The impact of climate change on coffee production in Central America

Los impactos del cambio climático para el Café en Centro América

Christian Bunn, Fabio Castro, Mark Lundy

International Center for Tropical Agriculture, Km 17 Recta Cali-Palmira, Apartado Aéreo 6713, Zip code: 763537, Cali, Colombia.

cbunn@cgiar.org

Spanish abstract

El cambio climático se ha convertido en una realidad que afecta a los productores de Café en todo el mundo. La priorización de las herramientas de adaptación para el Café no es una tarea trivial: los medios disponibles son limitados, el cambio climático no es homogéneo y cada grupo de interés de Café tiene un entorno de decisión diferente. Por lo tanto, la adaptación es eficiente cultivo-/lugar-/ y actor específico.

Para apoyar estrategias de la adaptación regional específico, se desarrolló el gradiente de impacto del cambio climático para la producción de café en Centroamérica. En primer lugar, se diferenciaron zonas agroecológicas (AEZ) para la producción de café utilizando localización de presencias y 20 variables bioclimáticas como datos de entrada. AEZ fueron descritas por sus características de la estación seca, incluyendo la duración de la estación seca, su temperatura y precipitación. La distribución espacial de AEZ se modelo utilizando el algoritmo de *machine learning* Random Forest bajo condiciones actuales y futuras para 19 proyecciones de modelos climáticos globales. Las diferencias en la distribución actual y más probable en el futuro dieron como resultado un gradiente de impacto.

Encontramos que aproximadamente un tercio del área actualmente se convertirá en no idónea para la producción de café sin adaptación. Un tercio de la superficie requerirá una adaptación sistémica que considere cambios sustanciales en el sistema de producción. El resto se verá menos afectado y solo requerirá cambios incrementales que mejoren la resiliencia del sistema. Se pudo encontrar una clara relación con la altitud de las regiones de producción, las zonas bajas se situaban 200 metros más altas que en las condiciones actuales. No se pudo encontrar una relación tan clara con las características de la estación seca, probablemente debido a la incertidumbre de las proyecciones de GCM.

English abstract

Climate change has become a reality that affects coffee producers across the world. The prioritization of adaptation tools for coffee is not a trivial task: available means are limited, climate change is not uniform and each coffee stakeholder group has a different decision environment Therefore, climate change adaptation is crop-/site- and actor-specific.

To support climate change adaptation strategies we developed a gradient of climate change impacts for coffee production in Central America. First, we differentiated different types of climates suitable for coffee production by clustering occurrence locations on 20 bioclimatic variables. The climate zones were described and ranked using their dry season characteristics, including its length, mean temperature and precipitation. The spatial distribution of these climate types was modeled using the machine learning algorithm Random Forest for current conditions

and future projections from 19 global climate models. The difference between current and the most likely future distribution resulted in the gradient of impacts

We found that about a third of currently potentially suitable area will become unsuitable for coffee production without adaptation. Another third will require substantial adaptation efforts to production systems. The remainder will be less affected and will only require incremental adaptation to improve the resilience of the system. We found a clear relationship of these impacts with altitude. The lowest regions were found 200m higher in altitude than under current conditions. We could not find a clear relationship between impacts and dry season characteristics, probably caused by the high modeling uncertainty of global climate model projections.

Introduction

Adaptation to climate change in agriculture refers to a change of cultivation practices as a result of observed or projected changes in the climatic environment of the production system. This change may either be spontaneous (e.g. migration during harsh drought) or planned (e.g. adopting a drought tolerant variety) (Füssel, 2007). Adaptation always bears a cost, e.g. in its most direct form adaptation requires monetary investments in physical infrastructure. But also the effort required to plan and implement the change of practices comes at the opportunity cost of not being able to invest the devoted time to alternative action. Thus, adaptation to climatic changes is often perceived as costly, while inaction is assumed to be cost free. This conflicts with the consensus that climate change is increasingly becoming a reality, and that projected changes can reasonably be assumed to have significant negative impacts on coffee production. Cost-effective adaptation therefore constitutes a vital challenge for the sector.

