Chapter 3: Climate suitability

Jeffrey Sachs, James Rising,
Tim Foreman, John Simmons, Manuel Brahm
The Earth Institute
Columbia University

October 1, 2015

Prepared for the Global Coffee Forum
Milan, Italy

Part of
The impacts of climate change on coffee: trouble brewing
http://eicoffee.net/

Land areas that are suitable to coffee production will shift drastically over the next 35 years. In this chapter, we develop a new approach to estimating suitability, drawing upon surveys, records, model data, and biological knowledge.

Historically, the coffee plant has already managed vast climatic transitions, spreading from Ethiopia and Yemen to over 70 countries. These may be an indication of further adaptive potential. However, when coffee is cultivated in marginal areas, bean quality drops and the plant becomes more susceptible to disease. Estimates of suitability are always uncertain, since we have never experienced a climate like that 2050. In light of this, it is important to develop an approach to suitability that represents the uncertainty of its estimates and is conservative in light of the lack of knowledge.

1 Observed suitability changes

Coffee yields have shifted over the past decade, as a result of many factors including climate change. Some areas have seen increases in per-hectare yields from improved agricultural practices and varieties, while others have been hit by expanded diseases. In some cases, these diseases are also driven by changes in climate: for example, the coffee berry borer and coffee white stem borer have benefited from increases in temperatures in Africa (Jaramillo et al., 2011; Kutywayo et al., 2013), and coffee rust responds to changes in humidity (Alves et al., 2011). Trends in yields reflect a combination of all of these factors.

As shown in figure 1, yields have shifted for each country since 2000. Many equatorial regions have been hit hardest, particularly central and west Africa. The greatest decrease in yields has been experienced by Zimbabwe, with an average of an almost 8% decrease in yields per year, from 14,000 Hg/Ha in 2000-2003 to 4,500 Hg/Ha in 2009-2012. The greatest increase is nearby, in Angola, from 1,100 Hg/Ha in 2000-2003 to 13,000 Hg/Ha in 2009-2012.

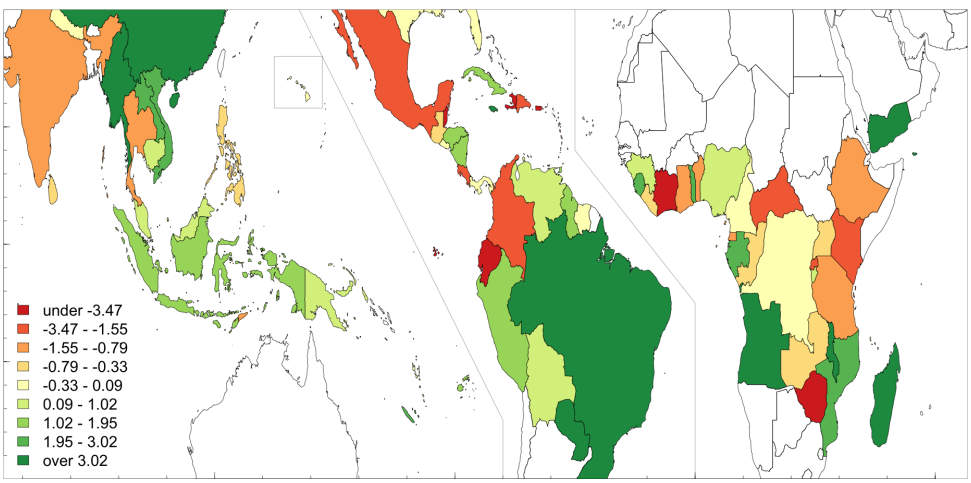


Figure 1: Trends in coffee yields since 2000 by country. Values represent the rate of yield change per year, since 2000 and relative to yields in 2000: Countries colored green have shown significant increases in per hectare yield, while those in red and orange have shown decreases.

We can explore the climate connection more closely in Brazil, where coffee yields are reported at the high-resolution municipality level. Trends across Brazil vary from positive to negative, as shown figure 2. Many of these trends are not the result of climate or weather. New management practices, seed varieties, and changes in the quality of land used to grow coffee can be important drivers.

However, in addition to these socioeconomic and biological drivers, yield changes over the past decade in Brazil are partly predicted be predicted by elevation, suggesting a climate-related driver. With the exception of large and relatively unproductive regions in the north, the regions with the largest negative trends tend to be on the edges of the broad coffee producing region, suggesting that shifts in suitability are squeezing these border regions out. Many of the areas with positive trends are in higher hills than those with negative trends.

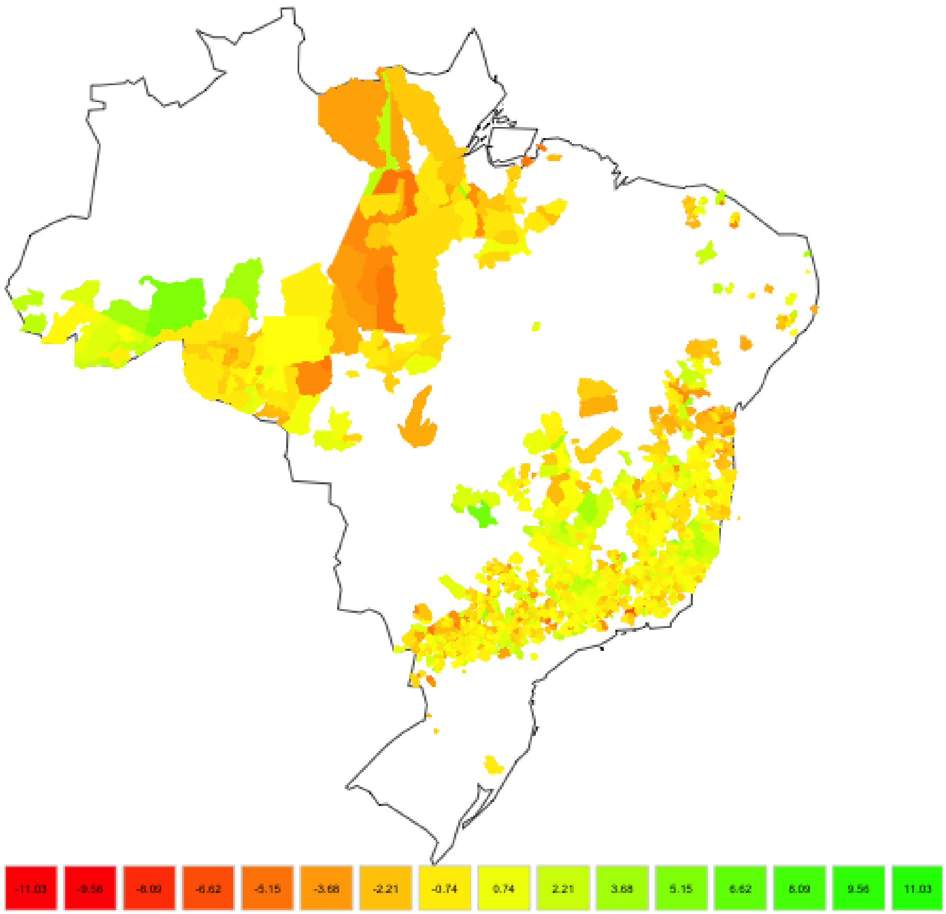


Figure 2: Trends in coffee yields since 2000 for Brazilian municipalities. Values represent the yearly decrease in percent terms: Countries colored green have shown significant increases in per hectare yield, while those in red and orange have shown decreases.

If temperatures are forcing coffee to higher elevations, it will be reflected in a fall in yields in municipalities at low elevations and increases at higher elevations. Figure 3 shows such a pattern from the municipality data. On average, counties of every elevation have increasing yields, reflecting the broader trend in Brazil. However, counties with high elevations (greater than 700 m) have on average higher increases yields than those with lower elevations (below 500 m). These lower averages at low elevations also reflect a greater number of municipalities with negative trends.

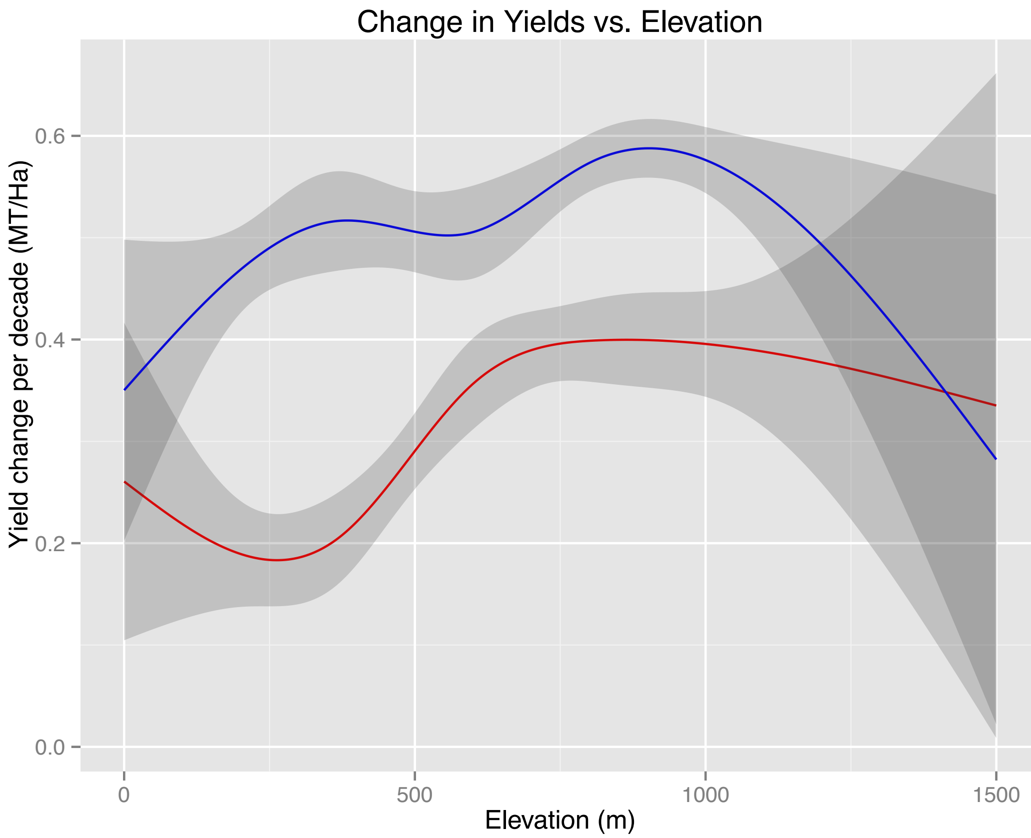


Figure 3: Changes in yields as a function of elevation. The red line shows municipality-level yields against elevation, showing a sharp increase in yields above 500 m. Blue shows the same relationship, but weighted by municipality harvests, and a more minor division around 700 m.

2 Previous coffee suitability literature

Suitable lands for coffee are expected to shift poleward and to higher elevations as temperatures rise. A number of regional estimates of these effects have been made, mostly using the Maximum Entropy (MaxEnt) methodology (see table 1). MaxEnt is a powerful technique in its ability to extrapolate suitability conditions from very sparse data, however robustness is difficult to assess with this techique. In this chapter we introduce a different approach we believe is more appropriate to the coffee context. We develop a Bayesian odds technique, which applies the data in our spatial coffee database.

Regions	**Approach**	**Reference**
Nicaragua, Mexico	MaxEnt	Laderach et al. (2009)
Kenya	MaxEnt	CIAT (2010)
Ethiopia	MaxEnt	Davis et al. (2012)
Haiti	MaxEnt	Eitzinger et al. (2013)
Uganda (data from Uganda, Tanzania, Kenya)	MaxEnt	Jassogne et al. (2013)
Rwanda	Qualitative criteria	Nzeyimana et al. (2014)
Indonesia	MaxEnt	Schroth et al. (2014)
Global	MaxEnt, SVM, Random Forest	Bunn et al. (2015)
Global	MaxEnt	Ovalle-Rivera et al. (2015)

Table 1: Recent analyses of current and future coffee suitability.

The most comprehensive previous estimates of changes in suitability are from the Global Agro-Ecological Zones (GAEZ) version 3.0 (2012), and from Bunn et al. (2015). GAEZ uses a potential yield model with soil physics and parameters derived from field experiments. Bunn et al. use a variety of data-mining methods, relating current occurrence to climate characteristics. The two approaches provide a useful comparison.

Figure 4 shows the GAEZ potential yield maps for the baseline period (1961 - 1990) and in 2050 under a business-as-usual trajectory (IPCC A2).

These maps account for the additional benefit of CO2 fertilization and an intermediate level of fertilizer inputs.

