cocoa locations. Clustering was performed using Ward hierarchical clustering using the dissimilarities as input. The number of clusters was determined based on visual inspection of a cluster dendrogram. Description of climate types was based on the difference of within cluster means to the global mean at all locations for selected climate variables.

To train the RF classifier to recognize the resulting suitable climate zones the selected variables and the GPS data of the cocoa presences were joined and were used as an input into the model. In addition, a random background sample set of points not know to produce cocoa was drawn to characterize the general environment at a sampling ration of 2:1 background to occurrence locations. Each RF forest classifier was configured to create 200 decision trees, and to be replicated 5 times ('forests'). In each repeat a different subset from the presence sample was drawn at the size equaling half the number of case in the smallest subgroup. Such reduction of ecological sampling bias has been shown to improve the capacity of niche based approaches to correctly predict species distributions (Varela et al. 2014). From this subset 80% were used for training, and 20% were used for evaluation.

With this configuration and inputs, the model was extrapolated in two different ways. First, the modal classification of all RF trees was used to determine the distribution of climate classes under current and future climate conditions using all climate variables. Next, we used the percentage of votes by individual trees in the forests to evaluate the model agreement whether a location belongs to one of the suitable classes or the background class.

We accounted for the possibility that unknown climate types may occur by including a novelty detection step in the data processing. Ensemble methods such as RF can provide a metric to measure proximity between samples (Zhou et al. 2015). For each sample from the spatial climate data that had to be evaluated we tested the frequency with which it ended in the same leaf node as other samples from the same class as would be expected from a reference case evaluation. If the test sample could not be clearly categorized we classified it as 'novelty'. Finally, we separated the novelty class into likely suitable, and a likely unsuitable climate by comparison with the suitability score.

Validation

The current distribution was validated using the multiclass area under receiver operating characteristic curve (AUC) (Hand and Till 2001) as implemented in the R package "pROC" (Robin et al. 2011). The AUC assumes values 0 – 1. An AUC of 0.5 indicates that the performance was no better than random sampling, while 1.0 is perfect classification. This definition of the AUC measure can be extended to multiclass problems by averaging all pairwise AUC comparisons to a multiclass AUC (Hand and Till 2001).

Results

We analyzed the impacts of climate change on cocoa in two ways. We first described the current distribution of climate types for cocoa production, and the change in future periods. Next, we assigned a suitability score that indicated how similar the climate at a grid cell was to climate at occurrence locations.

Distribution of climate types

Clustering the occurrence locations resulted in four distinct climate types (Figure 2). Cluster 1 was found to be distant from the other 3 clusters. Cluster 3 and 4 were most closely related. The resulting clusters were of similar sizes. Cluster 1 had 480 samples, cluster 2 408 samples, cluster 3 337 samples, and cluster 4 263 samples.

