Suitable areas for shade-grown coffee under future climate scenarios

An analysis to inform conservation strategy in Central and South America

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Introduction

Coffee cultivation has significant impacts on environmental conservation and social development goals in many tropical countries. While the most common strain sold on the market (*coffea arabica*) is native to Ethiopia, its popularity has expanded production to tropical regions globally, including Central and South America. Because *coffea arabica* grows best under particular conditions at higher altitudes, coffee plantations have historically been a major driver of tropical forest land use change in the mountainous regions of Southern Mexico, Central America and other key biodiversity hotspots (Gay, 2006). Furthermore, the majority of coffee is grown by small-scale farmers and supports the livelihoods of over 8.5 million people in just Mexico and Central America alone (The Climate Institute, 2016).

A key difference between coffee cultivation and other high-demand tropical commodities (ie. palm oil) is that specific agroforestry management practices can help mitigate the negative effects of cultivation on biodiversity (Perfecto et al 2004; Moorhead et al 2010, Karp et al 2013; Henders, Persson, & Kastner, 2015). These same management practices that result in better environmental outcomes also produce higher quality coffee (Vaast et al. 2005), representing a rare case where conservation goals and production goals can be somewhat aligned. Shade grown coffee plantations have even been proposed as a conservation strategy in some regions (Blackman et al., 2008; Marquette, 1998)

Nonetheless, coffee cultivation can act as a driver of deforestation. In the past, settlers entering previously intact regions via oil roads often cleared land to grow coffee as a cash crop (Marquette, 1998). Even though coffee farming is associated with less land cleared and more intact canopy than other tropical commodities, Marquette (1998) found that less cleared land can also correlated with a lower standard of welfare. Therefore, shade grown coffee as a conservation tactic may not be stable in the face of shifting markets or changing incentives. If farmers who clear more land for sun-grown coffee or other commodities fare better financially, this can undermine shade grown coffee operations, pushing farmers to higher land clearing practices in order to earn more income.

Coffee farmers also face uncertainties in future production due to climate change. *Coffea arabica* represents a case of a high-demand commodity that is particularly sensitive to changing temperatures. Gay et al (2006) used a multiple regression model incorporating both climate and economic determinants of coffee production to show that temperature had the strongest effect on coffee production in the Veracruz region in Mexico. Bioclimatic models have similarly shown a potential 65% reduction in suitable habitat for coffee that in its native region of Ethiopia by 2080 (Davis et al., 2012).

Predicting how coffee cultivation may respond to changes in climate is therefore key for helping to conserve tropical areas, prevent further land conversion and help secure livelihoods in the Central and South American region. Estimates of where coffee production may occur in the future can help preemptively plan best management practices for regions where it may expand or become more intensive, helping to maximize benefits for both people and nature. This project aims to apply techniques used in *c. arabica's* native regions to Central and South America to predict how areas most suitable for coffee cultivation may shift, and assess the resulting impacts on tropical landscapes.

Objectives

This project sets out to accomplish three main goals:

1. Model *coffea arabica* suitability in Central and South American using species distribution model MaxEnt under current conditions and 4 future climate scenarios
2. Analyze changes by calculating differences in suitable land area under each scenario, compared to the present
3. Assess how shifts in suitable areas for coffee cultivation may impact different types of land cover, with a focus forested areas

Methods

Preparation of Presence Data

Coffee is grown in many locations across the tropics, however because most of it is grown by small-scale farmers, it is difficult to determine distinct points that can be used as suitable presence data for modelling. The Smithsonian National Zoo and Conservation Biology Institute publishes the addresses and area size of coffee farms that have been bird-friendly certified (Smithsonian, 2017) in a publicly accessible spreadsheet, providing a convenient data source for the region of interest. In total, the coffee farms included on the list amount to 12,276 ha of cultivated land. These addresses were added to a Google Sheet online and geocoded into latitude and longitude points using the Google Sheets add-on AwesomeTable. The coordinates were then read into R Studio and converted into a spatial points object using the *sf* package. The full dataset (n = 43, Figure 1 a) was used to model coffee suitability for the whole world during the exploratory phase of the analysis, while a dataset with only points in Central and South America (n=40, Figure 1b) as used for the formal suitability analysis.

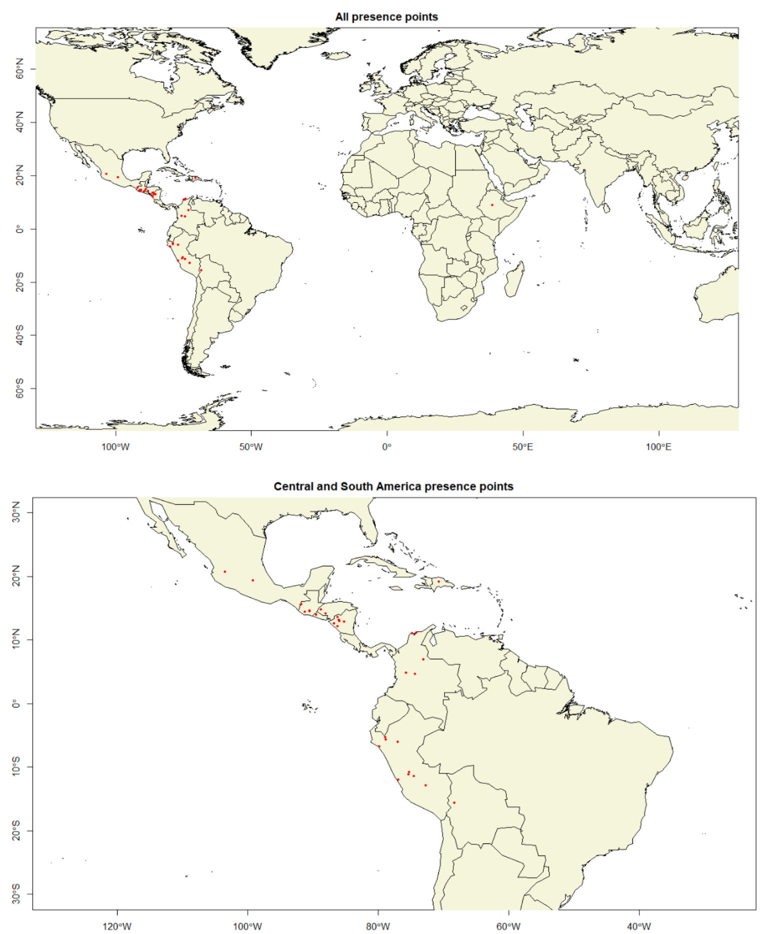


Figure 1. Presence points used for coffee a) globally and b) for the focus area of Central and South America

MaxEnt: Predicting future coffee suitability

MaxEnt (short for "maximum entropy") was used to model *c. arabica* suitability using the bird-friendly coffee farm presence points both globally and for Central and South America specifically. In addition to current conditions, suitability under two separate emissions and two different years were also modeled. MaxEnt uses a list of points where the species of interest has been confirmed present as well as environmental predictors to determine what conditions are most likely suitable for the species. It then compares background points (where presence is unknown) to these conditions to generate output describing how likely the species is to exist at a given point. Repeating this across a landscape results in a map that can be interpreted as a heat map of suitability for the species of interest (Merow C., Smith S., & Silander J. 2013). While the most common application of MaxEnt has been for wild animal and plant species, it has been used to model agricultural commodities in future climate scenarios, including coffee and wine (Davis et al., 2012; Lee et al., 2013).