The stronger the impacts from climate change will be, the stronger the benefit from adaptation. Climate smart coffee production and effective adaptive action therefore need to take into account the severity of climatic changes. A gradient of climate impacts is defined by the ratio of current climatic heterogeneity and the degree of climatic changes (Vermeulen et al., 2013). Associated with the climatic heterogeneity is the coping range which is the economically viable tolerance of sub-optimal growing conditions. In years in which climatic variability remains within this coping range, yields are sufficiently high because the production system is well adapted to such events. Rarely, an extreme event will fall outside of this coping range and cause economic damage. Investments to confront such events are uneconomical because of the low frequency of such events. However, with climate change, low frequency extreme events may become a new normal event (Hansen et al., 2012).

The degree of impact versus the feasible coping range is therefore an important determinant of the adaptation strategy. At locations where changed climatic variability is minor compared to historic climatic variability the available coping range may be sufficient. Incremental adaptations may be implemented by transferring adequate existing technological solutions (Vermeulen et al., 2013), such as changed pest and disease control. With increasing degree of climate impacts, systemic adaptation measures will have to be developed in joint public-private efforts that expand the climatic range in which coffee can be produced economically (e.g. novel varieties). Finally, when climate change causes frequent events that make adaptation uneconomical when comparing with the benefits from alternative crops a transformation out of the system has to be considered.

Thus, a forward looking adaptation approach to sustainable coffee production will enable stakeholders to avoid catastrophic impacts and to develop hazard specific responses. The effective design of response strategies will first evaluate the degree of the climate change impact and then identify hazards to the system from analysis of practitioner's knowledge, data analysis and climate simulations. This work presents an evaluation of the degree of climate change impacts on coffee production in Central America. First, we differentiated climate zones suitable for coffee and evaluated adaptation needs based on the projected differences between current and 2050s climate. Where the climate zones remained unchanged we concluded that incremental adaptation may be sufficient. Zones that change from one suitable type to another will require systematic changes in the production system because average climate conditions will change significantly. The highest degree of impact would mean that a currently suitable location becomes unsuitable for coffee under future conditions and would thus require transformative adaptation. In some cases climate change may improve conditions such that a location becomes newly suitable for coffee in coming decades. However, as projections for the 2050s are highly uncertain, in some cases no unambiguous recommendation may be provided so that the overall resilience of the system should be increased.

To identify climate zones suitable for coffee production in Central America we used a machine learning algorithm. We then ranked these zones according to the number of consecutive months that constitute a dry season for coffee, and the precipitation and temperature of the driest quarter. The suitability types are meant to describe small scale spatial differences between the different coffee zones for grid cell pixels with approximately 1km resolution.

Methods

Agro-ecological zones for coffee production in Central America were defined using a combination of spatial climate data from WorldClim (Hijmans et al., 2005) and a database of occurrences of coffee (*Coffea arabica*) production assembled from data used in Bunn et al. (2015) and Ovalle-Rivera et al. (2015). We stratified the dataset of 100459 occurrence locations of Arabica production to 14777 unique occurrence pixels on a 0.5 Arcmin grid (approx. 1km at equator). Outliers at extremely high or low locations were removed. To reduce computation time during training we used random set of a fifth of total presences in the analysis (2809) (Fig. 1).

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.