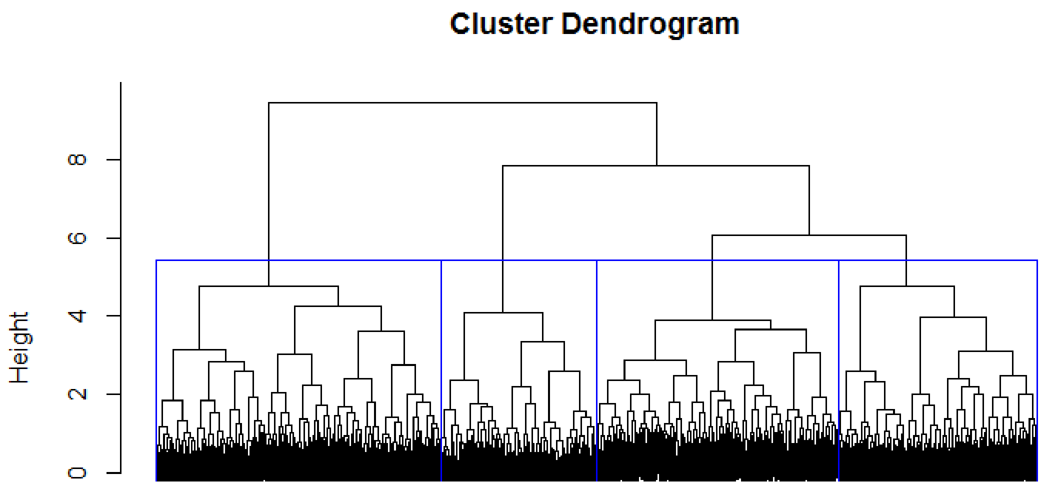

Figure 2 Cluster dendrogram of occurrence locations

We described these clustered based on their climatic properties (Figure 3). We used climatic variables that describes the seasonality and extremes of temperature and precipitation. We summarized these properties relative to the other cocoa climate types (Table 1).

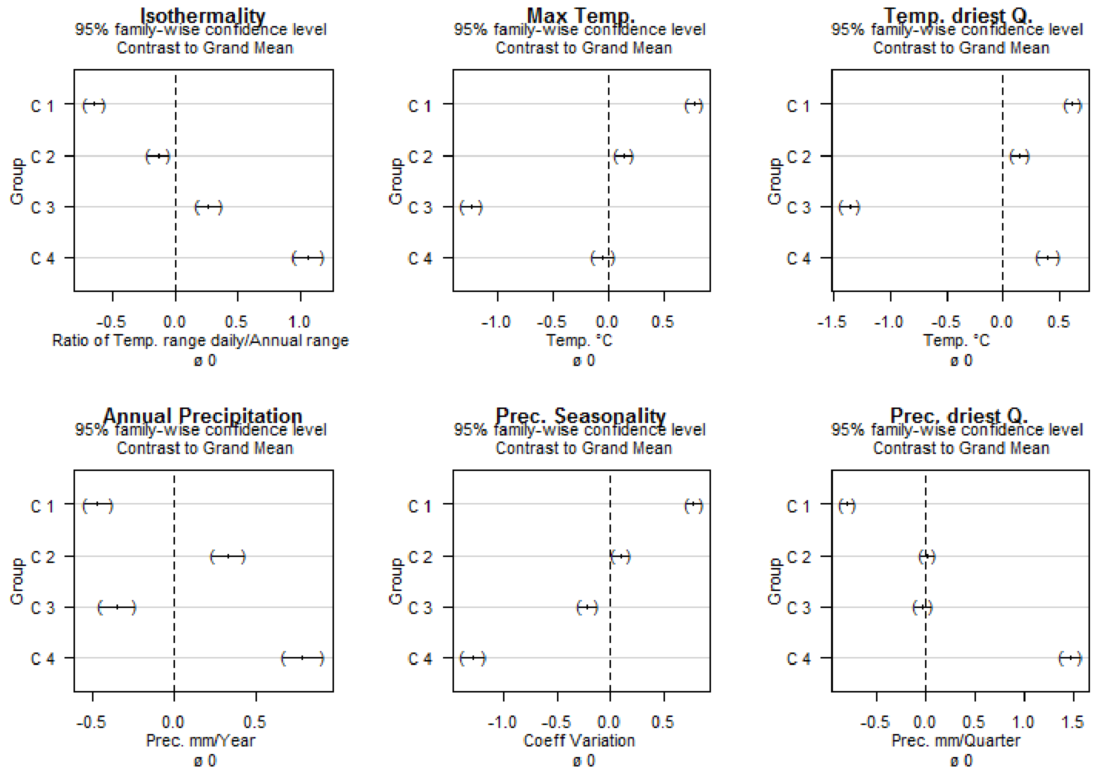

Figure 3 Contrast plots of confidence intervals within clusters compared to the grand mean for selected bioclimatic variables.

We labeled the clusters into climate types based on their geographic properties. Each cluster could typically be found in a certain cocoa region. We therefore assigned a symbol based on the representative region to the climate type (Table 1).