The presence points used correspond only to coffee farms that were able to meet the strict environmental standards for bird-friendly certification, and therefore would indicate areas suitable for coffee cultivation with minimal agrochemical inputs. This data allows for coffee presence to be modelled based more on abiotic conditions most suitable for the plant rather than high input agriculture. Environmental layers downloaded WorldClim from included: average temperature, maximum temperature, minimum temperature, precipitation and altitude.

These same layers were also downloaded for 4 future climate scenarios: representative concentration pathway (RCP) 2.6 in 2050 and 2070, and RCP 8.5 in 2050 and 2070. These scenarios were chosen as they represent upper and lower bounds of the amount of radiative forcing expected by 2100. RCP 2.6 predicts a radiative forcing of 2.6 W/m^2 in 2100, assuming a significant reduction in global greenhouse gas emissions. RCP 8.5 predicts a much higher radiative forcing value of 8.5 W/m^2, resulting from continued growth of greenhouse gas emissions at their current rate (Van Vuuren et al. 2011).

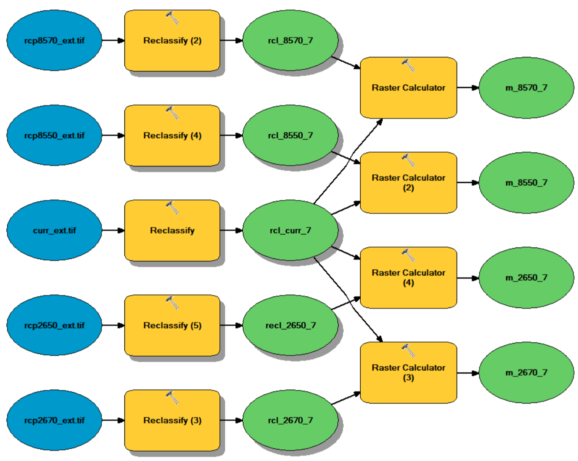
The global climate model used to produce future environmental variable layers was the Community Climate System Model, version 4 (CCSM4), a coupled model that runs four processes to model atmosphere, ocean, land surface and sea ice. Generally, the CCSM4 overestimates mean global surface temperature when compared to historical data, and contains a more realistic prediction of strong precipitation events in the tropics compared to previous models (Gent et al., 2011). As coffee grown in the Central and South American region is usually rain fed rather than irrigated, accurate future predictions in precipitation are key to predicting areas that are both suitable and feasible for cultivation.

All environmental data preparation and MaxEnt modelling occurred in RStudio using the *sdmpredictors* and *dismo* packages (Hijmans et al. 2017; Bosch et al., 2018). Full code can be found in Appendix A. First, the datasets were input into the MaxEnt function generating a variable "coffee_model" containing the output data. Next, the predict function was used to extrapolate the model to across the entire extent covered by the input data. This generated a raster layer with cell values ranging from 0 to 1, 1 representing areas where *c. arabica* would most likely be found, and 0 least likely to be found. This same analysis was re-run for each of the 4 climate scenarios (Appendix A, results in Appendix B).

Model Builder

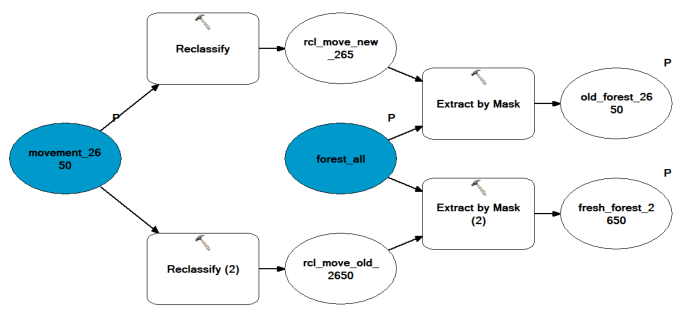
Assessing changes in suitable areas

A model was built in ArcGIS to compare the MaxEnt outputs from each climate scenario to current outputs (Figure B). The MaxEnt raster layers were reclassified so that any cell with a value over 0.70 was displayed as suitable for coffee. The narrow threshold was chosen to help mitigate the lack of precision in the MaxEnt model and isolate only areas that highly suitable for analysis. For the current layer, “1” was used to indicate suitable areas, and “2” was used to indicate suitable areas in future layers. Raster calculator was used to the values of the current layer with each future layer; this generated a new layer with “3” for areas where suitability will stay the same, “2” for new areas where coffee will be suitable in the future, and “1” where coffee is no longer suitable in the future. The resulting maps summarize where coffee suitability is projected to move under the four scenarios.



Assessing current land cover in suitable areas and future changes

A second model was built in ArcGIS to determine what types of land cover might be most threatened by changes in *c. arabica* suitability. The land cover map obtained from the European Space Agency (ESA, 2017) was reclassified into general categories most likely to represent natural areas. The categories used were: forest (canopy ranging from 15-40%), grasslands, shrub lands, and mosaic tree and shrub lands. A group containing rain fed crop land was also analyzed. Each land cover category was then used as a mask to extract cells on the summed suitability maps from each scenario that coincided with the specified land cover. This secondary model was designed using parameters so that the modeler can choose the scenario and the land cover to analyze upon running the model. A full list of the ESA land cover categories with the ones included in this analysis specified can be found in Appendix C.