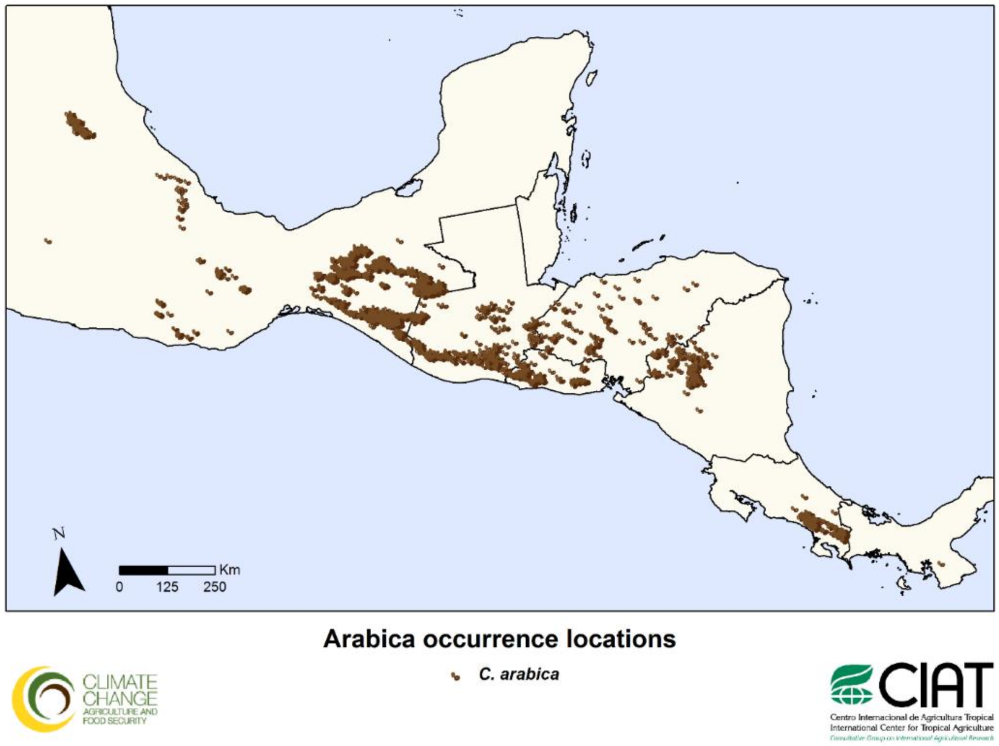

Fig. 1 Occurrence locations of Arabica coffee production in Central America.

To determine distinct suitability zones for coffee we used the RF classifier in unsupervised mode (Shi and Horvath, 2006) to calculate dissimilarities for use in Ward hierarchical clustering using 19 bioclimatic variables from WorldClim, plus a variable that describes the duration of the dry season for coffee (consecutive months with less than 40mm precipitation). The number of clusters was determined based on visual inspection of a cluster dendrogram. Suitability type descriptions were based on the number of consecutive months with less than 40mm precipitation, and the precipitation and temperature of the driest quarter. Each of these variables was ranked from favorable to unfavorable conditions and the final rank a combination of the individual ranks.

We then used the RF algorithm to extrapolate the spatial distribution of suitability types under current and future climate. Input variables were the 20 bioclimatic variables at 0.5' resolution from WorldClim (Hijmans et al., 2005) for current conditions and the corresponding downscaled and bias corrected data from 19 global climate models for the 2050s in the intermediate RCP6.0 emissions scenario (Fujino et al., 2006) from the CCAFS climate portal (Ramirez and Jarvis, 2008). We trained 50 individual forests with 500 trees each on random subsamples of the training data. The current distribution was validated using the multiclass AUC (Hand and Till, 2001) as implemented in the R package "pROC" (Robin et al., 2011). To reflect uncertainty we included the suitability classes "mixed" and "limitations". A grid cell was labeled "mixed" when it was suitable with high certainty but below the 5th percentile of classification confidence, i.e. the agreement of trees across all forests. A grid cell was labelled "limitations" when its most likely class was "unsuitable" but the combined probability to be in one of the suitable classes was higher than the 1st percentile at occurrence locations.

Based on the change from the current distribution of suitability types to the most likely future distribution (median of 19 projections) the gradient of impacts was developed to differentiate fundamental types of adaptation strategies: expansion, incremental changes, systemic changes, increased resilience, or transformational change (Vermeulen et al., 2013). These zones were defined as outlined in the introduction. A zone was defined as “uncertain” when less than 11 of the 19 global climate projections agreed on the future suitability classification.

Results

A total of 13 different suitability types were identified from visual inspection of the cluster dendrogram with the objective of reflecting the diversity of climate zones in Central America. The zones were sorted by their dry season characteristics (Table 1). The multiclass AUC on the median current distribution (AUC 0.9314) suggests a high capability of the classifier to distinguish the different climate zones. While approximately 13% of grid cells at 0.5ArcMin resolution in Central America were found to be potentially suitable for coffee production under current climate conditions, only 8% of grid cells are potentially suitable under future conditions. This is equivalent to a 42% loss of potentially suitable area.