A few results are visible in these figures. First, the current range of suitable climate is predicted to be large in many areas, particularly South America and central Africa. Actual coffee production areas are much more limited. The extent and quality of coffee producing areas in 2050 is predicted to be much smaller than the suitable areas in the baseline period, but also tends to more closely match existing areas of cultivation. Some countries are predicted to no longer have any land suitable for growing coffee (e.g., Ghana and Nigeria) while other regions have new potential (e.g., Florida and South Africa).

These shifts in coffee production can be seen more clearly in the difference between current coffee production potential to future coffee production, as shown in figure 5.

Most areas show large decreases in coffee production potential, except for Florida, southern Brazil, South Africa, Ethiopia, northern India, Myanmar, and China. The dashed lines show the tropics of Cancer and Capricorn, the traditional bounds of the coffee belt. Almost the entire region within these bounds decreases in suitability, while increases are generated in the region beyond it. A table of the country-by-country changes in amount of suitable area from GAEZ is included in Appendix .1.

Bunn et al. (2015) provide a more nuanced picture (see figure 6). While Bunn et al. still estimate

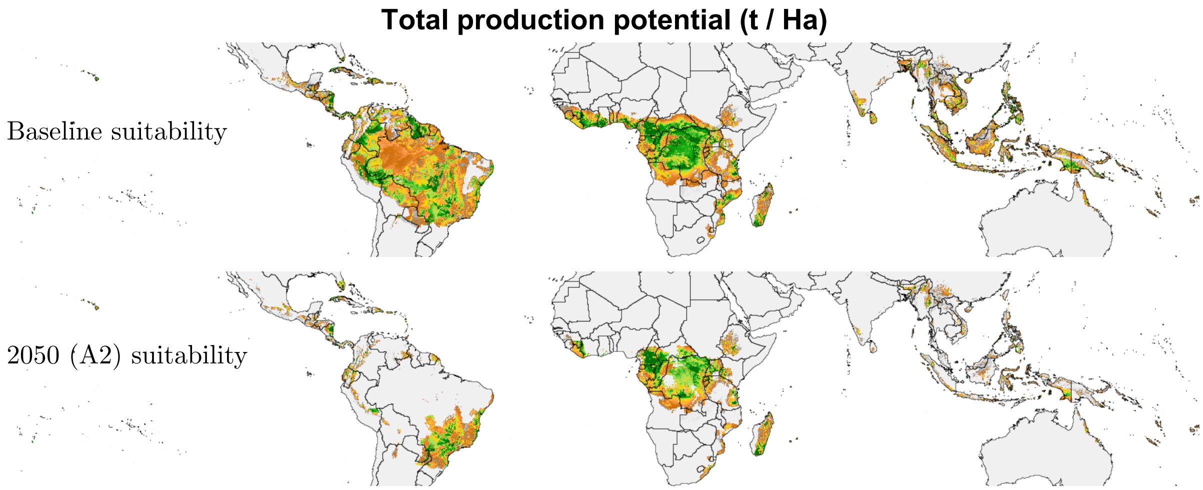


Figure 4: Coffee suitability maps for 1961-1990 (above) and for 2050 (below) under IPCC's A2 scenario (Hadley GCM). Color represent total production capacity, from 0 (grey) to .98 t/ha (green). Source: GAEZ

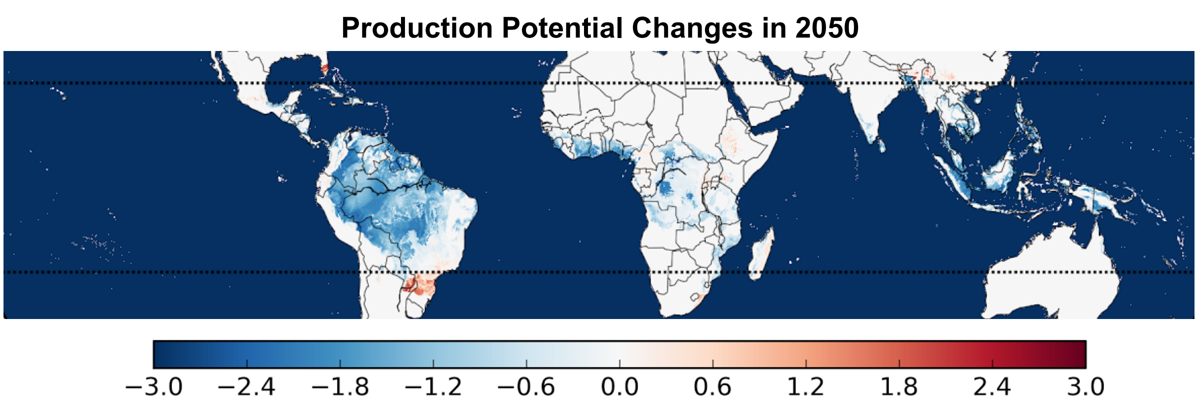


Figure 5: Changes in coffee suitability, in terms of production potential in t/ha, between 1961-1990 and 2050 under IPCC's A2 scenario, under a high-input farming system. Adapted from GAEZ.

decreases in climatic suitability between now and 2050 across much of the current coffee producing area, they also find neighboring areas in many cases that show increases in suitability. For example, regions in Colombia, Central America, and Indonesia can shift to higher elevations, and Brazil production can shift south. The coffee production potential in much of Uganda and Tanzania shifts into Kenya and the Democratic Republic of the Congo.

Changes in arabica and robusta climate suitability

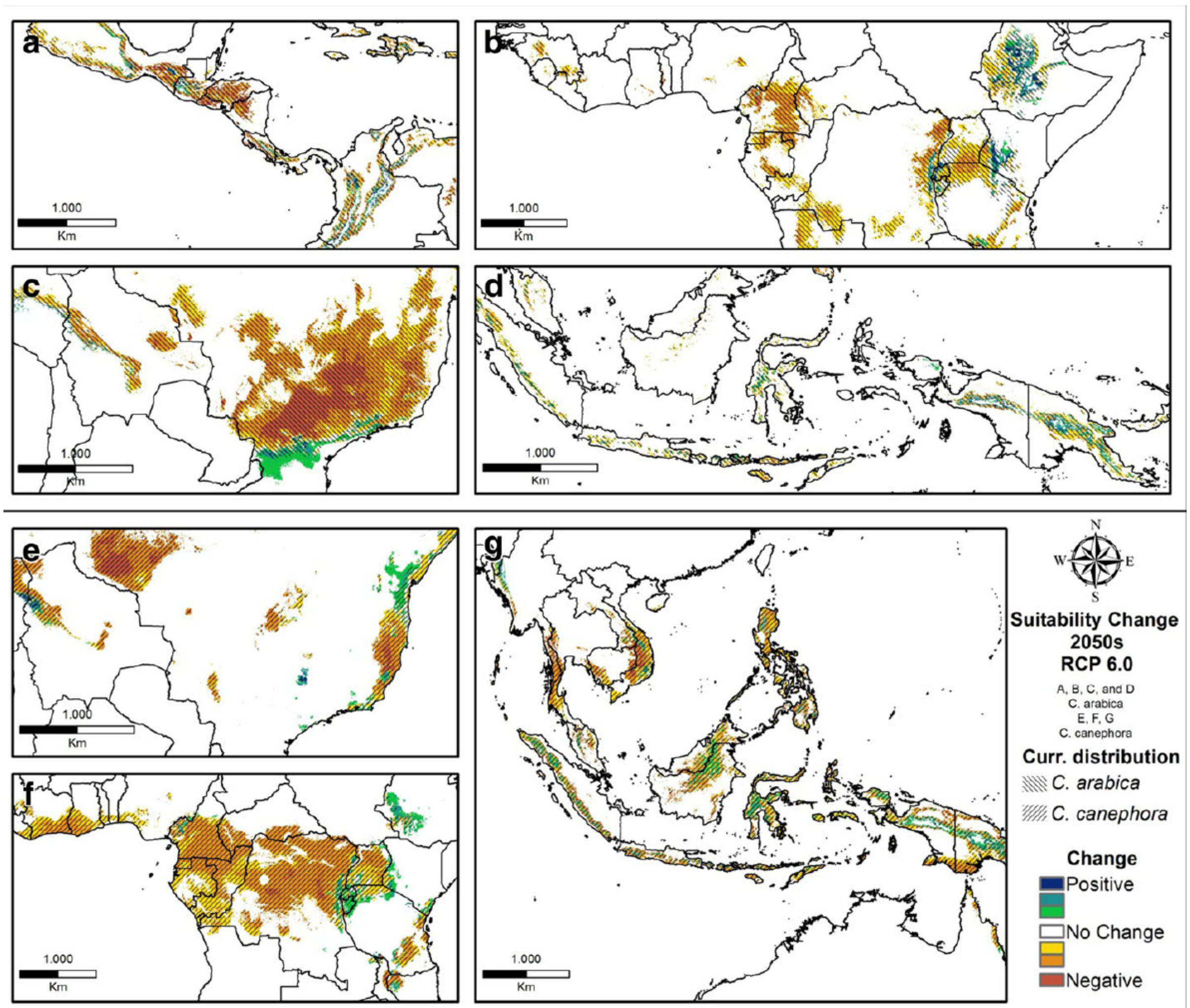
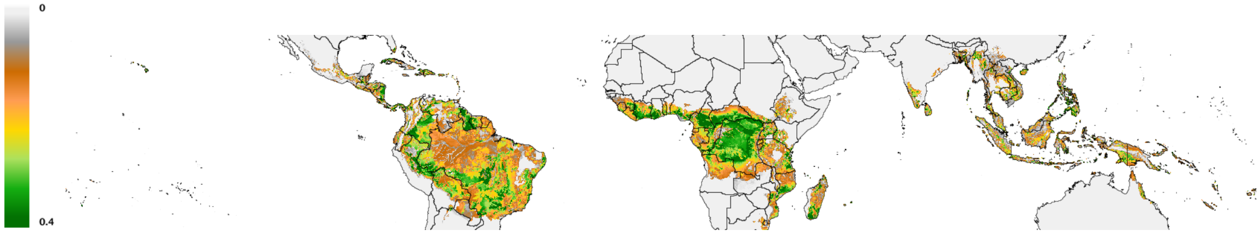


Figure 6: Suitability changes between present climate and 2050. Figures a - d show Arabica production and figures e - g show Robusta. Reproduced from Bunn et al. (2015).

2.1 The role of management

Fertilizer and irrigation use can open up new areas to coffee production. Figure 7 compares suitability according to GAEZ for low-input and high-input management. High-input management can produce yields 5 times that of low-input management.

Low Inputs, Rain-fed Suitability



High Inputs, Rain-fed Suitability

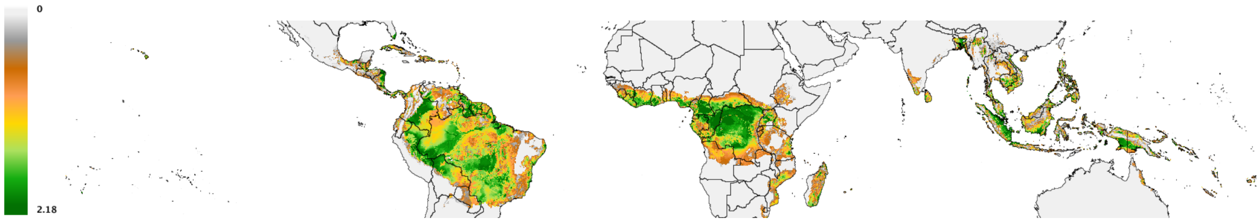


Figure 7: Both maps are copyright of IIASA and FAO.

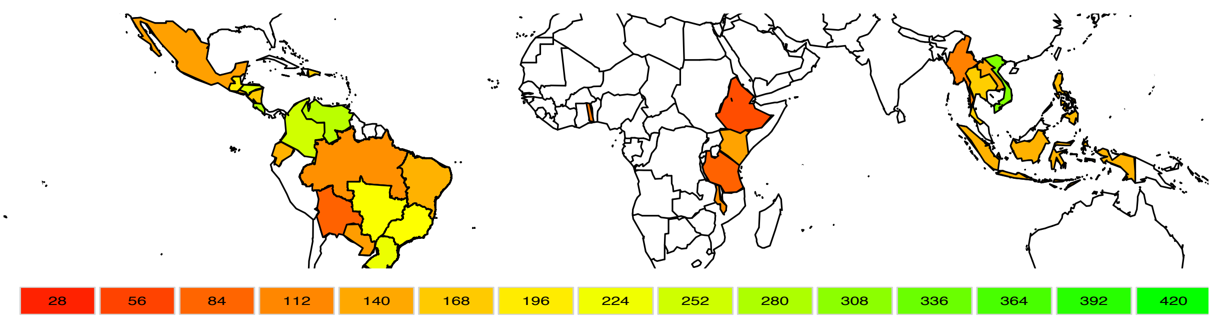


Figure 8: Average fertilizer use for coffee, from FertiStats (FAO), and including Brazil regional breakdown from `ftp://ftp.fao.org/agl/agll/docs/fertusebrazil.pdf` (FAO). The greatest amounts of fertilizer are used by Vietnam, Venezuela, and Costa Rica, and the least by Ethiopia and Tanzania.