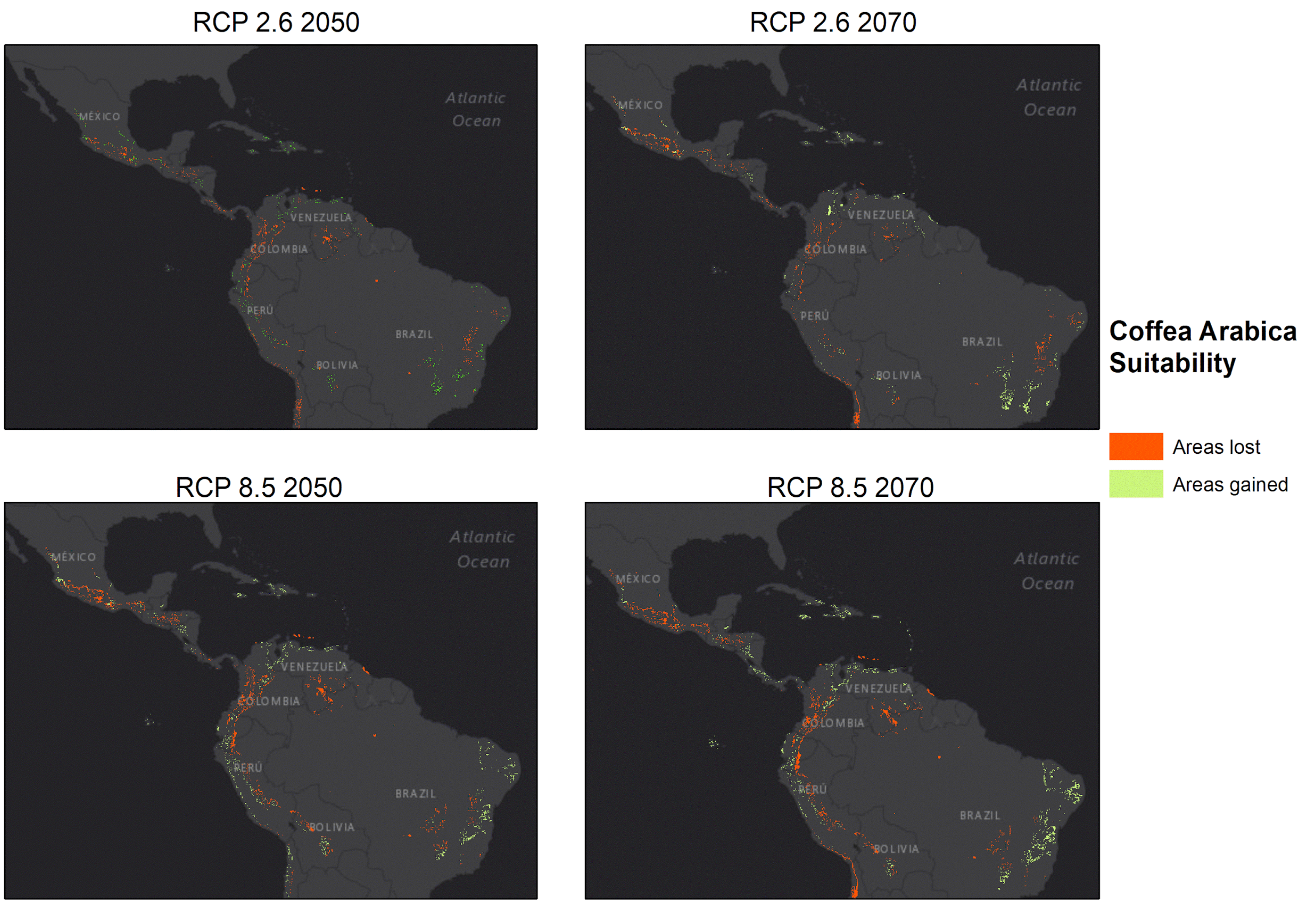


Results

Changes in suitable areas

Across both climate scenarios and both years, there was an overall reduction in areas suitable for coffee cultivation compared with current suitability. This reduction was largest for RCP 8.5 in year 2070, with a net overall loss of 33,820 km2, representing a 29.53% loss in suitable area. The scenario with the least amount of land lost was RCP 2.6 in 2070, with an 18.33% reduction in suitable area compared to the current suitability map. This contrasts with RCP 2.6 2050, which saw a 21.35% reduction in suitable area. Both RCP 2.6 climate scenarios in 2050 and 2070 saw a similar amount of suitable land lost - 15,240 km 2 and 15,330, respectively. However, in RCP 2.6 2070 there is a much larger gain in suitable areas helping to explain why this scenario had the lowest overall change (Table 1).

Figure 2 shows the overall distribution of areas lost and gained in each future scenario. While losses in suitability (shown in red) occur in all regions modeled, Southern Mexico and the Andean regions show some particularly large losses without many gains in all four scenarios. Conversely, the Dominican Republic and Eastern Brazil show considerable gains in suitable areas with few losses.



Data: WorldClim Global Climate Data, Smithsonian National Zoo & Conservation Biology Institute
Map created by: Madeline Berger
Date: Novembr 22nd, 2019

Figure 2. Distribution of suitable areas lost and gained across the entire study range for each climate scenario and year. Red areas depict land that loses suitability for *c. arabica*, while green depicts land that becomes suitable.

RCP	Year	Lost	Gained	Same	Total	Percent change	Net loss
2.6	2050	15240	6030	99300	90090	21%	24450
	2070	15330	9670	99210	93550	18%	20990
8.5	2050	21050	12540	93490	84980	26%	29560
	2070	25970	18120	88570	80720	30%	33820

Table 1. Amount of suitable land area lost, gained and unchanged for each climate scenario. All values are in units of km squared

Land Cover Analysis - Current

To assess the potential for future *c. arabica* cultivation to impact the landscape, the types of land cover that overlapped with current suitability were analyzed and compared with future shifts. Current coffee suitability occurs mostly in forests, with 56.57% of the area currently suitable in Central and South America overlapping with forest that has a 15-40% closed canopy (Table 2). This category includes both deciduous and evergreen forests. Shrub land represented the next largest type of land cover overlapping with *c. arabica* suitability at 15.60%. The last three categories (mosaic tree and shrub land, grasslands, and rain fed croplands) all had very low overlap with the current modeled suitability (Table 2). Overall, these 5 land cover categories accounted for 85.67% of the current suitable area modeled. The remaining 14.33% most likely occurred in land cover categories that were already heavily altered by human activity, which were not considered for this analysis.

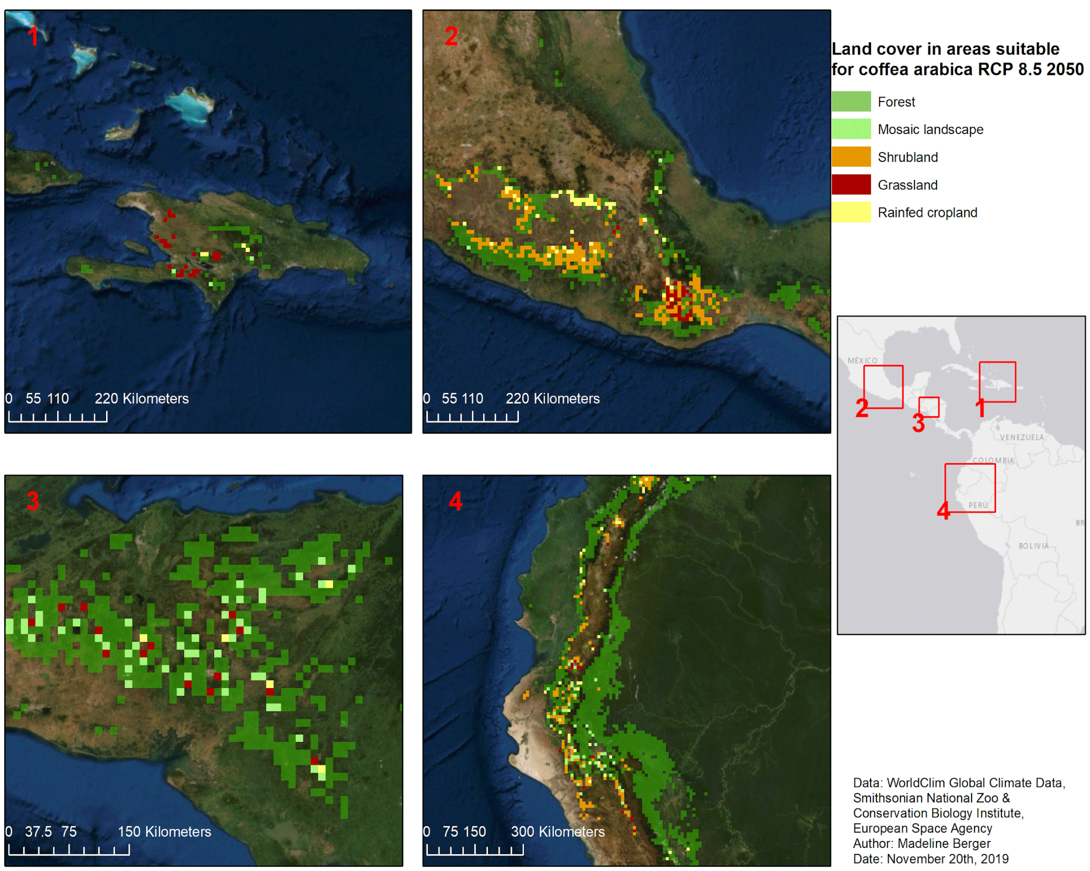


Figure 3. Land cover types in currently suitable areas in four focus regions. Dark green areas depict overlap with forest, light green depicts overlap with mosaic landscape, orange depicts overlap with shrub lands, and red depicts overlap with grassland. Rain fed crop area is depicted in yellow.