Table 1 Clusters and climate type description

CLUSTER	SYMBOL	TYPICAL REGION	TEMPERATURE	PRECIPITATION
1	WA	West Africa	High	Low, seasonal
2	SLA	Seasonal Latin America	Average	High, seasonal
3	High	Highlands	Low	Low
4	Ama	Amazon	Even	High

Cluster 1 climate was found to cover most of the West Africa region and therefore labelled 'WA'. Additional patches were found in Colombia's Arauca region, and Central America's Pacific coast Figure 4. Cluster 2 covered the Central American Atlantic coast, most of Brazilian Amazonas basin, but also parts of the Congo Basin and the Philippines. These regions all exhibited some seasonality of precipitation, i.e. at least some months below 100mm rainfall. This climate type was therefore labeled Seasonal Latin America. Cluster 3 ('Highlands') was found in Central American highlands, along the Andes, Cameroon, highland East Africa and the high elevations of Sumatra. Finally, cluster 4 covered the upper Amazonas region, central Congo and most of Indonesia and labelled according to the origin of the cocoa tree 'Amazon'. Novel climate type 1 covered the margins of cocoa type climates, large areas of the Congo basin, India and some regions in Indonesia. Novel climate 2 spanned large areas of Savanna climates in Brazil and Africa and the humid subtropical climates in Asia and Southern USA.

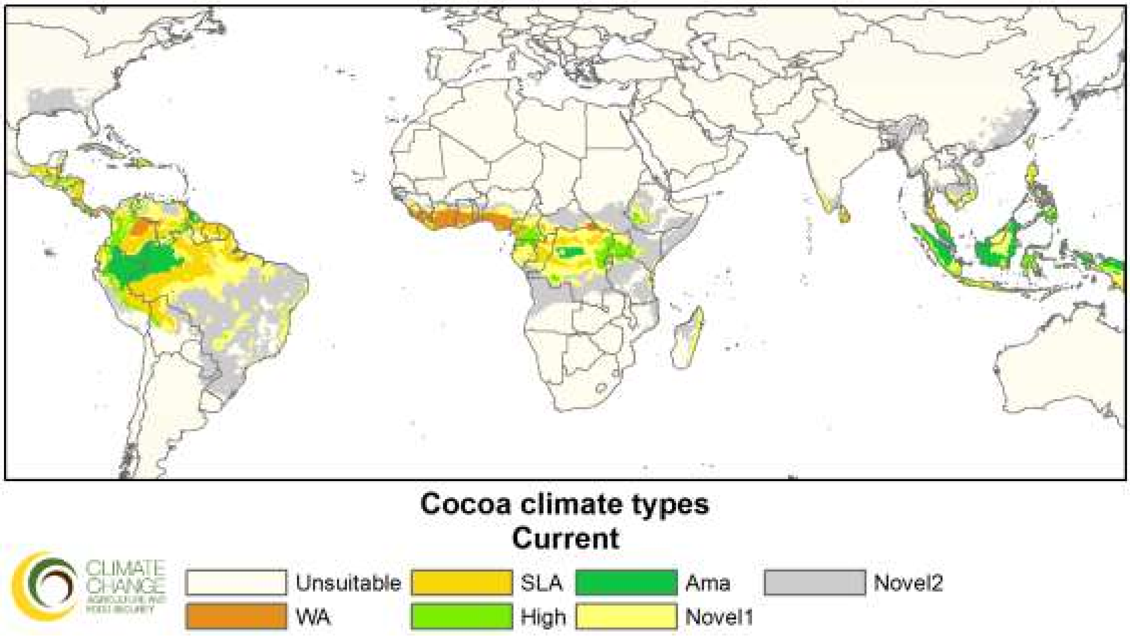

Figure 4 Current distribution of climate types for cocoa production

In the intermediate emissions scenario RCP 6.0 by the 2050 period the total area of suitable climate types was found to remain unchanged (Figure 5). Notable reductions of the 'WA' climate type were found in the Arauca region in Colombia and the margins of the West African cocoa belt. The 'SLA' climate expanded in the Congo region and in some parts of South East Asia. The 'high' climate type was reduced substantially by about 45%, while the 'Ama' and 'Novel 1' climates expanded in area Table 2.