Figure 8 shows the amount of fertilizer used by countries and distinguished for regions with Brazil, using FAO data (FertiStats). A wide range of fertilizer amounts are used, with the greatest amounts of fertilizer used by Vietnam, Venezuela, and Costa Rica, and the least by Ethiopia and Tanzania. This material is to be added to the production model.

3 A Bayesian suitability approach

Our approach to estimating suitability is diagrammed in figure 9. Using existing environmental characteristics, we compute a statistical model, which we apply to future environmental characteristics and compare the result to previous estimates. This section describes the basic principles used to construct that model.

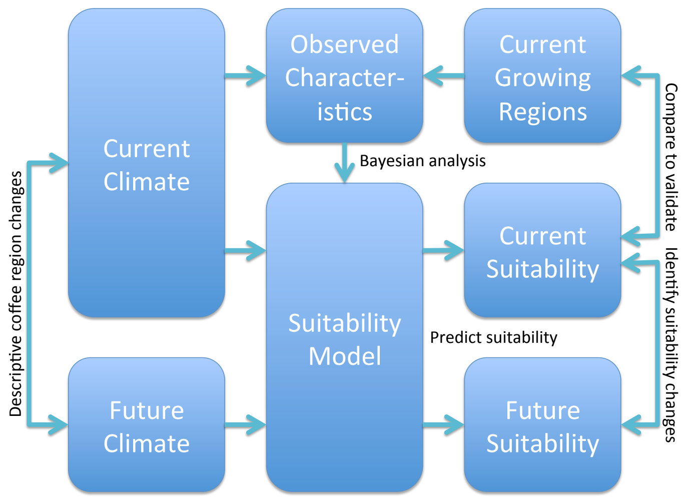


Figure 9: Diagram of the process for determining future climate suitability for coffee. On the left is global weather data, fed into both the model creation process and the model itself in the center. These then are used to produce current and future suitability maps.

Derivation of the Bayesian odds measure

Given any environmental condition, we can use Bayes rule to provide a empirical estimate of suitability. We write Bayes rule as an odds ratio:

$$\frac{p(\text{coffee} = 1|\vec{x})}{p(\text{coffee} = 1)} = \frac{p(\vec{x}|\text{coffee} = 1)}{p(\vec{x})}$$

The left-hand-side describes the ratio of the probability of coffee in a region given the observed conditions, to the probability of coffee generally. If this is greater than 1, the area is more suitable than the average location.

To calculate the coffee probability, the right-hand-side describes a ratio between the distribution of a property across harvested areas, and the distribution of that property across the entire region. As conditioning data, we use soil properties, climatic properties, elevation, and latitude.

Climatic and soil properties are not mutually independent, complicating our ability to calculate this ratio given the large number of properties we have available. We use the statistical "copulas" technique to disentangle the marginal distributions of each property from their dependence structure (Nelsen, 2013). We use a Gaussian copula, which captures the correlation between the various properties.

To incorporate a new property, we determine its unweighted distribution across the entire region from 30°N to 30°S. Then we create a weighted distribution, with properties from the region weighted by harvested area. Finally, we calculate Spearman's rho, between the new property and all existing properties, to represent the dependence structure.[1]

Then, to determine $p(\vec{x})$ and $p(\vec{x}|\text{coffee} = 1)$ for a given location, we reverse the normal copula process. In this case, we determine the span in $\vec{u}$-space (rank space) that a small region of $\vec{x}$-space represents ($\vec{x} \pm \vec{\Delta x}$), using each marginal distribution and the probability integral transform. If there is very little mass in the marginal distribution in the region of x_i, the corresponding Δu_i will be small. Then we evaluate

$$\int_{\vec{\Delta u}} c_R^{\text{Gauss}}$$

Above, c_R^{Gauss} is the Gaussian copula, which can be written as,

$$c_R^{\text{Gauss}}(u) = \frac{1}{\sqrt{\det R}} \exp\left(-\frac{1}{2} \begin{pmatrix} \Phi^{-1}(u_1) \\ \vdots \\ \Phi^{-1}(u_d) \end{pmatrix}^T \cdot \left(R^{-1} - \mathbf{I}\right) \cdot \begin{pmatrix} \Phi^{-1}(u_1) \\ \vdots \\ \Phi^{-1}(u_d) \end{pmatrix} \right)$$

where Φ^{-1} is the inverse cumulative distribution function of a standard normal (Arbenz, 2013), and R is the matrix of correlations, equal to $2 \sin \rho_{ij} \frac{\pi}{6}$ for each Spearman's rho, ρ_{ij}, between property i and property j.[2]

3.1 Comparing MaxEnt and Bayesian odds techniques

Both the MaxEnt and Bayesian techniques are sophisticated and represent the uncertainty of their result with high integrity. Table 2 provides a comparison of the main strengths and weaknesses of the two techniques.

MaxEnt has been used to study species suitability for a long time, and is designed for situations where a species is observed only at particular locations. The spatial coffee database gives us a much clearer picture of where coffee currently is grown and is not.

MaxEnt is most appropriate when there are underlying motivations for the constraints that are used as a central part of the method: for example, a common constraint is to require that that the mean and variance of temperatures for observed coffee match the mean and variance for future coffee. Unfortunately, MaxEnt constraints are often chosen arbitrarily and without a physical foundation. The Bayesian odds approach incorporates the entire distribution of environmental indicator values where coffee is grown, rather than a small collection of moments.

	MaxEnt	**Bayesian Odds**
Form of observation data	A set of point locations, for where the species was observed	A weighted grid of presence across all space
Use of environmental data	Mean and other moments of the environmental data are used, based on the constraints chosen	The full distribution of values for any environmental indicators are included
Use of constraints	Constraints are central to the technique	Constraints are not used
Result uncertainty	Fully maintained	Fully maintained
Key simplification	Only chosen constraints describe the distribution of environmental indicators	Dependence between indicators is assumed to be captured by a rank correlation.

Table 2: Comparison between the features of MaxEnt and Bayesian odds methods.

3.2 Suitability data

We calculate suitability using the following environmental variables, all available at 5 arc-minute resolution. These are shown in figure 10.

- Soil texture data from the Harmonized World Soil Database (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012). This consists of three macro-soil components (sand, silt, and clay), and three trace components (organic carbon, calcium carbonate, and gypsum). These six properties are available at high resolution (a 0.5' or about 1km grid) for the topsoil (0 cm to 30 cm) and again for the subsoil (30 cm to 100 cm).
- Land elevation from the SRTM elevation database (Jarvis et al., 2008).
- Gridded bioclimatic data from the WorldClim dataset (Hijmans et al., 2005). This database includes 19 variables, including annual mean temperature, diurnal range, maximum and minimum temperatures, annual precipitation, maximum and minimum precipitations, temperatures in wet and dry months, and precipitation in hot and cold months.
- Urban areas from Natural Earth and derived from 2002-2003 MODIS satellite data (Schneider et al., 2003).
- Protected regions from the World database on protected areas (WDPA Consortium, 2004). Protected areas and urban areas are important both as constraints on current coffee producing regions and on future ones.

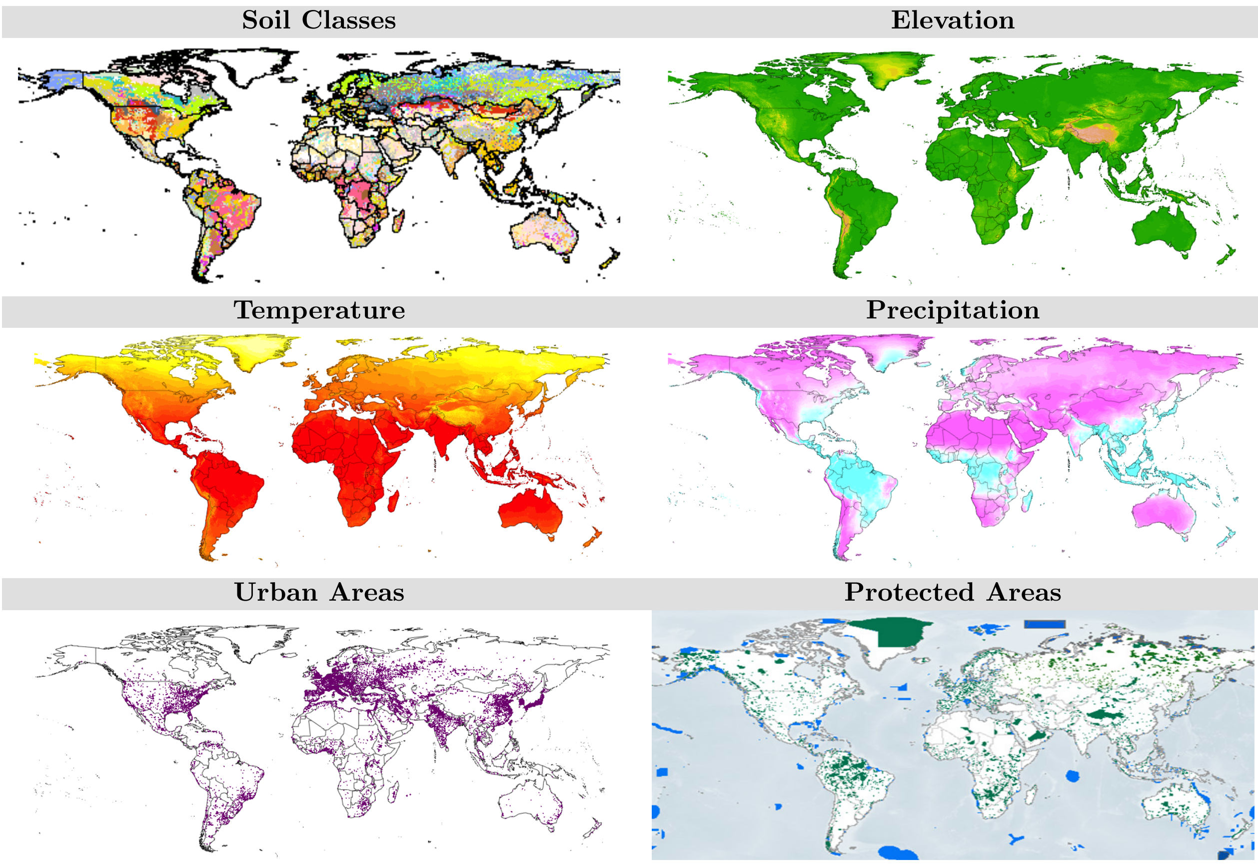
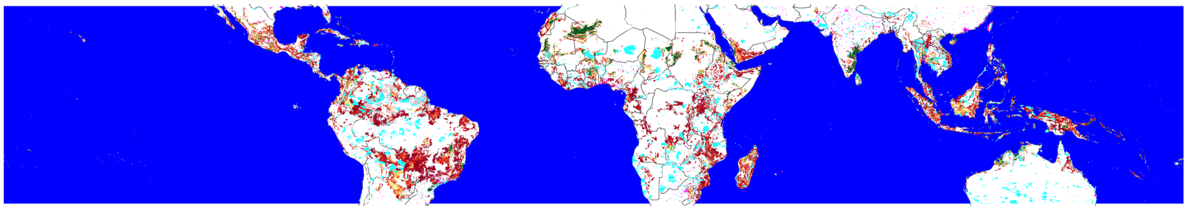


Figure 10: Inputs to the suitability analysis. See the text for details.

4 Baseline Bayesian odds map

The result of the Bayesian odds procedure for current coffee suitability is shown in figure 11. Dark green regions (high suitability) are rare, unlike the analyses by GAEZ and Bunn et al.. While they typically match areas of actual coffee growth (in Brazil, Colombia, and Central America), there are several places where there are large mismatches (in North Africa and Western India). While this provides a high resolution and data-driven map, it cannot stand alone.