Composition of land currently suitable		
Land Cover	km	Percent
Forest	6482	56.59%
Grass	387	3.38%
Shrub	1787	15.60%
Mosaic	401	3.50%
Rain fed Crop	756	6.60%
Total	9813	85.67%

Table 2. Land cover composition of currently suitable areas. Percentages represent what percent of total currently suitable land overlaps with each land cover of interest.

Land Cover Analysis - RCP 2.6 and RCP 8.5 in 2050

Only climate scenarios in year 2050 were analyzed for land cover, in order to both identify possible conservation priority areas in the nearer future as well as to simplify the scope of analysis. Of most interest for this particular analysis were areas that were newly suitable under each climate scenario, as these areas represent places where *c. arabica* cultivation will be most likely to encroach on currently intact land. For RCP 2.6 2050, 46.49% of newly suitable land overlapped with forested areas, amounting to 5,830 km^2. The rest of the land cover categories analyzed had comparatively little overlap with areas newly suitable (Table 3). However, this general trend was not consistent across the entire extent modeled. While the Dominican Republic and the region intersecting Nicaragua, Honduras and El Salvador and South Central Mexico (Figure 4.1 4.2 & 4.3) showed significant future overlap with forests,

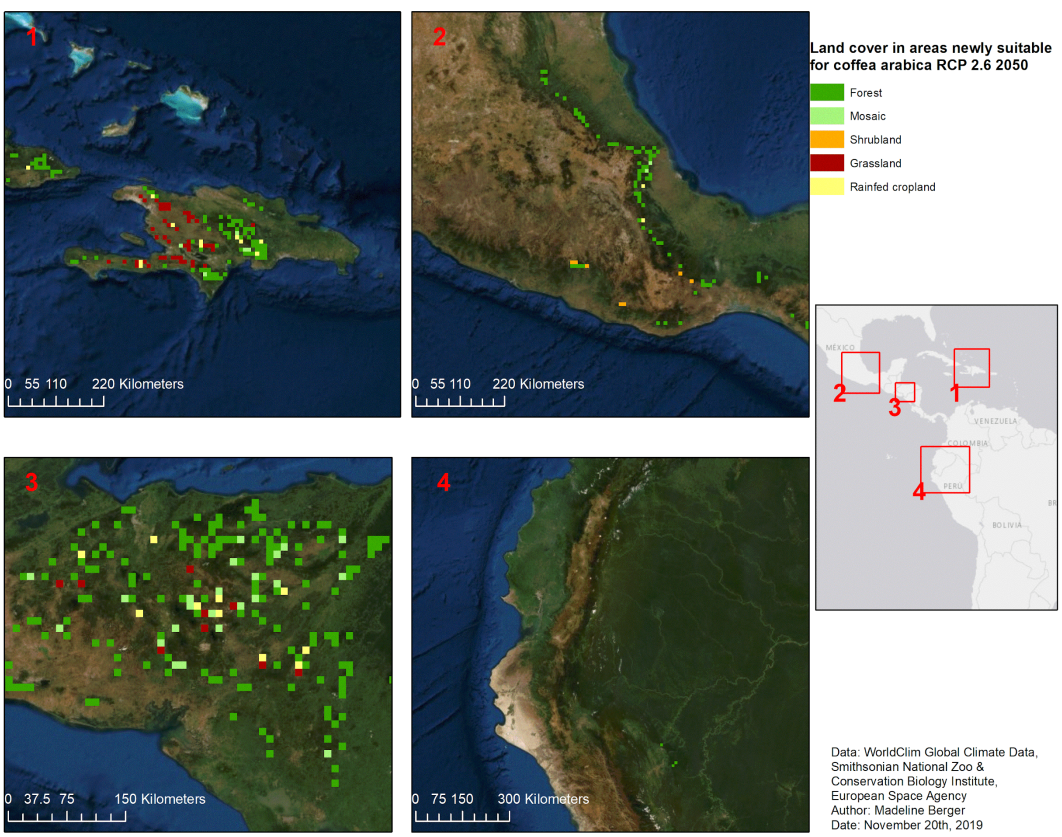


Figure 4. Land cover types in areas expected to be newly suitable under RCP 2.6. Dark green areas depict overlap with forest, light green depicts mosaic landscape, orange depicts shrub lands, and red depicts grassland. Rain fed crop is depicted in yellow.

the Andean region of Peru and Ecuador had almost none (Figure 4.4). In total, about 60% of newly suitable land under this scenario overlapped with land cover types that currently do not have significant human impacts.

Composition of newly suitable areas in 2.6		
Land Cover	km	Percent of new
Forest	5830	46.49%
Grass	690	5.50%
Shrub	310	2.47%
Mosaic	400	3.19%
Rain fed Crop	290	2.31%
Totals	7520	59.97%

Table 3. Land cover composition of newly suitable areas under RCP 2.6 in 2050. Percentages represent what percent of newly suitable land overlaps with each land cover of interest. These figures do not take any areas that remained suitable compared to the current scenario, or areas that have lost suitability. Units are kilometers squared

Furthermore, analysis of land cover overlap was quite different for all 4 regions under RCP 8.5 2050 scenario (Figure 5). Across the entire extent analyzed, the amount of newly suitable land overlapping with forest did not change significantly (Table 4). In fact, the land cover that saw the largest magnitude of change between the 2 RCP scenarios was grassland, gaining about 2%. However, regional analysis revealed more dramatic differences at smaller scales. The Dominican Republic shows a decrease in newly suitable area overlapping with forests with an increase in overlap with grasslands. The central American region has considerably more overlap with mosaic landscapes than under RCP 2.6. South Central Mexico still shows most of the newly suitable areas overlapping with forest, but with a completely different distribution, shifting somewhat from eastern mountain ranges to western ranges. The Andean region shows considerably more overlap of newly suitable areas in this climate scenario. Total overlap with “natural” areas under this scenario rose slightly to 62% (Table 4).

Composition of newly suitable areas in 8.5		
Land Cover	Km	Percent of new
Forest	5840	46.57%
Grass	910	7.26%
Shrub	210	1.67%
Mosaic	410	3.27%
Rain fed Crop	420	3.35%
Totals	7790	62.12%

Table 4. Land cover composition of newly suitable areas under RCP 8.5 in 2050. Percentages represent what percent of newly suitable land overlaps with each land cover of interest. These figures do not take any areas that remained suitable compared to the current scenario, or areas that have lost suitability. Units are in kilometers squared.