Table 1 Suitability types, current dry season characteristics and percentages of total potentially suitable area under current and 2050s conditions (modal projection across 19GCMs for the RCP 6.0 emissions scenario). Percentages for the area with limitations and unsuitable class are percent grid cells of all grid cells of the region.

Type	Precipitation of the driest quarter	Mean temp. of the driest quarter	Cons. months <40mm	Current percent of suitable area	2050s percent of suitable area	Absolute loss of suitable grid cells in %
Type 1	44	22.1	4.3	5%	4%	57
Type 2	31	20.7	4.6	7%	6%	47
Type 3	22	20.8	3.4	5%	3%	67
Type 4	41	21.3	3.3	2%	3%	32
Type 5	89	23.2	1.6	2%	1%	45
Type 6	100	22.4	2.4	9%	9%	37
Type 7	38	18.7	3.8	8%	7%	47
Type 8	78	19.0	2.8	10%	8%	54
Type 9	176	22.1	0.5	6%	7%	35
Type 10	247	23.8	0.0	4%	5%	31
Type 11	184	21.1	0.6	1%	0%	85
Type 12	154	19.0	0.3	4%	3%	56
Type 13	172	18.7	0.0	3%	3%	35
Mixed				35%	41%	32
Limitations				6%	3%	
Unsuitable				81%	89%	

Some suitability types were projected to be more affected than others. However, no clear relationship with the dry season ranking could be found with this simple analysis that only regards absolute grid cell counts and doesn’t account for migration of area. E.g. the type with the highest dry season temperatures (type 10) retains most area, while the type with low temperatures and high precipitation loses most area (type 11). It is likely that the latter ideal conditions are no longer found in the future, while the rather high temperatures become rather common.

Under current conditions the Eastern side of Central America was found to have less harsh dry season conditions than the Pacific side. E.g. Oaxaca has a stronger dry season than Veracruz, Northern Chiapas is wetter than Southern Chiapas (Fig. 2). About a third of area was found to be of the “mixed” class. This area is likely suitable but could not be classified into one of the suitability classes with high certainty. Surrounding the suitable area grey patches indicate locations that have a low probability to be suitable.