Arabica Bayesian Odds Suitability



Robusta Bayesian Odds Suitability

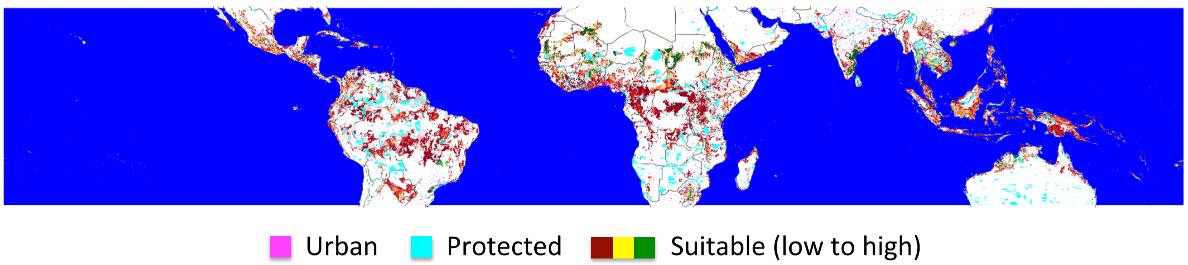


Figure 11: Suitability for Arabica coffee (top) and Robusta coffee (bottom). Colors range from red (slight suitability odds) to yellow to green (very strong suitability odds). The map also shows protected areas (cyan), urban areas (purple), and managed areas (faded).

5 Incorporating biological process

The Global Agro-ecological Zones (GAEZ) project uses biologically-motivated calculations to estimate suitability. GAEZ suitability indexes are normalized to be between 0 and 100, so a comparison between the Bayesian results and GAEZ requires constructing a common scale. We do this by comparing the results in ranks, rather than levels. In other words, we look for differences in the percentile quality of land (see figure 12).

Some areas match closely (southern Brazil, Colombia, and parts of Indonesia), while GAEZ attributes suitability to large regions not supported by the Bayesian methods, such as Amazonian and Congo rainforest. This indicates a complementarity between GAEZ and the Bayesian odds approach, where GAEZ provides physical constraints while the Bayesian approach forces the results to match observed data.

Computing a combined metric

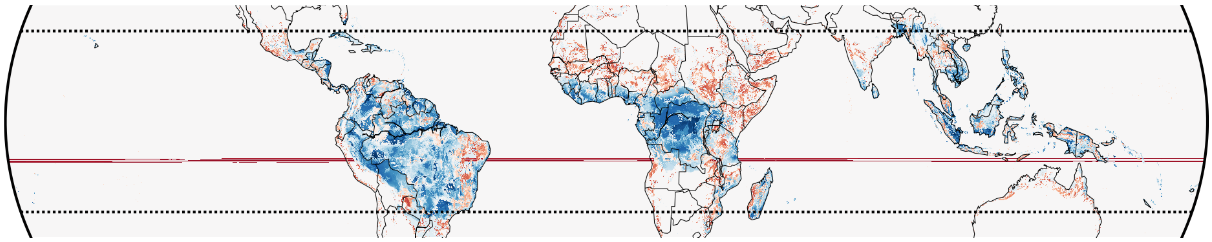


Figure 12: Comparison between GAEZ and the Bayesian odds technique for Arabica. Blue regions have greater quantile suitability in GAEZ than for the Bayesian odds approach; red regions show lower suitability in GAEZ, and white regions agree.

We combine the two approaches by mapping the following:

$$s(x, y) = p(x, y)\frac{b(x, y)}{1 + b(x, y)}$$

This attributes zero suitability where either approach specifies it, and otherwise allows them to reinforce each other. The results are shown in figure 13. It also normalizes the result to match GAEZ 0 - 100 scale.

The combined result shows high suitability in many fewer places, scattered based on where both techniques support their suitability. This provides a stronger basis for identifying the shifts in suitability, conservatively matched to only the highly suitable regions.

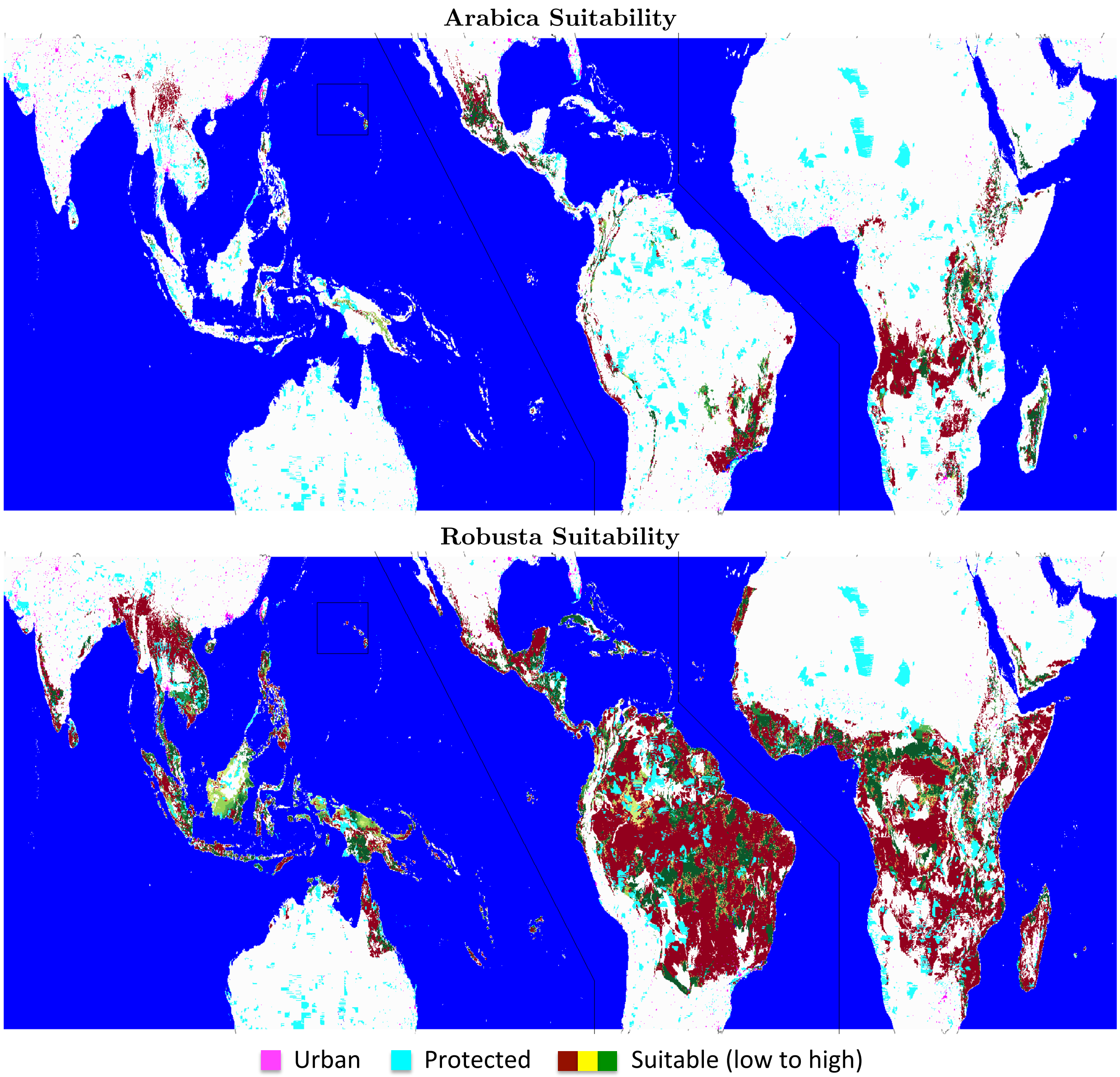


Figure 13: Combined Bayesian and GAEZ results for Arabica and Robusta.

6 Suitability comparison with Bunn et al.

A recent paper by Bunn et al. (2015) uses data mining methods, such as MaxEnt, on coffee-growing presence at 42 000 individual farms to estimate suitability. Above, we build upon this work by incorporating the coffee presence map from their paper into our database. We also use the same collection of 19 bioclimactic variables, on top of which we add soil variables, and we extend the study of future uncertainty by using 12 additional global climate model results. While we believe that our approach, based on Bayesian updating of presence and absence information, is better grounded theoretically and less arbitrary than their MaxEnt and other data-mining techniques, Bunn et al. provides an important comparison for our results.

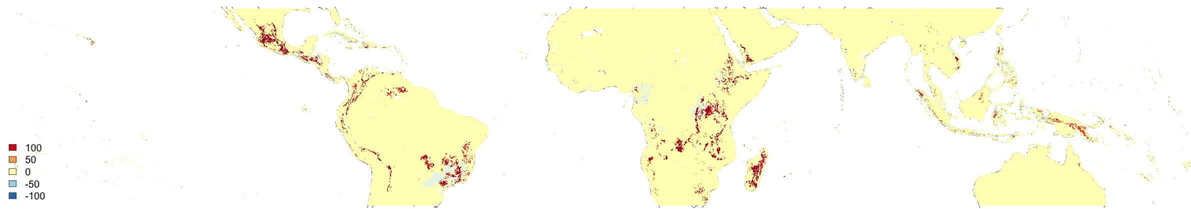


Figure 14: Comparison between Bunn et al. (2015) and the combined Bayesian-GAEZ approach. Blue areas have higher suitability in the baseline map produce by Bunn et al., while red is higher using our approach.

Figure 14 displays a comparison of current suitability between the two methods. Most of the world in this figure is colored yellow, where both techniques specify very little suitability. Some areas, such as Brazil and Kenya, show differing patterns between the two approaches. In these cases, our approach produces a result that more closely matches the patterns in the coffee database.

7 Future suitability

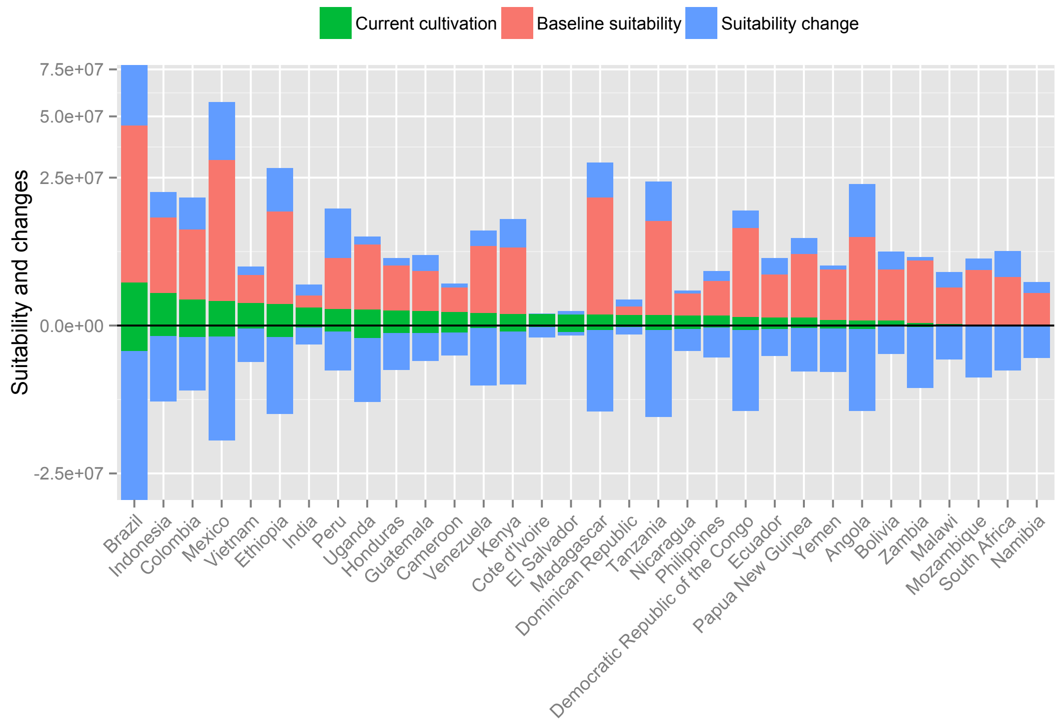
Estimating future suitability requires taking careful account of the uncertainties involved in future predictions. We estimate suitability for each of 17 GCMs for Bioclim and 4 GCMs for GAEZ. We display three maps for each of Arabica and Robusta suitability. The first is just the measure of median changes in suitability, without protected and urban areas. The second shows the level of confidence that the direction of the suitability change is as shown. The third shows the full map, where areas are also faded in proportion to their level of uncertainty.

The maps show that many traditional coffee growing areas are going to experience large losses in suitability by 2050. This includes parts of Brazil, southern Mexico, Kenya, and Madagascar. Few places show increases, but these include other parts of Brazil and Angola.

Appendix .3 shows the total area by country expected to increase and decrease, both by suitability and within harvested regions. These are summarized at the global level in table 3.