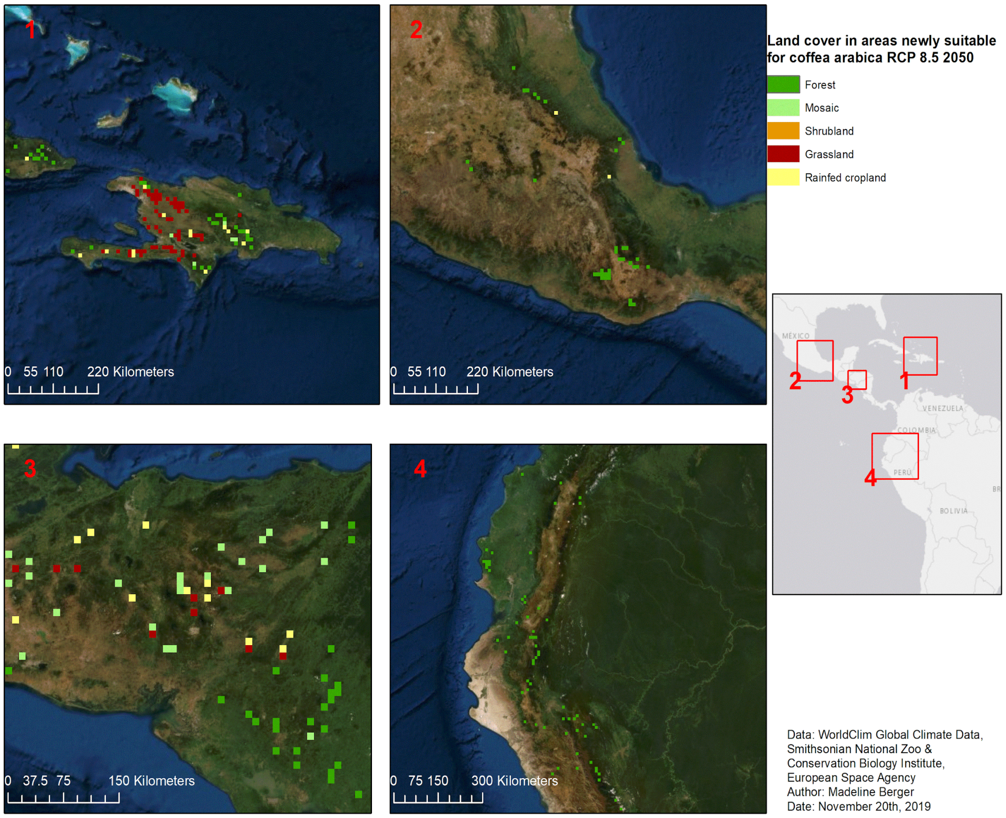


Figure 5. Land cover types in areas expected to be newly suitable under RCP 8.5. Dark green areas depict overlap with forest, light green depicts mosaic landscape, orange depicts shrub lands, and red depicts grassland. Rain fed crop is depicted in yellow.

Changes in forested suitable areas

To better assess what effect changes in coffee suitability may have on forested areas in particular, new suitable areas (shown in red) and areas that had lost suitability (shown in orange) that overlapped with forests were mapped side by side. In the Dominican Republic and Central America (Figure 6.1 & 6.2) there is essentially no forested areas that lost suitability, only forested areas that become more suitable. South central Mexico shows forested areas on the Eastern mountain ranges becoming more suitable for *c. arabica* and Western areas losing suitability (Figure 6.3). The Andean region shows an overwhelming loss in forest areas that are suitable (Figure 6.4).

Under RCP 8.5, there is considerably less newly suitable land overlapping with forests for all regions except the Andean region.

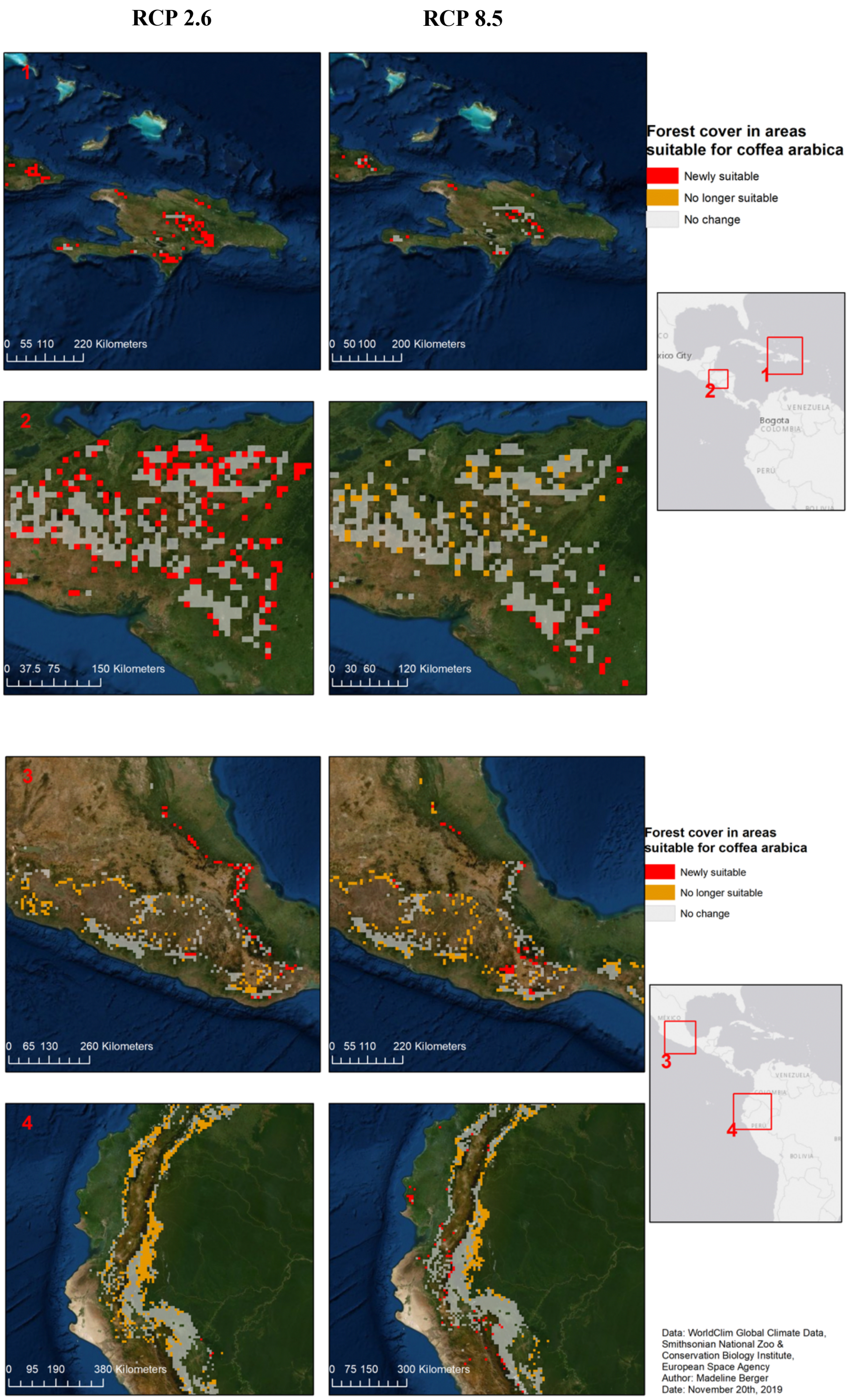


Figure 6. Impact on forest compared across two different climate scenarios in 2050 for 4 focus regions. The left column depicts all four focus areas under RCP 2.6, while the right depicts RCP 8.5. All results are for the year 2050. Red areas show land that becomes newly suitable under the specified climate scenario, orange areas show land that loses suitability, and grey areas are unchanged compared to the current suitability modeled using the same data and methods.

Discussion

Conservation Implications

An overall reduction in suitable areas for coffee cultivation can be interpreted in two different ways, both of which have important implications for land use and conservation in the Central and South American region. On one hand, a reduction in suitability may make it difficult to cultivate in these areas, as small-scale farmers often rely on more heavily on environmental conditions (i.e., rain) than industrial farmers, and may have less advanced technology. Under this assumption, areas that are no longer suitable for coffee could be areas to target for potential future restoration or may be less prioritized compared to suitable areas that are still intact.