Table 2 Number of global grid cells of climate types in current and 2050s conditions (RCP 6.0)

CLIMATE TYPE	CURRENT	2050	% CHANGE
UNSUITABLE	37899	37515	-1
WA	793	710	-10
SLA	2835	3114	10
HIGH	1376	752	-45
AMA	1858	1992	7
N1	5657	6206	10
N2	9442	9571	1

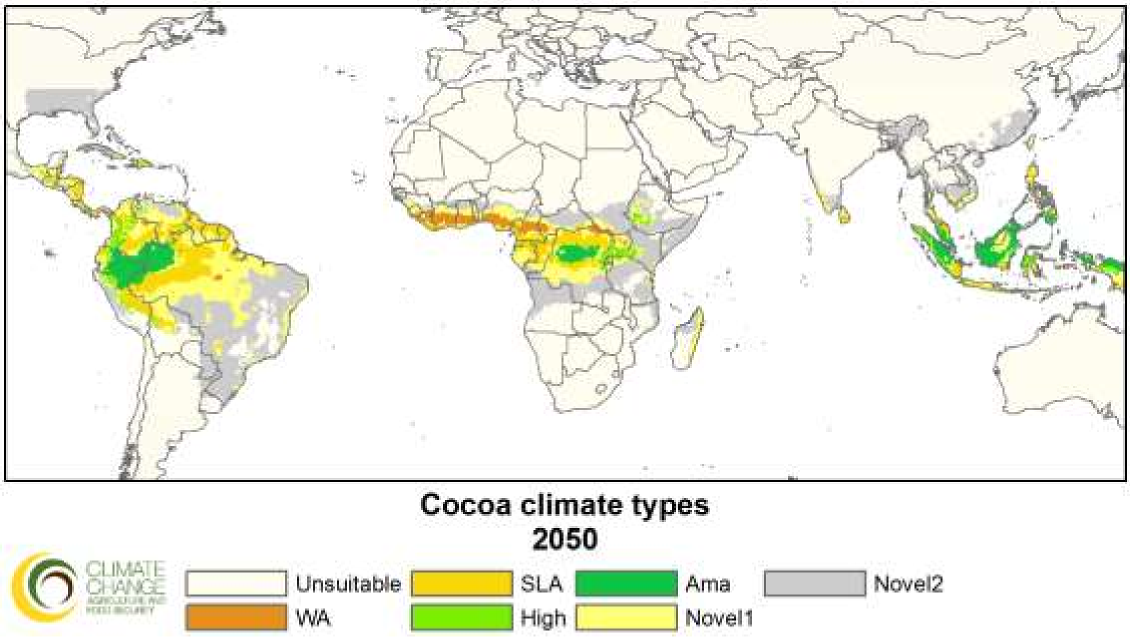

Figure 5 2050s distribution of climate types for cocoa production in the RCP 6.0 scenario

The multiclass AUC (.84) showed a good capacity of the classifier to differentiate the climate types.

Distribution of suitability scores

The suitability score was based on the number of trees across all forests that cast a vote for a cocoa climate type, not considering the novel climate types. Thus, the score can be interpreted as a measure of similarity of the climate at a grid cell to climate at known cocoa occurrences locations. The score was truncated at 37%, the value of the 1st percentile at known occurrences. Thus 99% of occurrences had a suitability score of 37% and higher. 90% of locations had a score of 70% and higher.

Under current climate conditions highly suitable climate closely resembled the distribution of the occurrence location database (Figure 6). Highly suitable areas were found in Central America, the Amazonas region, West Africa and South East Asia. Suitability scores were comparatively lower in the Congo Basin and India.