In absolute suitability changes, Brazil has the most lost of suitability in regions that are currently suitable, and the most gain in new regions becoming suitable. As a fraction of the current suitable area, a number of countries are tied in losing all of their suitable land: Belize, the Central African Republic, Côte d'Ivoire, Republic of Congo, Fiji, Gabon, Guinea, Equatorial Guinea, Cambodia, Paraguay, Sierra Leone, and Thailand. Although Taiwan also losses its entire allotment of suitable areas (of which it is

Suitability changes for Arabica



Suitability changes for Robusta

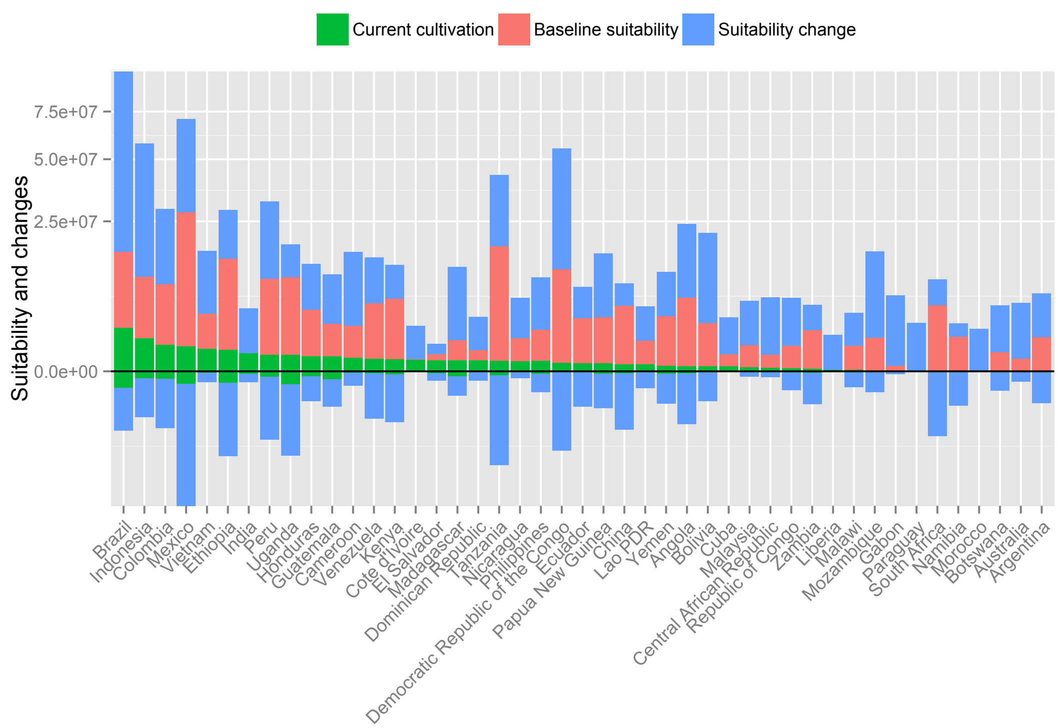
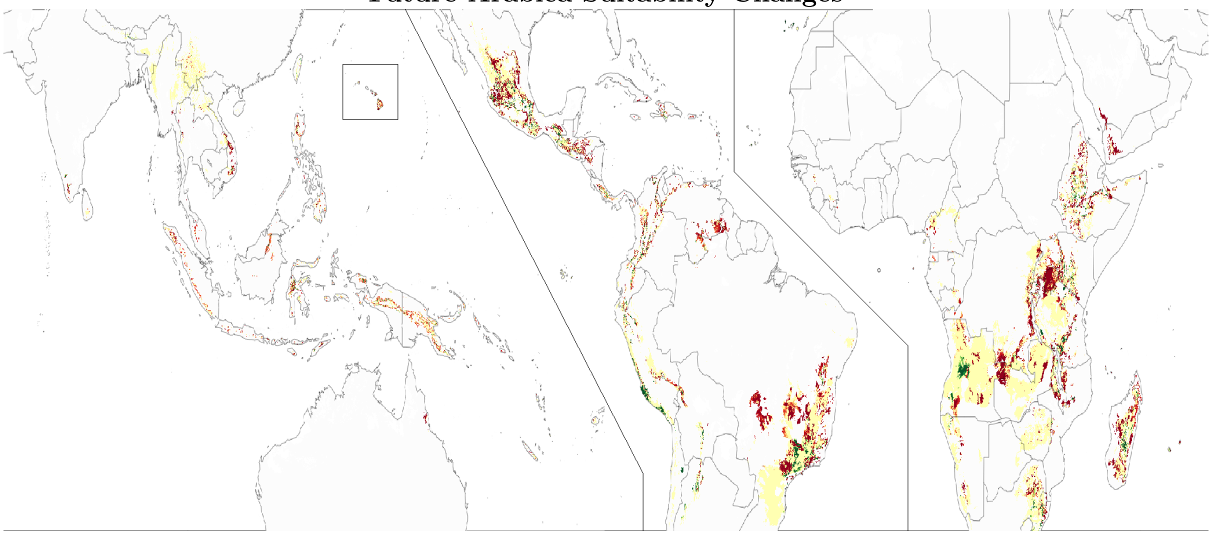


Figure 15: Increases and decreases in suitability and current cultivation by 2050. Green bars above the line describe current harvest areas; green below the line is the median predicted loss by 2050. Red above the line is the total baseline suitability. Blue above the line is new areas of suitability by 2050, and blue below the line lost areas.

Future Arabica Suitability Changes



Future Arabica Change Confidence

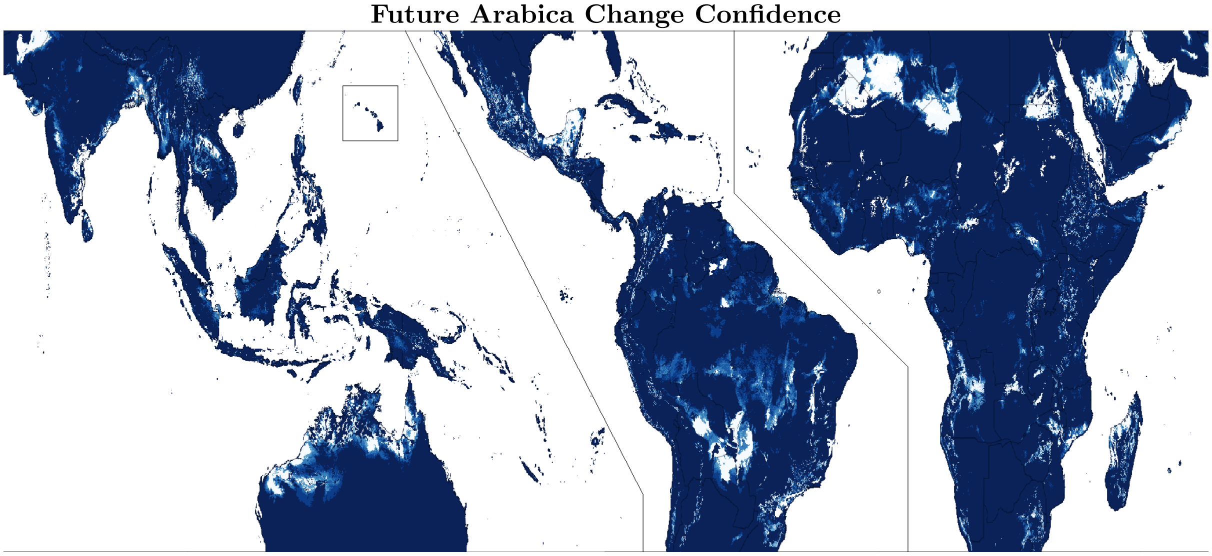


Figure 16: Maps of future Arabica suitability changes, showing the median suitability change (top) and the confidence level behind the direction of that change (bottom).

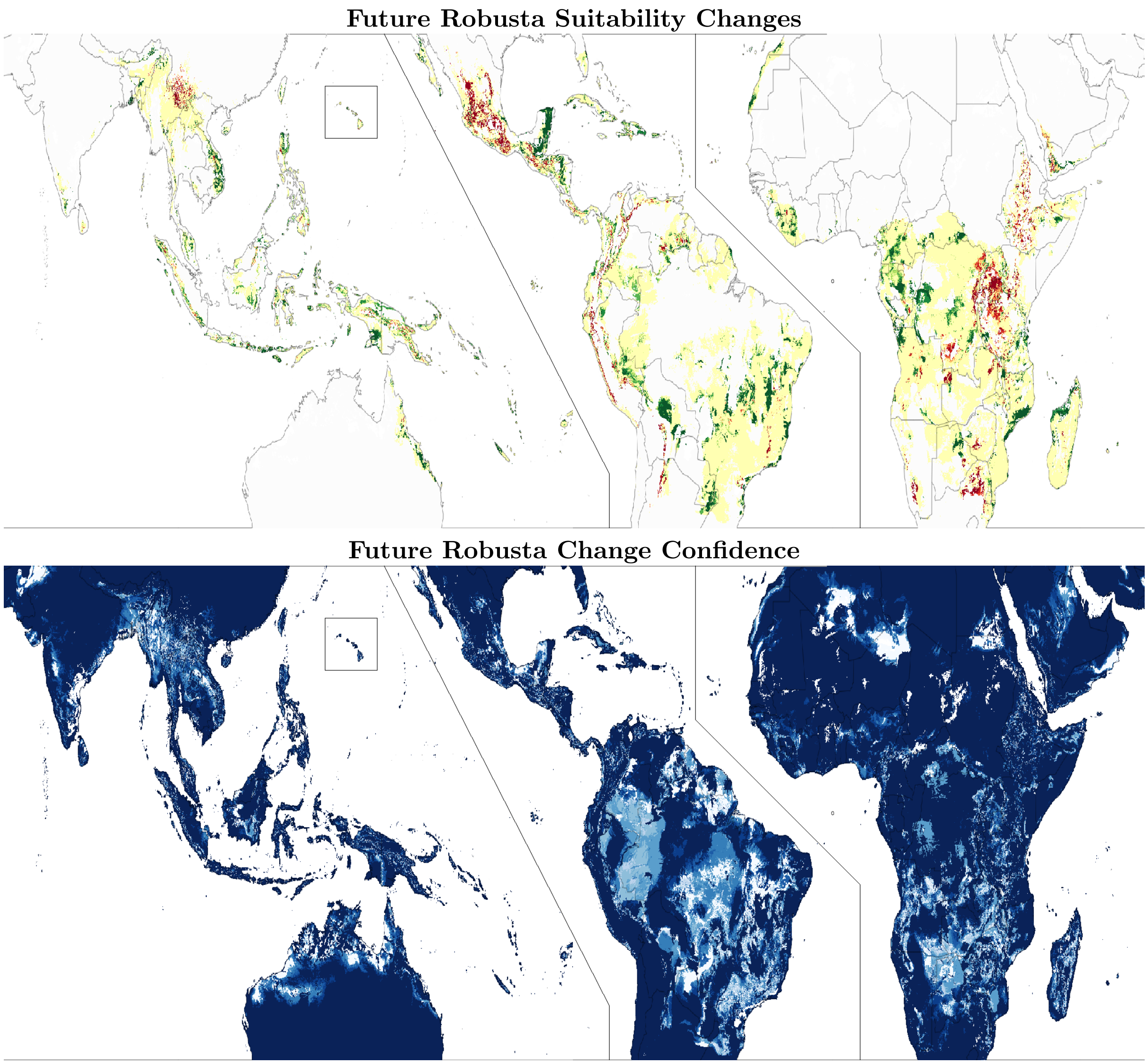


Figure 17: Maps of future Robusta suitability changes, showing the median suitability change (top) and the confidence level behind the direction of that change (bottom).