However, because the data used for coffee presence only represented farms using the most stringent environmental safeguards, what these results really show are suitable areas for exceptionally low input coffee cultivation. It therefore may be better to interpret the areas that are no longer suitable as areas that may have coffee cultivation in the future using more intensive management practices. Intensive coffee cultivation closely resembles a monoculture, with little to no canopy or coupling with other plant species. There also may be increased chemical inputs in the form of fertilizer and pesticides, which can negatively impact surrounding natural areas and local water quality. It is therefore important to consider the areas that have lost suitability in this analysis as areas that still may be threatened by coffee cultivation - perhaps even more so if cultivation practices must intensify to adapt.

The results also suggest that areas that are both currently suitable for *coffea arabica* and suitable in the future may pose a threat to areas that currently have few human impacts. Tropical forest in particular had significant overlap with current suitable areas for *coffea arabica*. Forested areas also account for almost half of the newly suitable land under both RCP 2.6 and RCP 8.5 emission scenarios in 2050. Differences in regional analyses hint at ways to interpret and prioritize areas for specific conservation activities, depending on the current and future patterns exhibited. For example, results for the Dominican Republic and Central American region suggest a large amount of forested land may become suitable for coffee under RCP 2.6, but very little land loses suitability (Figure 5.1). Therefore, we may hypothesize that these areas may have intact forest that could be threatened by coffee expansion in the future even if emissions are significantly reduced. Conversely, the Andean region shows almost no new suitability in forested areas (Figure 5.4), but a large amount of area that loses suitability under RCP 2.6. Conservation strategies in this region may therefore focus on landscape level and economic planning to help farmers maintain their livelihoods and adapt to climatic changes without significantly intensifying cultivation. For some regions, such as South central Mexico, this analysis may reveal particular “hot spots” for coffee suitability in forests and help focus conservation to specific areas or eco-regions. In this case, high elevation areas in the eastern part of the country should be prioritized for forest conservation.

Uncertainty regarding how much humans will be able to lower emissions and combat climate change complicates these results as regional patterns diverge significantly for RCP 8.5. The framework described above does not hold across all regions under RCP 8.5 - Central America shows significant losses in addition to some gains in suitability, and the Andean region also shows very different patterns compared to RCP 2.6. South central Mexico still has concentrated areas of suitability gains, but in a completely different “hot spot” than under RCP 2.6.

Overall, this suggests that conservation planning in areas with high coffee cultivation needs to be adaptive. Plans incorporating continual monitoring and flexibility are recommended, rather than more static, traditional stronghold conservation methods that may not be successful as landscapes shift.

Model uncertainties

While these results help generate broad insights into the effects climate change may have on *coffea arabica*, this analysis would benefit from significant improvements to the input data and model. The presence data for *coffea arabica* represented a very small sample, and therefore may have easily contained biases not accounted for in the model. Overall, the 40 coffee farms used only represented about 12,000 ha of coffee cultivation, or approximately 2,000 kg/yr of green coffee (Coltro et al. 2006). This is a tiny fraction of the 169.1 million kg produced each year worldwide (USDA, 2019). Because there were so few points to begin with, none of the data was withheld for testing, which is recommended for future analyses to better refine results. Lastly, including biotic factors in the MaxEnt model, such as soil type or a vegetation layer would be highly beneficial in producing more accurate suitability results. Lack of data availability for this particular region was the main impediment in doing so for this analysis.

Another major shortcoming of this analysis is the coarse nature of the land cover data. Lacking other publicly available data, land categories were selected for this analysis that best represented areas with minimal human impact, however it is unlikely that these broad categories provided accurate estimates on where “natural” landscapes really were. Furthermore, lacking public data that modeled future land cover change in this region, the analysis on how newly suitable land under future climate scenarios may encroach on future ecosystems was not fully accurate.

Lastly, there is very little spatial data on where coffee cultivation is actually occurring now at the regional level. Shade grown coffee especially is particularly difficult to map as it is difficult for current remote sensing techniques to distinguish it from unaltered forest. A better understanding of baseline coffee cultivation would help contextualize and test future suitability models.

Improvement in these areas will help build on the foundation established here to generate more specific targeted conservation objectives for regions highly dependent on coffee exports in Central and South America.

Final Recommendations

- Collect more substantial spatial data on where coffee is currently being cultivated in Central and South America, both to improve future suitability models and to help predict likely areas land clearing for coffee will expand
- Prioritize intact forested areas in Central America and the Caribbean for conservation and continue to monitor for land clearing threats in these areas
- Assess current coffee cultivation practices in the Andean region and help farmers implement forest-friendly adaptation strategies.

References

About Bird Friendly Coffee. (2017, January 30). Retrieved December 5, 2019, from Smithsonian's National Zoo website: https://nationalzoo.si.edu/migratory-birds/about-bird-friendly-coffee

A Brewing Storm: the climate change risks to coffee | The Climate Institute. (n.d.). Retrieved October 9, 2019, from http://www.climateinstitute.org.au/coffee.html

Blackman, A., Albers, H. J., Ávalos-Sartorio, B., & Murphy, L. C. (2008). Land Cover in a Managed Forest Ecosystem: Mexican Shade Coffee. *American Journal of Agricultural Economics*, *90*(1), 216–231. https://doi.org/10.1111/j.1467-8276.2007.01060.x

Bosch, S., Tyberghein, L., De Clerck, O. (2018). Sdmpredictors: Species distribution Modelling Predictor Datasets. R package version 0.2.8 http://www.samuelbosch.com/p/sdmpredictors.html

Coltro, L., Mourad, A., Oliveira, P., Baddini, J., & Kletecke, R. (2006). Environmental Profile of Brazilian Green Coffee (6 pp). *The International Journal of Life Cycle Assessment*, *11*(1), 16–21. https://doi.org/10.1065/lca2006.01.230

Davis, A. P., Gole, T. W., Baena, S., & Moat, J. (2012). The Impact of Climate Change on Indigenous Arabica Coffee (Coffea arabica): Predicting Future Trends and Identifying Priorities. *PLOS ONE*, *7*(11), e47981. https://doi.org/10.1371/journal.pone.0047981

Gay, C., Estrada, F., Conde, C., Eakin, H., & Villers, L. (2006). Potential Impacts of Climate Change on Agriculture: A Case of Study of Coffee Production in Veracruz, Mexico. *Climatic Change*, *79*(3), 25

Gent, P. R., Danabasoglu, G., Donner, L. J., Holland, M. M., Hunke, E. C., Jayne, S. R., ... & Worley, P. H. (2011). The community climate system model version 4. *Journal of Climate*, *24*(19), 4973-4991.

Hannah, L., Roehrdanz, P. R., Ikegami, M., Shepard, A. V., Shaw, M. R., Tabor, G., … Hijmans, R. J. (2013). Climate change, wine, and conservation. *Proceedings of the National Academy of Sciences*, *110*(17), 6907–6912. https://doi.org/10.1073/pnas.12101271109–288. https://doi.org/10.1007/s10584-006-9066-x

Henders, S., Persson, U. M., & Kastner, T. (2015). Trading forests: Land-use change and carbon emissions embodied in production and exports of forest-risk commodities. *Environmental Research Letters*, *10*(12), 125012. https://doi.org/10.1088/1748-9326/10/12/125012

Hijmans, R. J., Phillips, S., Leathwick, J., Elith, J., & Hijmans, M. R. J. (2017). Package 'dismo'. *Circles*, *9*(1), 1-68.