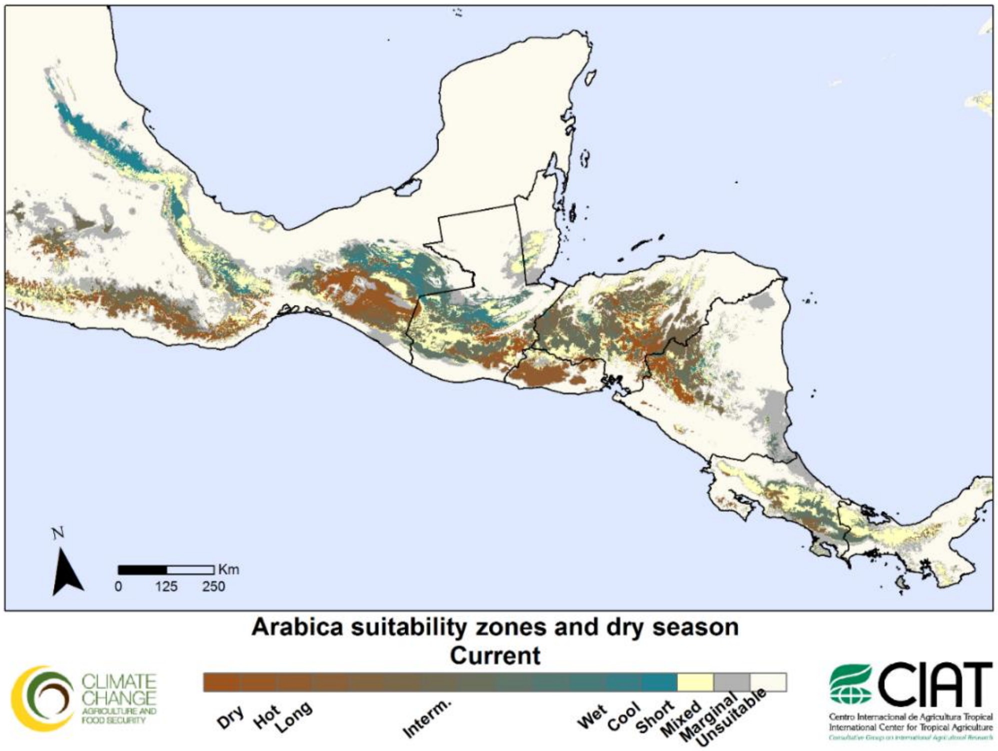

Fig. 2 Current distribution of suitability types. Suitability types have been sorted according to dry season conditions ranging from earthy colors for types with a harsh dry season to turquoise colors with higher precipitation, lower temperatures and shorter duration. Light yellow reflects classification uncertainty, grey area is likely unsuitable.

The visual impression of the map of the most likely future distribution (the mode across 19GCMs in the intermediate RCP 6.0 emissions scenario) (Fig. 3) confirms the overall reduction in suitable area and a notably higher proportion of area of the uncertain “mixed” class. The overall pattern of wet Caribbean side and dry Pacific side was not projected to change. Low lying areas were projected to be likely unsuitable.

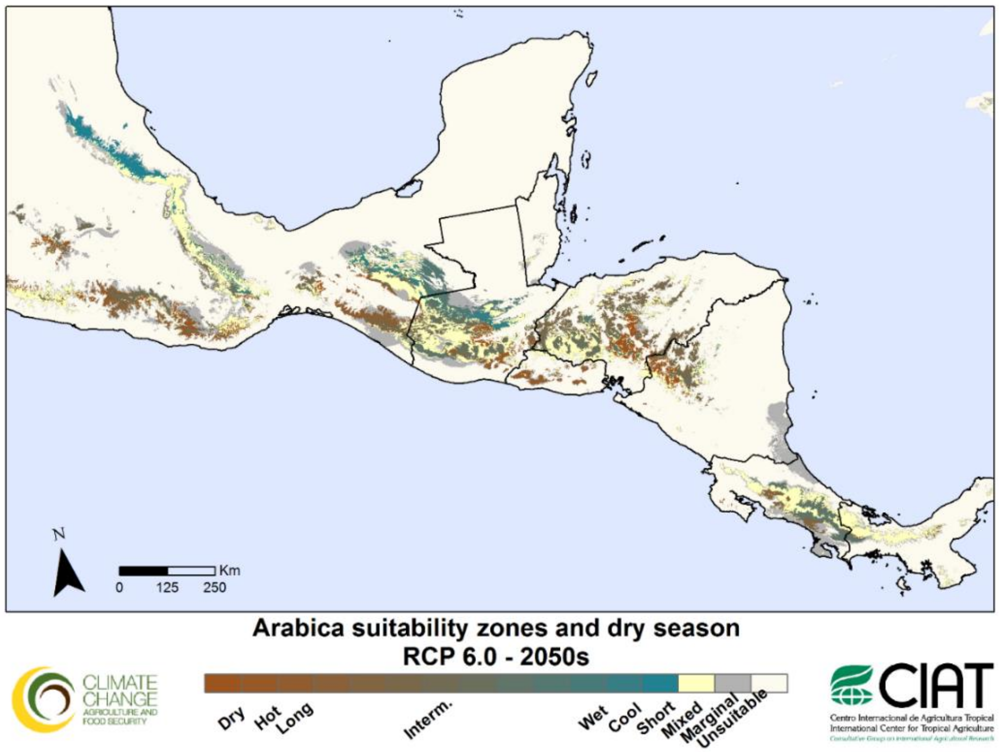

Fig. 3 2050s distribution of suitability zones in the RCP 6.0 emissions scenario. Suitability types have been sorted according to dry season conditions ranging from earthy colors for types with a harsh dry season to turquoise colors with higher precipitation, lower temperatures and shorter duration. Light yellow reflects classification uncertainty, grey area is likely unsuitable.