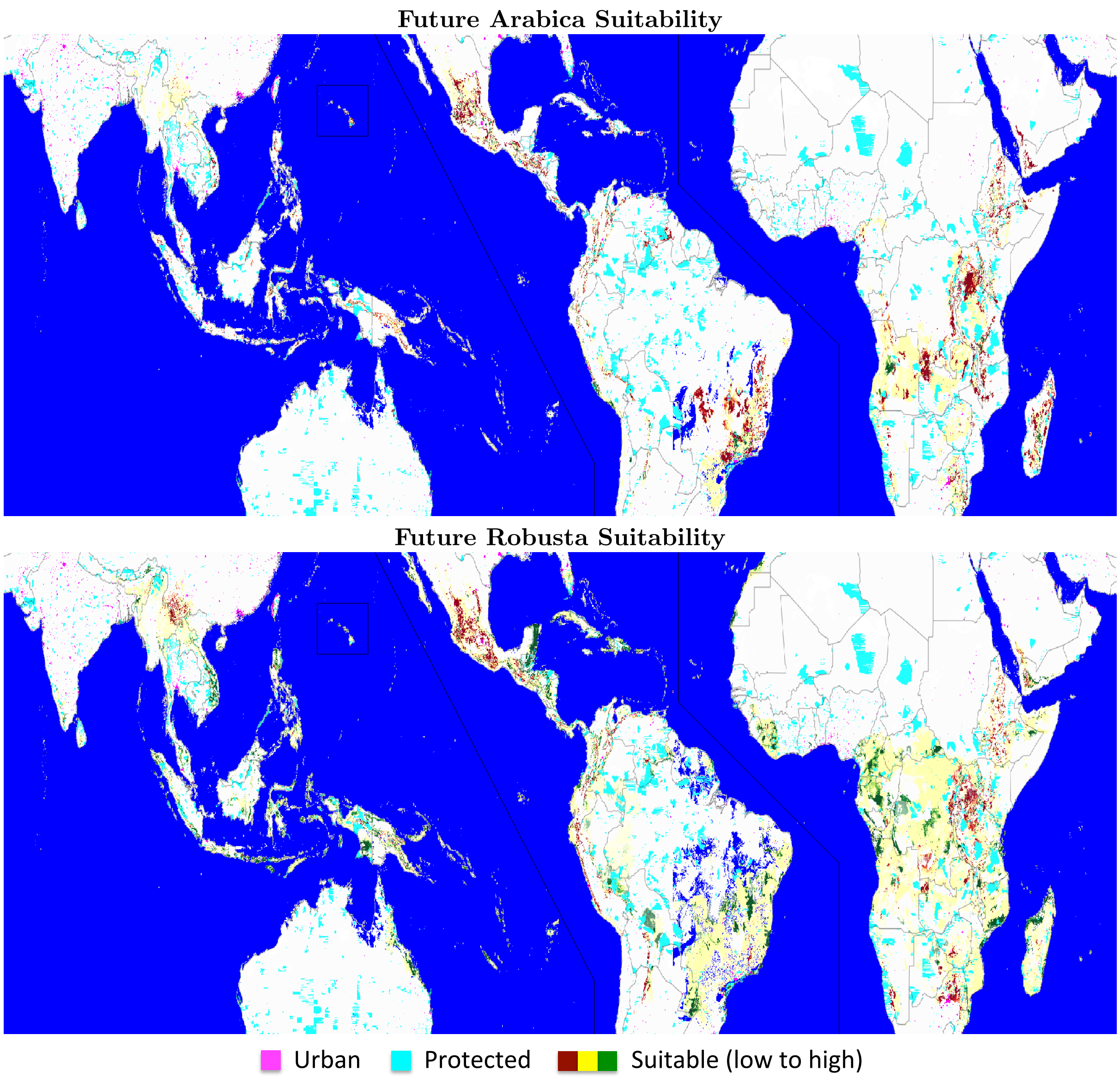


Figure 18: Maps of future Arabica and Robusta suitability as combined land use maps with suitability changes faded according to confidence.

	Arabica	Robusta
Baseline suitable area (Ha)	187626000	14663700
New suitable area (Ha)	27247000	21598800
Existing suitability loss (Ha)	-132070000	-88827000
Loss from baseline (%)	-70.4	-60.6
Change from baseline (%)	-55.9	86.7
Current harvest (Ha)	10034618	10069911
Loss from harvested areas (%)	-24.3	-12.1

Table 3: Global changes in suitability for Arabica and Robusta varieties. Robusta is expected to see large increases in general, while Arabica will experience decreased suitability.

currently using none), it also shows the largest percentage increase in suitable regions, gaining 50% more than it loses.

This result is more extreme than most suitability results in the literature, which typically do not predict losses in suitability beyond 95% in any country (Jaramillo, 2013). It is a consequence of our estimation approach, which relies on both biological and statistical factors. There are currently regions within these countries that satisfy both criteria, suggesting that they are likely to be highly productive. It may be that these areas will continue to be capable of producing quality coffee, but we predict that they will experience significant losses in their capacity.

Across the globe and under the median change, 130 million hectares of currently suitable land will be lost, and only 30 million hectares will be gained. Coffee is currently harvested on 10 million hectares.

These changes apply to suitable land, whether or not it coincides with our data on changes within areas of current cultivation. However, the story for current cultivation is similar: the countries that lose all of their harvested land are exactly the same as those that lose all of their suitable land. In total, 19 countries lose more than half of their currently harvested land to losses in suitability by 2050.

.1 Changes in suitability by country for GAEZ

Country	Baseline (1000 Ha)	A2 2050 (1000 Ha)	Change (1000 Ha)	%
Angola	63738	40508	-23230	(-36%)
Argentina	9047	12173	+3126	(+35%)
Australia	13870	7593	-6277	(-45%)
Bahamas	3487	1821	-1666	(-48%)
Bangladesh	11677	298	-11379	(-97%)
Belize	2652	1642	-1010	(-38%)
Benin	4129	0	-4129	(-100%)
Bhutan	0	1216	+1216	(new)
Bolivia	76211	7791	-68420	(-90%)
Brazil	785103	235221	-549882	(-70%)
Cambodia	15559	1084	-14475	(-93%)
Cameroon	39370	34157	-5213	(-13%)
Central African Republic	56584	33494	-23090	(-41%)
Chad	861	17	-844	(-98%)
China	21597	30291	+8694	(+40%)
Colombia	100541	27018	-73523	(-73%)

Country	Baseline (1000 Ha)	A2 2050 (1000 Ha)	Change (1000 Ha)	%
Congo, Dem. Rep.	230509	199389	-31120	(-14%)
Congo, Rep.	34477	33530	-947	(-3%)
Costa Rica	5659	2653	-3006	(-53%)
Cote d'Ivoire	30012	5965	-24047	(-80%)
Cuba	14109	5786	-8323	(-59%)
Dominican Republic	5481	3381	-2100	(-38%)
Ecuador	20067	16909	-3158	(-16%)
El Salvador	2331	1369	-962	(-41%)
Equatorial Guinea	2933	2675	-258	(-9%)
Ethiopia	39590	41674	+2084	(+5%)
French Guiana	8592	4058	-4534	(-53%)
Gabon	27151	26178	-973	(-4%)
Ghana	13116	770	-12346	(-94%)
Guatemala	10667	6718	-3949	(-37%)
Guinea	18599	8595	-10004	(-54%)
Guinea-Bissau	1348	0	-1348	(-100%)
Guyana	21534	2672	-18862	(-88%)
Haiti	3382	754	-2628	(-78%)
Honduras	11616	7657	-3959	(-34%)
India	34293	18979	-15314	(-45%)
Indonesia	213246	104505	-108741	(-51%)
Jamaica	1176	0	-1176	(-100%)
Japan	164	39	-125	(-76%)
Kenya	20565	17816	-2749	(-13%)
Lao PDR	22976	12597	-10379	(-45%)
Lesotho	0	268	+268	(new)
Liberia	9908	9293	-615	(-6%)
Madagascar	53116	48359	-4757	(-9%)
Malawi	8475	4583	-3892	(-46%)
Malaysia	35720	14051	-21669	(-61%)
Mexico	54345	34878	-19467	(-36%)
Mozambique	62931	35267	-27664	(-44%)
Myanmar	47616	31854	-15762	(-33%)
Nepal	0	3312	+3312	(new)
Nicaragua	12968	7975	-4993	(-39%)
Nigeria	28792	1717	-27075	(-94%)
Panama	8959	4500	-4459	(-50%)
Papua New Guinea	51723	25520	-26203	(-51%)
Paraguay	29591	10163	-19428	(-66%)
Peru	74724	24262	-50462	(-68%)
Philippines	38768	15724	-23044	(-59%)
Rwanda	2296	2486	+190	(+8%)
Senegal	411	0	-411	(-100%)
Sierra Leone	7631	2006	-5625	(-74%)
Solomon Islands	5322	2921	-2401	(-45%)
South Africa	6796	14140	+7344	(+108%)
South Sudan	24980	3986	-20994	(-84%)
Sri Lanka	6507	1144	-5363	(-82%)
Sudan	272	0	-272	(-100%)

Country	Baseline (1000 Ha)	A2 2050 (1000 Ha)	Change (1000 Ha)	%
Suriname	14810	447	-14363	(-97%)
Swaziland	1516	708	-808	(-53%)
Tanzania UR	82305	61876	-20429	(-25%)
Thailand	34606	5546	-29060	(-84%)
Timor-Leste	1803	1242	-561	(-31%)
Togo	4082	409	-3673	(-90%)
Uganda	21578	21028	-550	(-3%)
United States of America	3960	7218	+3258	(+82%)
Venezuela	83978	12959	-71019	(-85%)
Viet Nam	27213	11551	-15662	(-58%)
Zambia	56972	39304	-17668	(-31%)
Zimbabwe	3194	992	-2202	(-69%)

.2 Suitability condition distributions

.2.1 Soils and nutrients

Coffee is very sensitive to soil conditions. The Harmonized World Soil Database (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012) contains six soil components for both the topsoil and subsoil, to study this. The comparison between the distribution across the entire tropics, and across coffee regions for Arabica farms is shown in figures 19 and 20.

From the first figure, coffee is more common in soils that have a larger share of sand and smaller share of silt than the norm. Clay also shows effects where coffee is less frequently grown in regions with intermediate quantities of clay. From the second figure, it appears that coffee is suitable in regions with intermediate quantities of calcium carbonate and low levels of gypsum.

.2.2 Elevation

The distributional analysis shows a very wide range of elevations, possibly reflecting inaccuracies in the maps of Arabica and Robusta cultivation. See figure 21.

Arabica shows clear diminished presence at low elevations (below 550 m) and increased presence at all higher elevations. However, there is still probability mass below 550 m. Similarly, Robusta has extra presence of elevations below 50 m, but still has some elevated presence between 550 m and 1200 m.

The most important result of elevation for coffee cultivation is the temperatures it produces. Hawaii, for example, has excellent coffee-growing temperatures from sea level to 610m, and Arabica coffee is grown across this entire range (Thurston et al., 2013). However, the distributions shown in figure 21 are probably much more broad than is accurate. This data problem does not undermine the method, except that it increases the amount of uncertainty in the results.

.2.3 Bioclimatic variables

Figure 22 shows the distributions for all bioclimatic variables. These distributions are more erratic, because of the uneven spread of the observations within them: several bins in these histograms have no locations within their range, because of the discrete valuation of the Bioclim variables.

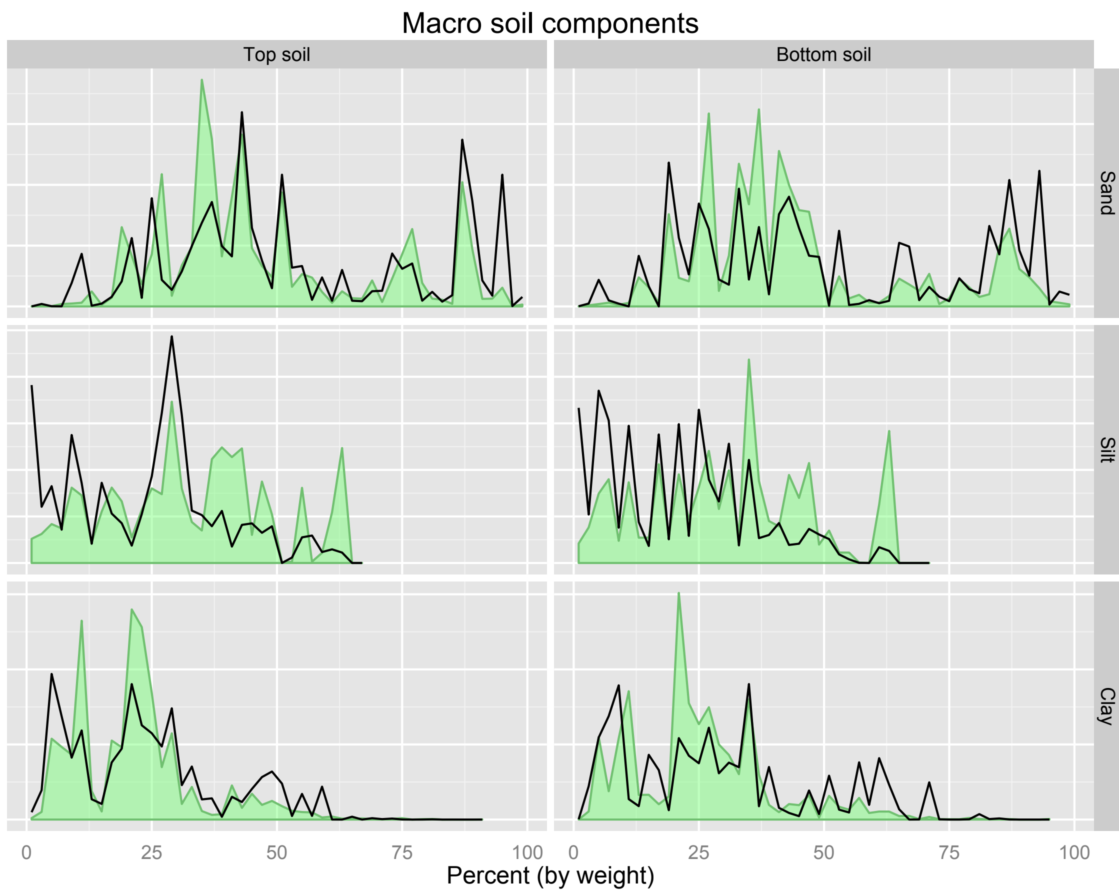


Figure 19: Comparison of distributions of texture soil components. The faded area shows the distribution of soils generally between 30°N and 30°S. The line shows the distribution of soils, weighted by coffee planting densities.