Karp, D. S., Mendenhall, C. D., Sandí, R. F., Chaumont, N., Ehrlich, P. R., Hadly, E. A., & Daily, G. C. (2013). Forest bolsters bird abundance, pest control and coffee yield. *Ecology Letters*, *16*(11), 1339–1347. https://doi.org/10.1111/ele.12173

Merow, C., Smith, M. J., & Silander, J. A. (2013). A practical guide to MaxEnt for modeling species' distributions: What it does, and why inputs and settings matter. Ecography, 36(10), 1058–1069. https://doi.org/10.1111/j.1600-0587.2013.07872.x

Moorhead, L. C., Philpott, S. M., & Bichier, P. (2010a). Epiphyte Biodiversity in the Coffee Agricultural Matrix: Canopy Stratification and Distance from Forest Fragments. *Conservation Biology*, *24*(3), 737–746. https://doi.org/10.1111/j.1523-1739.2009.01430.x

Perfecto, I., Vandermeer, J. H., Bautista, G. L., Nunñez, G. I., Greenberg, R., Bichier, P., & Langridge, S. (2004). Greater Predation in Shaded Coffee Farms: The Role of Resident Neotropical Birds. *Ecology*, *85*(10), 2677–2681. https://doi.org/10.1890/03-3145

Rudel, T. K., Defries, R., Asner, G. P., & Laurance, W. F. (2009). Changing Drivers of Deforestation and New Opportunities for Conservation. Conservation Biology, 23(6), 1396–1405. https://doi.org/10.1111/j.1523-1739.2009.01332.x

Vaast, P., Van Kanten, R., Siles, P., Dzib, B., Franck, N., Harmand, J.-M., & Génard, M. (2005). *Shade: A key factor for coffee sustainability and quality*. Retrieved from http://agris.fao.org/agris-search/search.do?recordID=FR2019171022

Van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., ... & Masui, T. (2011). The representative concentration pathways: an overview. Climatic change, 109(1-2), 5.

Appendix A: R Code for MaxEnt Analysis

```
```{r, message=FALSE, warning=FALSE}

#load packages
library(raster)
library(tidyverse)
library(sf)
library(rgdal)
library(dplyr)
library(maptools)
library(dismo)
library(rJava)

library(fasterize)
library(rgeos)
library(scales)
library(sdmpredictors)

library(RColorBrewer)

#rJava will only run on a computer with Java

#read in presence data - coffee lat lon data (global)

coffee <- read_csv("coffee_bird_latlon_all.csv")
```
```

Setting up parameters

```
```{r, message=FALSE, warning=FALSE}
#Set up paramaters needed for analysis

projection <- "+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs"

ext <- extent(-120, -35, -30, 30)
```
```

Switch columns and remove Ethiopia points

```
```{r, message=FALSE, warning=FALSE}

coffee_world <- coffee[c("lon","lat")]

coffee_cropped <- coffee_world[-c(41,38,34),] #numbers refer to the row numbers to be removed
```
```

Convert presence data to vector or SpatialPoints with correct projection

```
```{r, message=FALSE, warning=FALSE}
coffee_points <- st_as_sf(coffee, coords = c("lon", "lat"), crs = projection) #this isn't useful

coffee_spatialpts <- SpatialPoints(coffee_cropped,proj4string = CRS("+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs"))

coffee_spatialpts_all <- SpatialPoints(coffee_world,proj4string = CRS("+proj=longlat +ellps=WGS84 +datum=WGS84 +no_defs"))
```
```

Plot Points

```
```{r, message=FALSE, warning=FALSE}
#read in world map

data("wrld_simpl")

#plot coffee points
plot(wrld_simpl, xlim=c(-90,90), ylim=c(-70,70), axes=TRUE, col="beige", main = "All presence points")

points(coffee_world$lon, coffee_world$lat, col="red", pch=20, cex=0.75)

#plot just the extent

plot(wrld_simpl, xlim=c(-120,-35), ylim=c(-30,30), axes=TRUE, col="beige", main = "Central and South America presence points")

points(coffee_correct$lon, coffee_correct$lat, col="red", pch=20, cex=0.75)
```
```

Download climate data - Current

```{r, message=FALSE, warning=FALSE, results=FALSE}

#set directory where the layers should be saved
#options(sdmpredictors_datadir="<>")

#Explore the datasets that come in the raster package

list_datasets()
list_layers()

#Layers for coffee - current conditions
#annual_t = WC_bio1
#t_min = WC_bio6
#t_max = WC_bio5
#precipitation = WC_bio12

current_wc <- load_layers(c("WC_alt","WC_bio1", "WC_bio5", "WC_bio6", "WC_bio12"))

#make a raster layer with predictor variables you just downloaded, crop to the
extent

predictors_current <- stack(current_wc) #use this one for world analysis
predict_current <- crop(predictors_current,ext)

```

Download climate data - Future

```{r, results=FALSE}
#Explore future layers

list_layers_future("WorldClim") %>%
  filter(current_layer_code=="WC_bio6")


#load future layers - dataframes by rcp and
#first get layers to match current environmental variables
#then load layers, these will already be stacked
#crop raster stack

alt <- load_layers("WC_alt")

future_rcp26_2050 <- get_future_layers(c("WC_bio1", "WC_bio5", "WC_bio6",
"WC_bio12"), scenario = "rcp26", year = 2050) %>%
  filter(model== "CCSM4")
f_rcp26_2050 <- load_layers(future_rcp26_2050, datadir = "env_26_50")
alt_clim_2650 <- stack(alt, f_rcp26_2050)#use this one for world analysis
rcp26_2050 <- crop(alt_clim_2650, ext)


future_rcp26_2070 <- get_future_layers(c("WC_bio1", "WC_bio5", "WC_bio6",
"WC_bio12"), scenario = "rcp26", year = 2070) %>%
  filter(model == "CCSM4")
f_rcp26_2070 <- load_layers(future_rcp26_2070, datadir = "env_26_70")
alt_clim_2670 <- stack(alt, f_rcp26_2070)#world
rcp26_2070 <- crop(alt_clim_2670, ext)


future_rcp85_2050 <- get_future_layers(c("WC_bio1", "WC_bio5", "WC_bio6",
"WC_bio12"), scenario = "rcp85", year = 2050) %>%
  filter(model == "CCSM4")
f_rcp85_2050 <- load_layers(future_rcp85_2050, datadir = "env_85_50")#world
alt_clim_8550 <- stack(alt, f_rcp85_2050)
rcp85_2050 <- crop(alt_clim_8550, ext)


future_rcp85_2070 <- get_future_layers(c("WC_bio1", "WC_bio5", "WC_bio6",
"WC_bio12"), scenario = "rcp85", year = 2070) %>%
  filter(model == "CCSM4")
f_rcp85_2070 <- load_layers(future_rcp85_2070, datadir = "env_85_70")
alt_clim_8570 <- stack(alt, f_rcp85_2070)
rcp85_2070 <- crop(alt_clim_8570, ext)


```

2. Run for only Central and South America, and Carribbean

a. run current layers, cropped

```
```{r, message=FALSE, warning=FALSE, results=FALSE}
#get java folder - this is where you should save the download

system.file("java", package="dismo")

#run maxent
#this only works if you use prescence data in a "spatial points" object


jar <- paste(system.file(package="dismo"), "/java/maxent.jar", sep='')
if (file.exists(jar)) {
  coffee_model <- maxent(predict_current, p = coffee_spatialpts)
}