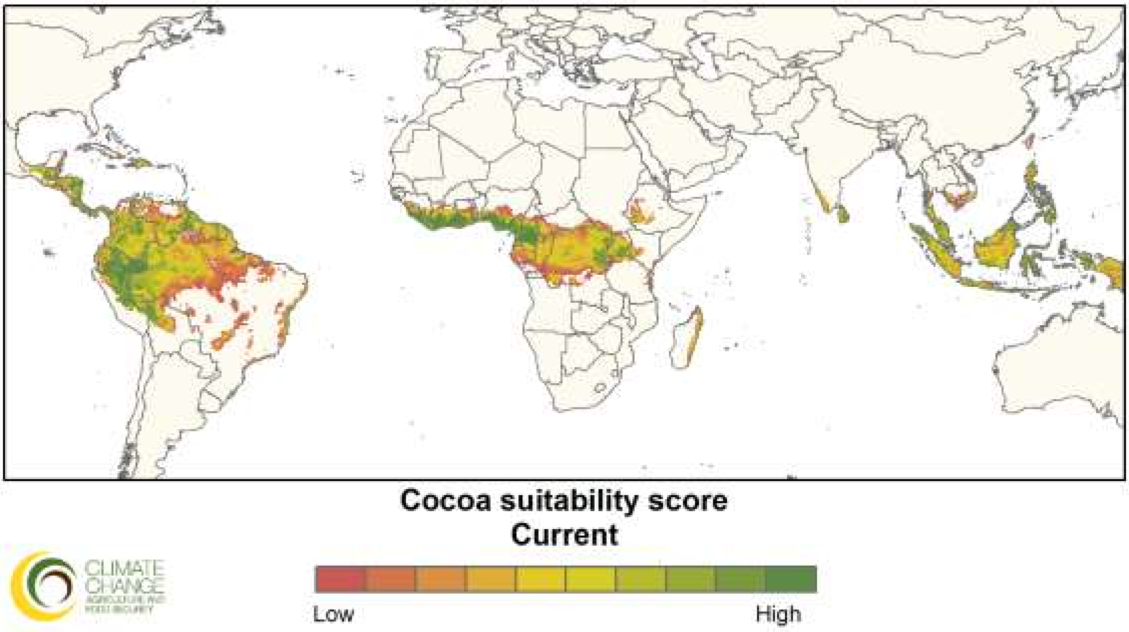

Figure 6 Suitability score for cocoa production under current climate conditions.

In the intermediate emissions scenario by the 2050 period the main cocoa regions received a lower share of suitable votes than under current conditions. On the other hand, potentially suitable regions without major cocoa production were projected to become more similar to current cocoa locations.

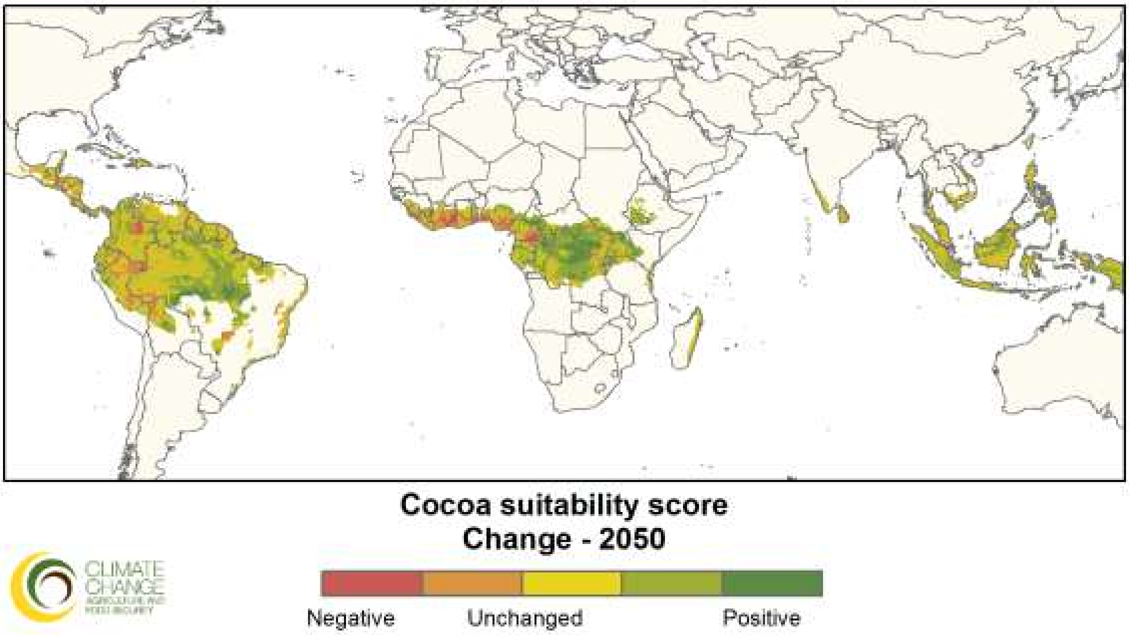

Figure 7 Mean suitability score change for cocoa production under 2050s climate conditions (RCP 6.0).