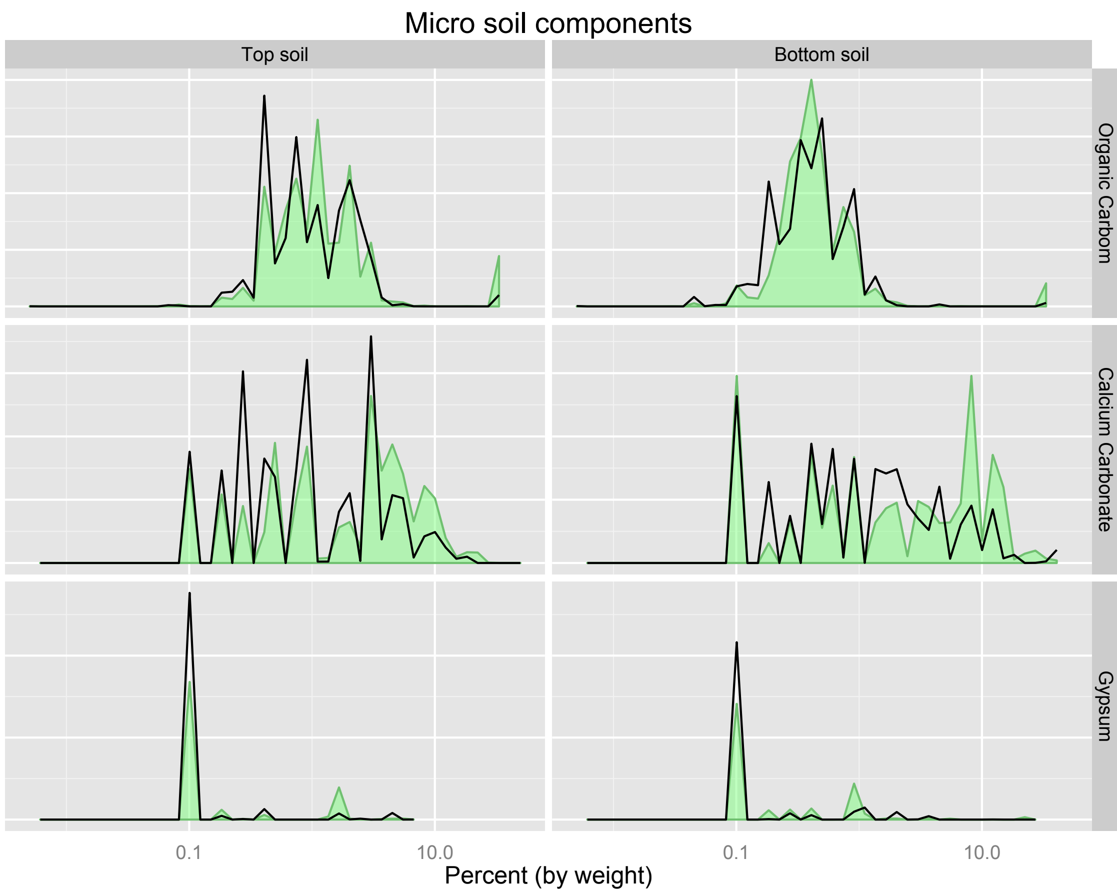


Figure 20: Comparison of distributions of trace soil components. The faded area shows the distribution of soils generally between 30°N and 30°S. The line shows the distribution of soils, weighted by coffee planting densities.

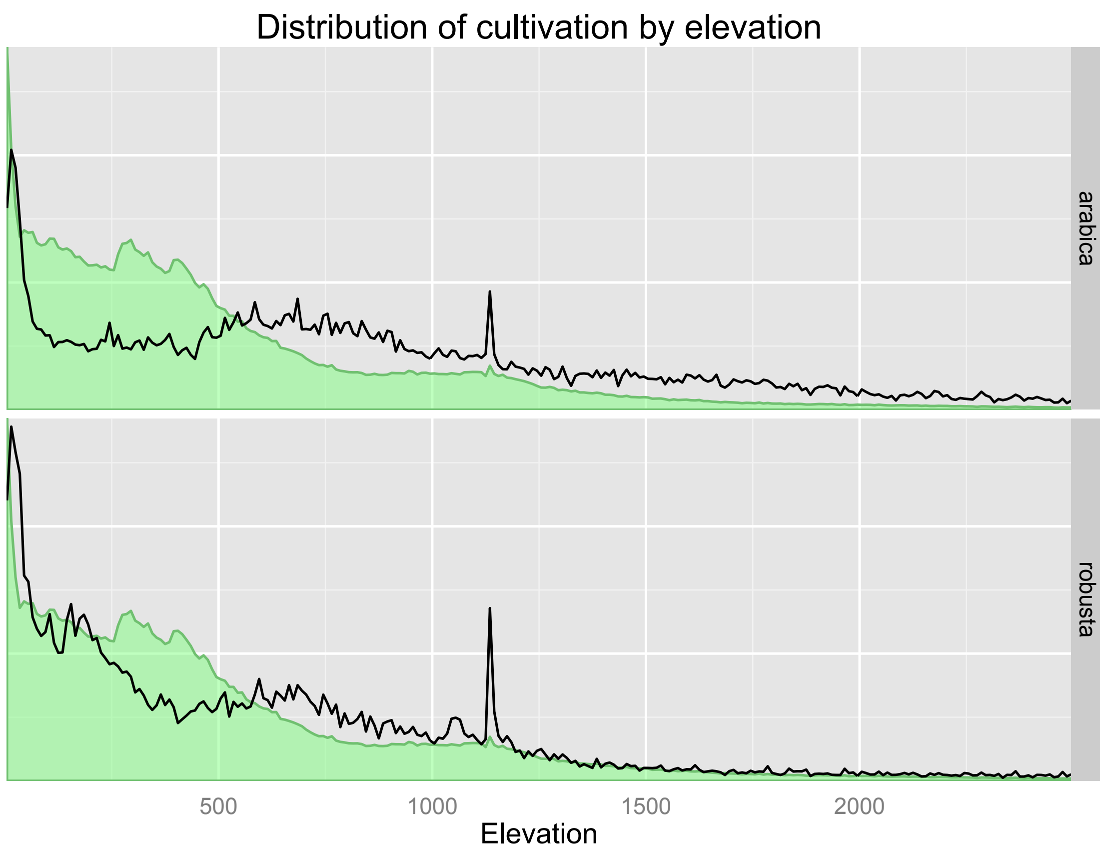


Figure 21: Distributions of elevation for Arabica and Robusta (lines) and for the tropics in general (green).

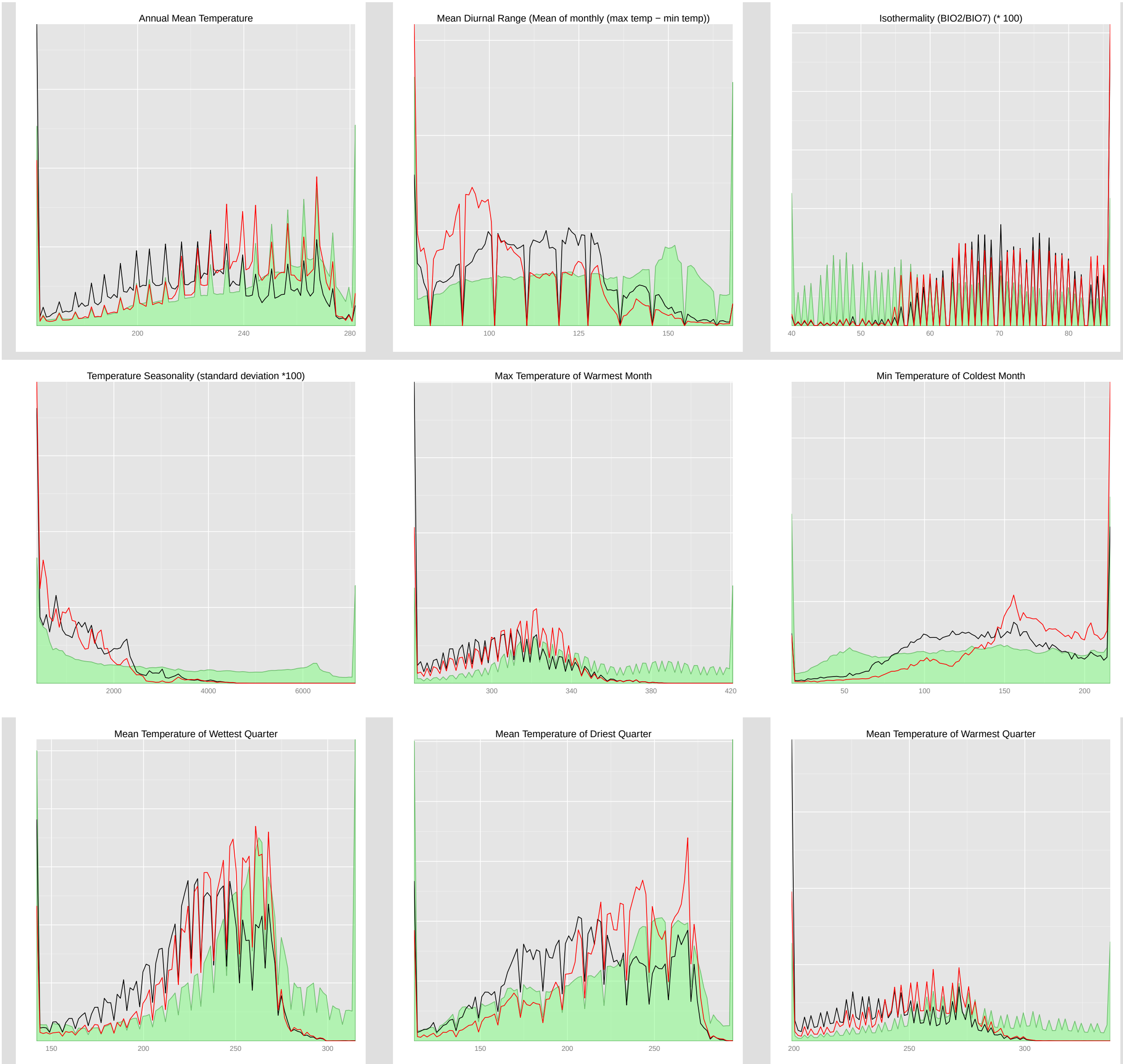


Figure 22: First set of nine of the 19 variables in the Bioclim dataset, with coffee region distributions shown in black (Arabica) and red (Robusta). We dropped one, the Annual Temperature Range, since the technique implicitly infers it from the minimum and maximum temperatures.