Comparing the current and future distribution resulted in the gradient of impacts which indicates the degree of climate change impact and suggests an adaptation strategy (Fig. 5). High altitudes (Ø~1400masl; stdev=680m) will not change the characteristics of the zone and may be able to cope with minor, incremental adaptation. Locations at low altitudes (Ø~680masl, stdev=395m) may have to transform to other crops or make substantial changes to the production system. Adjustment sites were found to be equally high at Ø~1360masl (stdev=460m). Sites with uncertain climate projections could be found at slightly lower altitudes (Ø~1200masl, stdev=660m) (Fig. 4).

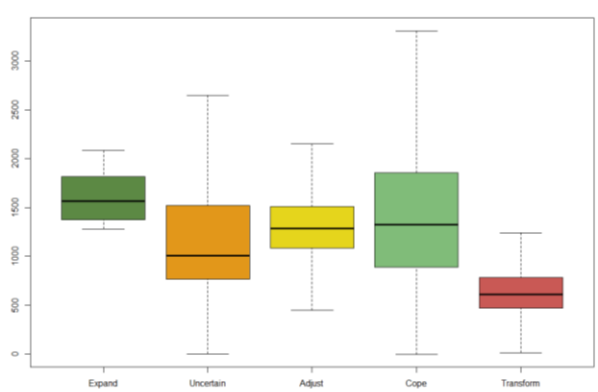

Fig. 4 Boxplot of altitudinal distribution of impact zones.

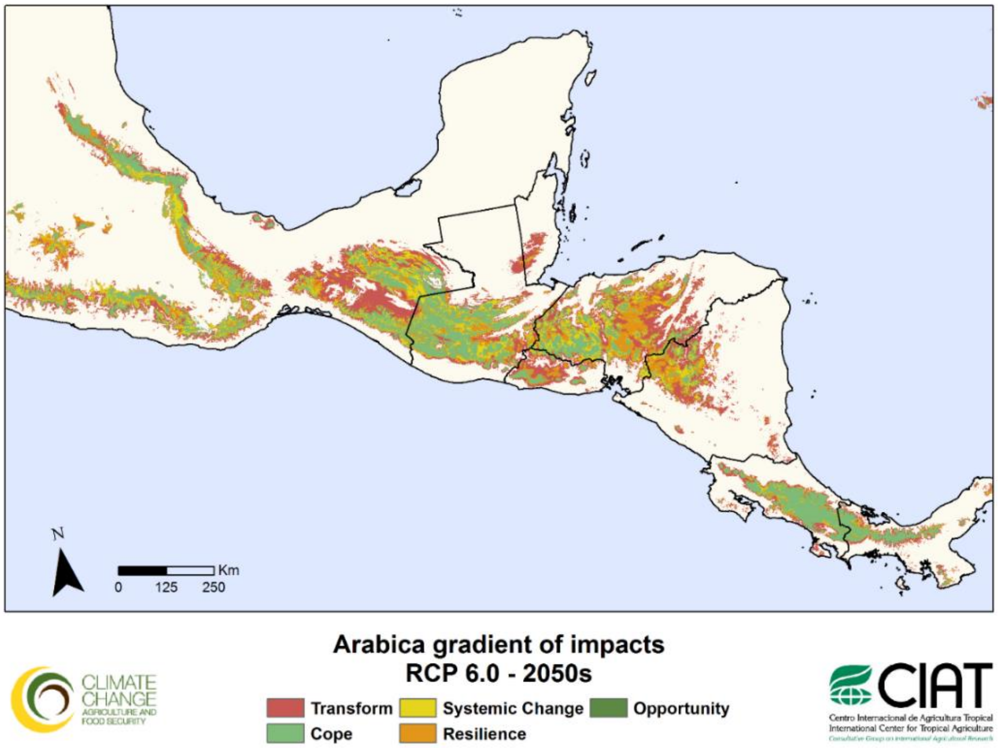

Fig. 5 Impact gradient for Arabica coffee in Central America in the 2050s in the RCP 6.0 emissions scenario. Red area will likely transform to other crops, light green may be able to cope with currently available production practices, light yellow area may require systemic changes as suitability type characteristics change. For orange colored area global climate projections did not result in unambiguous projections. Dark green area represents opportunity area that newly becomes suitable (none found here).