The changes of suitability score differed between major cocoa regions (Figure 8). To compare the change of suitability score we restricted analysis to highly suitable locations. The median suitability score change was -9%. Locations with suitability scores more negative would be relatively worse affected by climatic change than locations with a higher value.

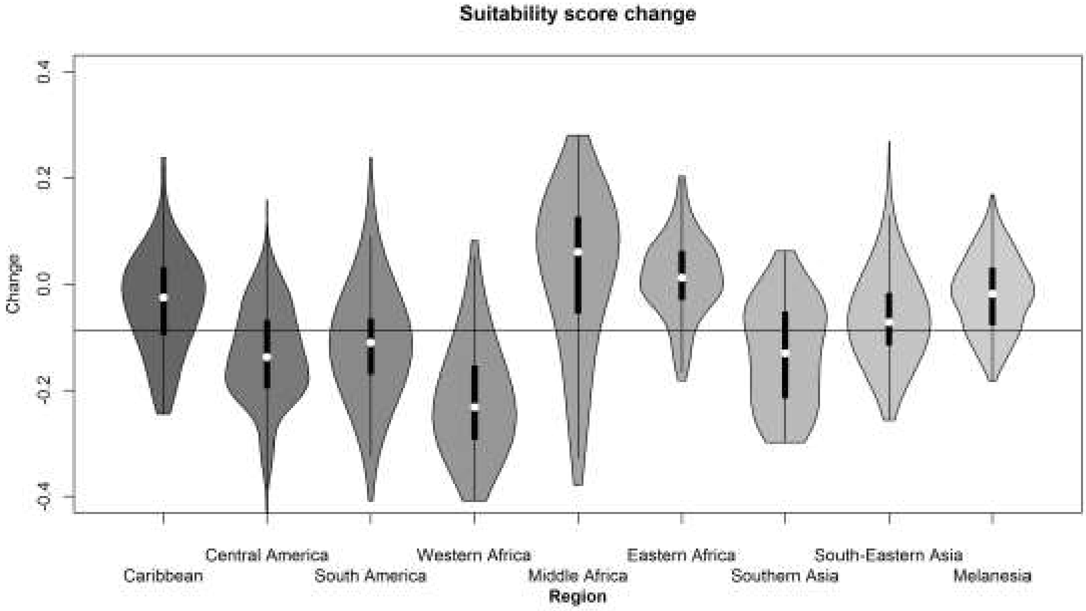

Figure 8 Suitability score changes in highly suitable areas for macro-regions. The dot represents the median change, the thick vertical bars the interquartile range and whiskers show the 90% confidence interval. The body shows the density. The horizontal line is the global median value.

Central and South American, West African and Southern Asian locations would likely be relatively worse off in the climate change scenario. Caribbean, Middle and Eastern Africa and South East Asia may be relative beneficiaries of climate change. The West Africa region was found to have the most negative suitability score changes. Middle African locations were found to be most likely to see neutral or positive suitability score changes (Figure 8).

Discussion

Across the most important cocoa origins decreases of climatic suitability were projected. We found that available area of high suitability will be diminished while area with low suitability scores may be increasingly available. Furthermore, we found that projected impacts will be unlikely to make major cocoa producing regions unsuitable altogether. These findings may be partially explained with the high uncertainty of precipitation projections of global climate models.

Most of the positive suitability changes were found in regions that hold high forest cover (Hansen et al. 2013). In the past cocoa has been closely associated with deforestation (Ruf and Schroth 2004). Regional climatic change could not be shown to drive deforestation (Ruf et al. 2015) but it seems to naïve to rule such effects out given the formidable task to adapt to climate change. However, to date it is difficult to quantify the effect of cocoa-driven deforestation e.g. in Congo (Beule et al. 2014).