#predict distritbution of coffee

coffee_pr_ext <- predict(coffee_model, predict_current)

current_ext_tiff <- writeRaster(coffee_pr_ext, filename=file.path("curr_ext.tif"),
format="GTiff", overwrite=TRUE)

coffee_model

```
```

b. create image of Maxent output

```
```{r, message=FALSE, warning=FALSE}

#get values for legend

cx <- range(coffee_pr_ext@data@values, na.rm = TRUE)

cx2 <- rev(as.character(round(c(cx[1],NA,mean(cx),NA,cx[2]),2))) #round

#create map

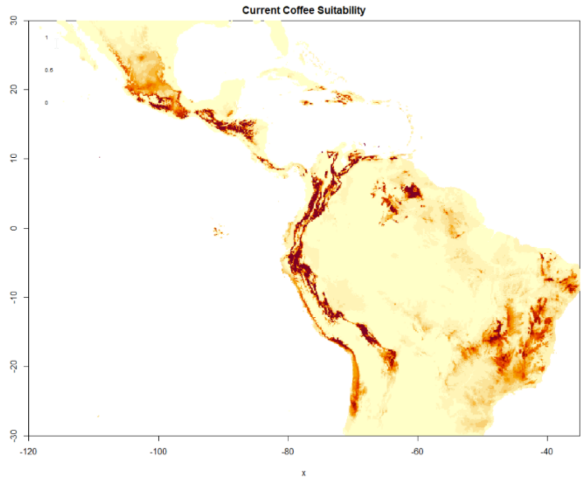
map1 <-image(coffee_pr_ext, main = 'Current Coffee Suitability')

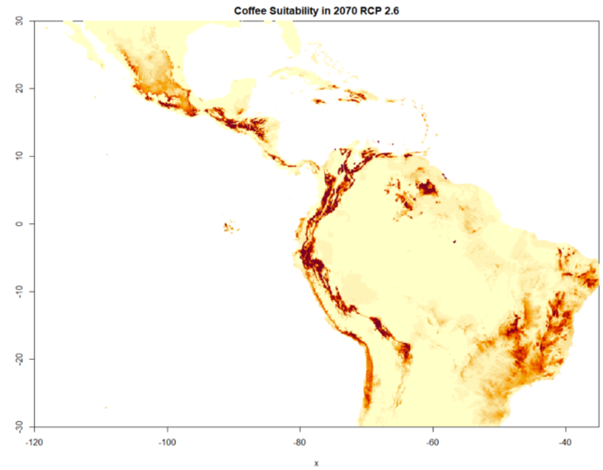
legend("topleft", cx2, horiz=FALSE, cex=.6, bty="n")

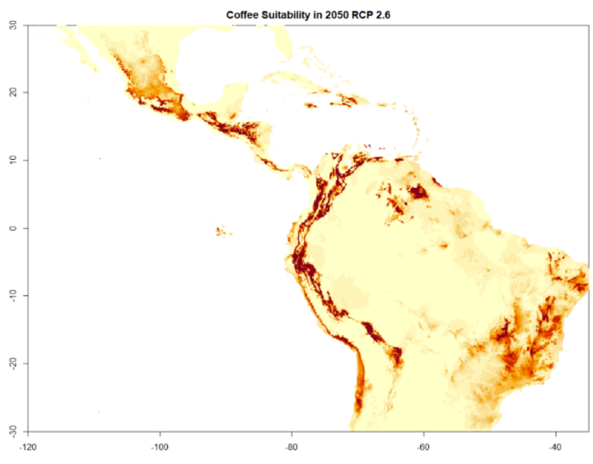

```
```

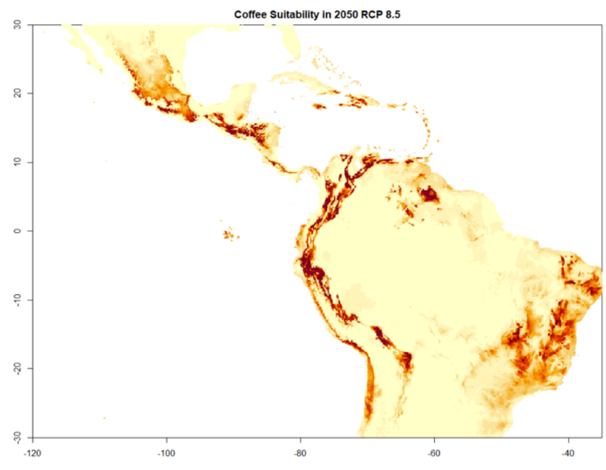
The code in the two chunks above was repeated exactly for the 4 climate scenarios

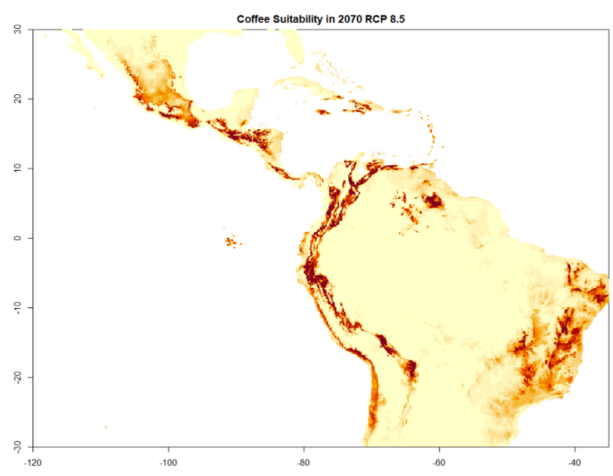
<u>Appendix B – Results from MaxEnt Analysis</u>











Appendix C - Land Cover Categories from the European Space Agency

IPCC Classes considered for the change detection		LCCS legend used in the CCI-LC maps	
1. Agriculture		10, 11, 12	Rainfed cropland
		20	Irrigated cropland
		30	Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%)
		40	Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (< 50%)
2. Forest		50	Tree cover, broadleaved, evergreen, closed to open (>15%)
		60, 61, 62	Tree cover, broadleaved, deciduous, closed to open (> 15%)
		70, 71, 72	Tree cover, needleleaved, evergreen, closed to open (> 15%)
		80, 81, 82	Tree cover, needleleaved, deciduous, closed to open (> 15%)
		90	Tree cover, mixed leaf type (broadleaved and needleleaved)
		100	Mosaic tree and shrub (>50%) / herbaceous cover (< 50%)
		160	Tree cover, flooded, fresh or brakish water
		170	Tree cover, flooded, saline water
3. Grassland		110	Mosaic herbaceous cover (>50%) / tree and shrub (<50%)
		130	Grassland
4. Wetland		180	Shrub or herbaceous cover, flooded, fresh-saline or brakish water
5. Settlement		190	Urban
6. Other	Shrubland	120, 121, 122	Shrubland
	Sparse vegetation	140	Lichens and mosses
		150, 151, 152, 153	Sparse vegetation (tree, shrub, herbaceous cover)
	Bare area	200, 201, 202	Bare areas
	Water	210	Water

From this full list of categories, the following were chosen as they were assumed to best mimic land cover that had minimal human impact:

Forest values: 50, 60, 61, 61, 70, 71, 72, 80, 81, 82, 90, 100, 160, 170

Grassland: 130

Mosaic: 110

Shrub land: 120, 121, 122

Rain fed crop: 10, 11, 12