Discussion

Our modeling approach is a comparison of the distribution of climate zones in which coffee is currently produced and their distribution under future climate scenarios. This means that we considered the adaptive range currently available in Central America, 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 coffee may be produced profitably may result in alternative developments of the distribution of coffee in the future.

In addition, we didn't consider socio-economic variables. Our model did not take into account improved market access, rising labor costs or changing coffee prices. Doing so might alter the outcome of projections, especially at the time scales considered here. However, it would also add uncertainty to the modeling approach. The added model complexity would hamper results analysis. The results therefore only refer to a changing climate and consider all other aspects equal.

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 (i.e. projecting the onset of the rainy season or the probability of intermittent rains would be highly uncertain). 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.

Nevertheless, our analysis was robust in when considering climate modeling uncertainty. We considered several global climate model projections and made the modeling uncertainty explicit in our results. When presenting suitability zones, the classes “mixed” and “with limitations” refer to area that a) is suitable, but not clearly in one class, or b) area that is likely unsuitable but only with intermediate confidence. In the same way the gradient of impacts shows projected impacts where global climate models largely agree on the quality of impact. Area for which global climate models show uncertainty were indicated with the “systemic resilience” class. In these areas adaptation should focus on the expanding the coping range of the production systems to prepare for an uncertain future.

Acknowledgements

This work was implemented as part of the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), which is carried out with support from CGIAR Fund Donors and through bilateral funding agreements. For details please visit https://ccafs.cgiar.org/donors. The views expressed in this document cannot be taken to reflect the official opinions of these organizations.

Literature

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

Bunn, C., Läderach, P., Jimenez, J.G.P., Montagnon, C., Schilling, T., 2015. Multiclass Classification of Agro-Ecological Zones for Arabica Coffee: An Improved Understanding of the Impacts of Climate Change. PloS One 10, e0140490.

Fujino, J., Nair, R., Kainuma, M., Masui, T., Matsuoka, Y., 2006. Multi-gas mitigation analysis on stabilization scenarios using AIM global model. Energy J. 343–354.

Füssel, H., 2007. Adaptation planning for climate change: concepts, assessment approaches, and key lessons. Sustain. Sci. 2, 265–275. doi:10.1007/s11625-007-0032-y

Hand, D.J., Till, R.J., 2001. A simple generalisation of the area under the ROC curve for multiple class classification problems. Mach. Learn. 45, 171–186.

Hansen, J., Sato, M., Ruedy, R., 2012. Perception of climate change. Proc. Natl. Acad. Sci. doi:10.1073/pnas.1205276109

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., Jarvis, A., 2005. Very high resolution interpolated climate surfaces for global land areas. Int. J. Climatol. 25, 1965–1978.

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

Ovalle-Rivera, O., Läderach, P., Bunn, C., Obersteiner, M., Schroth, G., 2015. Projected Shifts in Coffea arabica Suitability among Major Global Producing Regions Due to Climate Change.

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

Ramirez, J., Jarvis, A., 2008. High resolution statistically downscaled future climate surfaces. Int. Cent. Trop. Agric. CIAT.

Robin, X., Turck, N., Hainard, A., Tiberti, N., Lisacek, F., Sanchez, J.-C., Müller, M., 2011. pROC: an open-source package for R and S+ to analyze and compare ROC curves. BMC Bioinformatics 12, 77.

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

Thornton, P.K., Ericksen, P.J., Herrero, M., Challinor, A.J., 2014. Climate variability and vulnerability to climate change: a review. Glob. Change Biol. 20, 3313–3328. doi:10.1111/gcb.12581

Vermeulen, S.J., Challinor, A.J., Thornton, P.K., Campbell, B.M., Eriyagama, N., Vervoort, J.M., Kinyangi, J., Jarvis, A., Läderach, P., Ramirez-Villegas, J., Nicklin, K.J., Hawkins, E., Smith, D.R., 2013. Addressing uncertainty in adaptation planning for agriculture. Proc. Natl. Acad. Sci. 110, 8357–8362. doi:10.1073/pnas.1219441110