Our modeling approach was a comparison of the distribution of climate zones in which cocoa is currently produced and their distribution under future climate scenarios. This means that we considered the adaptive range currently available in globally, but not a possible expansion of this range by novel technologies or technology transfer from other countries. Adoption of adaptive agricultural practices (e.g. novel varieties, irrigation, or shading) that expand the climatic range under which cocoa may be produced profitably may result in alternative developments of the distribution of cocoa in the future.

Equally, climate is usually defined as a multi-decadal average of weather conditions. Thus, when this study compares climate across time it takes into account monthly average temperature and precipitation over three decades. Global climate models were often not in agreement even at this temporal scale. We therefore did not look at more detailed analysis of climate variables even where they are important for on-farm decision making. Also, projections about the variability between years as may happen from increasing frequencies of ENSO have not been considered. For many farmers two consecutive years with low harvests may be more decisive even if the decadal average harvest is sufficient (Thornton et al. 2014). To answer these concerns additional research should be considered.

We conclude that cocoa production will continue to threaten biodiverse forests across tropical countries. Cocoa production is a primary beneficiary of ecosystem services provided by resilient landscapes. Deforestation will exacerbate the effects of climate change by resulting in locally reduced precipitation, addition to emissions from land use change, and diminished barriers to pest and disease spread. Efforts to make cocoa deforestation free are therefore in the self-interest of the cocoa sector.

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Literature

Acheampong K, Hadley P, Daymond AJ (2013) Photosynthetic activity and early growth of four cacao genotypes as influenced by different shade regimes under West African dry and wet season conditions. Exp Agric 49:31–42.

Allen RG, Pereira LS, Raes D, Smith M (1998) Crop evapotranspiration-Guidelines for computing crop water requirements-FAO Irrigation and drainage paper 56. FAO Rome 300:D05109.

Almeida A-AF de, Valle RR (2007) Ecophysiology of the cacao tree. Braz J Plant Physiol 19:425–448.

Anim-Kwapong GJ, Frimpong EB (2008) Climate change on cocoa production. Ghana Clim Change Impacts Vulnerability Adapt Assess 263–314.

Beule H de, Jassogne L, van Asten P (2014) Cocoa: Driver of deforestation in the Democratic Republic of the Congo?

Breiman L (2001) Random Forests. Mach Learn 45:5–32. doi: 10.1023/A:1010933404324

Dai A (2013) Increasing drought under global warming in observations and models. Nat Clim Change 3:52–58.

Daymond AJ, Hadley P (2008) Differential effects of temperature on fruit development and bean quality of contrasting genotypes of cacao (Theobroma cacao). Ann Appl Biol 153:175–185. doi: 10.1111/j.1744-7348.2008.00246.x

FAO (2007) ECOCROP. http://ecocrop.fao.org/ecocrop/srv/en/home. Accessed 11 Jun 2014

Fujino J, Nair R, Kainuma M, et al (2006) Multi-gas mitigation analysis on stabilization scenarios using AIM global model. Energy J 343–354.

Global Biodiversity Information Facility (2015) GBIF. In: Free Open Access Biodivers. Data GBIForg. http://www.gbif.org/. Accessed 13 Oct 2015

Hand DJ, Till RJ (2001) A simple generalisation of the area under the ROC curve for multiple class classification problems. Mach Learn 45:171–186.

Hansen MC, Potapov PV, Moore R, et al (2013) High-Resolution Global Maps of 21st-Century Forest Cover Change. Science 342:850–853. doi: 10.1126/science.1244693

Hargreaves GH, Samani ZA (1985) Reference crop evapotranspiration from temperature. Appl Eng Agric 1:96–99.

Hijmans RJ, Cameron SE, Parra JL, et al (2005) Very high resolution interpolated climate surfaces for global land areas. Int J Climatol 25:1965–1978.

INEI (2012) IV Censo Nacional Agropecuario. Instituto Nacional De Estadistica E Informatica, Lima, Peru

Kingston DG, Todd MC, Taylor RG, et al (2009) Uncertainty in the estimation of potential evapotranspiration under climate change. Geophys Res Lett 36:n/a-n/a. doi: 10.1029/2009GL040267

Kra EY, Ofosu-Anim J (2010) Modeling maize planting date to minimize irrigation water requirements. Aust J Agric Eng 1:66.

Läderach P, Martinez-Valle A, Schroth G, Castro N (2013) Predicting the future climatic suitability for cocoa farming of the world's leading producer countries, Ghana and Côte d'Ivoire. Clim Change 119:841–854.

Lass RA, Wood GAR (1985) Cocoa Production. Washington, D.C., U.S.A.

Liaw A, Wiener M (2002) Classification and Regression by randomForest. R News 2:18–22.

Mielke MS, Almeida A-AF de, Gomes FP (2005) Photosynthetic traits of five neotropical rainforest tree species: interactions between light response curves and leaf-to-air vapour pressure deficit. Braz Arch Biol Technol 48:815–824. doi: 10.1590/S1516-89132005000600018

R Core Team (2014) R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria

Ramirez J, Jarvis A (2010) Disaggregation of Global Circulation Model Outputs.

Riahi K, Grübler A, Nakicenovic N (2007) Scenarios of long-term socio-economic and environmental development under climate stabilization. Technol Forecast Soc Change 74:887–935.

Robin X, Turck N, Hainard A, et al (2011) pROC: an open-source package for R and S+ to analyze and compare ROC curves. BMC Bioinformatics 12:77.

Ruf F, Schroth G (2004) Chocolate forests and monocultures: a historical review of cocoa growing and its conflicting role in tropical deforestation and forest conservation. Agrofor Biodivers Conserv Trop Landsc Isl Press Wash 107–134.

Ruf F, Schroth G, Doffangui K (2015) Climate change, cocoa migrations and deforestation in West Africa: What does the past tell us about the future? Sustain Sci 10:101–111. doi: 10.1007/s11625-014-0282-4

Schroth G, Läderach P, Martinez-Valle AI, et al (2016) Vulnerability to climate change of cocoa in West Africa: patterns, opportunities and limits to adaptation. Sci Total Environ 556:231–241.

Sena Gomes AR, Kozlowski TT (1987) Effects of temperature on growth and water relations of cacao (Theobroma cacao var.Comum) seedlings. Plant Soil 103:3–11.

Shi T, Horvath S (2006) Unsupervised learning with random forest predictors. J Comput Graph Stat 15:118–138.

Sillero N (2011) What does ecological modelling model? A proposed classification of ecological niche models based on their underlying methods. Ecol Model 222:1343–1346. doi: 10.1016/j.ecolmodel.2011.01.018

Stocker TF, Qin D, Plattner G-K, et al (2013) Climate Change 2013. The Physical Science Basis. Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change-Abstract for decision-makers. Groupe d'experts intergouvernemental sur l'evolution du climat/Intergovernmental Panel on Climate Change-IPCC, C/O World Meteorological Organization, 7bis Avenue de la Paix, CP 2300 CH-1211 Geneva 2 (Switzerland)

Thornton PK, Ericksen PJ, Herrero M, Challinor AJ (2014) Climate variability and vulnerability to climate change: a review. Glob Change Biol 20:3313–3328. doi: 10.1111/gcb.12581

van Vuuren DP, Den Elzen MG, Lucas PL, et al (2007) Stabilizing greenhouse gas concentrations at low levels: an assessment of reduction strategies and costs. Clim Change 81:119–159.

Varela S, Anderson RP, García-Valdés R, Fernández-González F (2014) Environmental filters reduce the effects of sampling bias and improve predictions of ecological niche models. Ecography 37:1084–1091. doi: 10.1111/j.1600-0587.2013.00441.x

Zhou Q-F, Zhou H, Ning Y-P, et al (2015) Two approaches for novelty detection using random forest. Expert Syst Appl 42:4840–4850. doi: 10.1016/j.eswa.2014.12.028

Zuidema PA, Leffelaar PA, Gerritsma W, et al (2005) A physiological production model for cocoa (Theobroma cacao): model presentation, validation and application. Agric Syst 84:195–225.