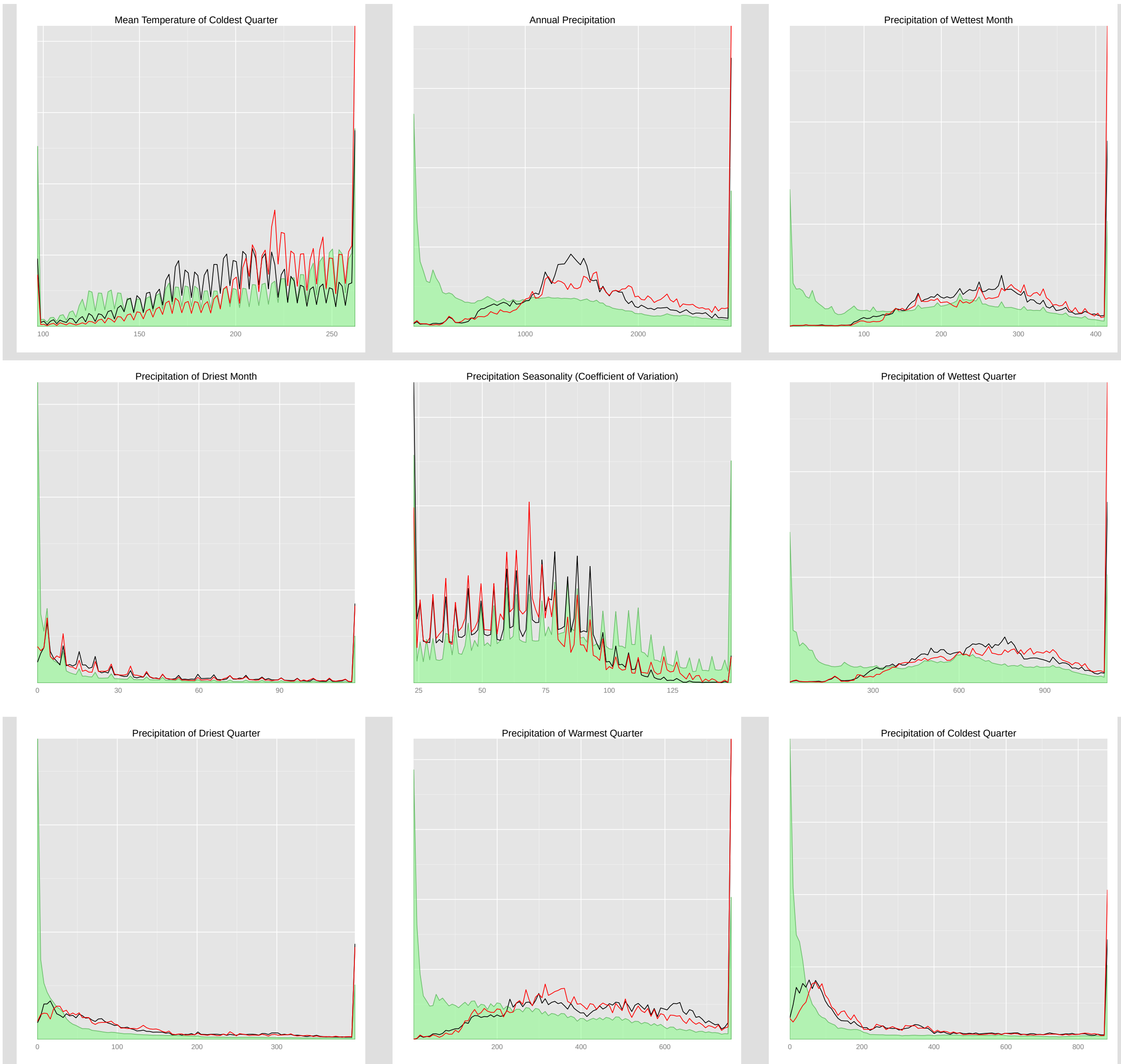


Figure 23: Second set of nine of the 19 variables in the Bioclim dataset, with coffee region distributions shown in black (Arabica) and red (Robusta). We dropped one, the Annual Temperature Range, since the technique implicitly infers it from the minimum and maximum temperatures.

.2.4 Latitude

We also incorporate latitude itself (see figure 24). Even if there are increases in temperature, different latitudes will provide different levels of suitability, because of the tilt of the Earth and other processes. We cannot be certain whether coffee will grow effectively outside of these latitudes, even if they appear climatically similar in the future to lower latitudes now. Including the distribution of latitude imposes a slight conservativism on our estimate which is supported by the data.

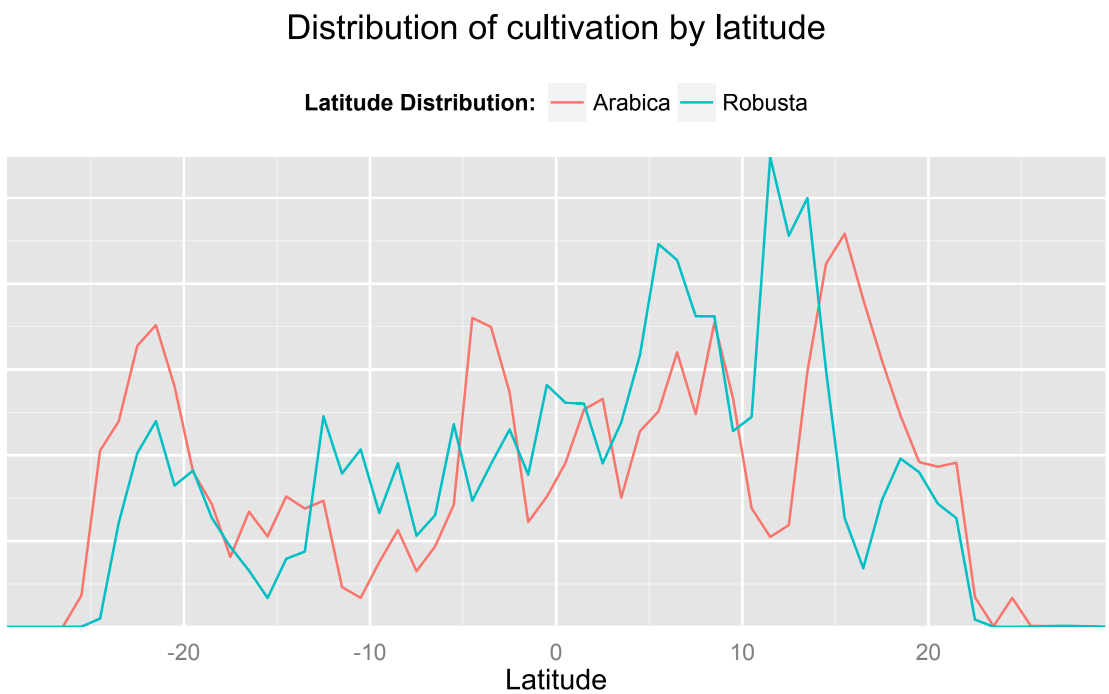


Figure 24: The distribution of coffee production for Arabica (red) and Robusta (blue) across latitude.

.3 Changes in suitability by country for our model

Arabica Changes, Baseline - 2050, RCP 8.5

	Suitable Areas						Harvested Areas	
Country	Baseline (Ha)	Increase (Ha)	Decrease (Ha)	Conf. (%)	Loss (%)	Chng. (%)	Harvest (Ha)	H. Loss (%)
Angola	7832331	3163478	-7540076	96.66	-96.30	-55.90	31000.00	-43.90
Argentina	703607	500422	-362311	91.07	-51.50	19.60		0.00
Australia	324109	0	-320158	97.77	-98.80	-98.80		0.00
Burundi	642525	46216	-463559	87.50	-72.10	-65.00	27000.00	-25.70
Belize	28658	0	-28658	100.00	-100.00	-100.00	47.00	-100.00
Bolivia	2975159	361779	-849786	100.00	-28.60	-16.40	30000.00	-5.40
Brazil	30031272	4064511	-25719629	97.67	-85.60	-72.10	2120080.00	-34.70
Bhutan	0	93542	0	70.01				0.00
Botswana	2559	0	-2559	100.00	-100.00	-100.00		-100.00
Central African Republic	17019	0	-17019	100.00	-100.00	-100.00	14000.00	-100.00
Chile	327	242076	-327	99.11	-99.80			0.00
China	267924	31940	-250819	91.15	-93.60	-81.70	62000.00	-37.90
CÙte d'Ivoire	34259	0	-34259	100.00	-100.00	-100.00	160000.00	-100.00
Cameroon	901606	15973	-637133	100.00	-70.70	-68.90	210000.00	-25.50
Democratic Republic of the Congo	9054217	328050	-7382600	95.55	-81.50	-77.90	86000.00	-29.40
Republic of Congo	274260	0	-274260	100.00	-100.00	-100.00	10500.00	-100.00
Colombia	6333379	1130339	-3333722	94.51	-52.60	-34.80	778084.00	-19.30
Comoros	51817	603	-39930	96.12	-77.10	-75.90	885.00	0.00
Cape Verde	552	8183	-552	99.44	-100.00		0.00	-100.00
Costa Rica	680983	125192	-388387	97.31	-57.00	-38.60	93774.00	-14.70
Cuba	155472	0	-155387	98.11	-99.90	-99.90	28000.00	-7.40
Dominican Republic	212045	47801	-64205	93.88	-30.30	-7.70	133342.00	-2.10
Ecuador	2169018	291030	-820424	90.98	-37.80	-24.40	78709.71	-17.50
Eritrea	616234	11180	-443696	100.00	-72.00	-70.20		0.00
Spain	0	145055	0	97.54				0.00
Ethiopia	10236225	2117081	-6834556	92.96	-66.80	-46.10	528571.00	-28.00
Fiji	28317	0	-28317	100.00	-100.00	-100.00	30.00	-100.00
France	138260	32780	-45329	92.31	-32.80	-9.10	120.00	0.00
Gabon	9451	0	-9451	100.00	-100.00	-100.00	310.00	-100.00
Guinea	101123	0	-101123	100.00	-100.00	-100.00	66000.00	-100.00
Equatorial Guinea	141982	0	-141982	100.00	-100.00	-100.00	12500.00	-100.00
Guatemala	2019079	287541	-934956	90.05	-46.30	-32.10	250000.00	-25.70
Guyana	694669	1504	-664846	99.68	-95.70	-95.50	360.00	-5.20
Honduras	2549303	62862	-1593540	99.31	-62.50	-60.00	266000.00	-22.90
Haiti	336450	17876	-208607	98.68	-62.00	-56.70	92000.00	-27.00
Indonesia	7617814	705740	-4902428	96.51	-64.40	-55.10	1233900.00	-10.90
India	523680	133453	-329003	96.62	-62.80	-37.30	368687.00	-1.00
Jamaica	49008	0	-42530	100.00	-86.80	-86.80	7500.00	-19.80
Kenya	5106633	888046	-3200314	91.90	-62.70	-45.30	160000.00	-27.10
Cambodia	2239	0	-2239	100.00	-100.00	-100.00	430.00	-100.00
Lao PDR	216682	0	-211843	100.00	-97.80	-97.80	56875.00	-19.00
Sri Lanka	48813	1895	-26470	97.22	-54.20	-50.30	8460.00	-0.70
Lesotho	0	1623	0	76.47				0.00
Morocco	0	0	0	0.35				0.00

Arabica Changes, Baseline - 2050, RCP 8.5

	Suitable Areas						Harvested Areas	
Country	Baseline (Ha)	Increase (Ha)	Decrease (Ha)	Conf. (%)	Loss (%)	Chng. (%)	Harvest (Ha)	H. Loss (%)
Madagascar	15676837	1359696	-7488575	96.47	-47.80	-39.10	138000.00	-18.90
Mexico	23046243	3759088	-12251072	96.23	-53.20	-36.80	695350.00	-21.10
Myanmar	82547	4844	-79233	93.42	-96.00	-90.10	12000.00	-17.60
Mozambique	3368146	143380	-2974523	96.50	-88.30	-84.10	980.00	-18.40
Mauritius	63460	0	-48142	100.00	-75.90	-75.90	0.00	0.00
Malawi	1545688	256879	-1272351	90.01	-82.30	-65.70	2580.00	-1.10
Malaysia	561747	19748	-492026	96.17	-87.60	-84.10	19300.00	-0.50
Namibia	1209730	134161	-1171642	96.62	-96.90	-85.80		0.00
New Caledonia	116243	4	-100629	99.37	-86.60	-86.60	95.00	0.00
Nigeria	3391	109	-3372	92.22	-99.40	-96.20	2200.00	-2.20
Nicaragua	657690	9958	-545072	100.00	-82.90	-81.40	123000.00	-13.70
Nepal	0	0	0	63.34			1780.00	0.00
Oman	0	0	0	100.00	-100.00	-100.00		-100.00
Panama	379618	40024	-221501	94.76	-58.30	-47.80	30000.00	-20.30
Peru	3254385	2747945	-1723632	92.61	-53.00	31.50	312251.00	-13.80
Philippines	1451866	102893	-996757	97.58	-68.70	-61.60	119999.00	-5.40
Papua New Guinea	4652101	274890	-2134348	96.37	-45.90	-40.00	73000.00	-10.60
Puerto Rico	148890	0	-123066	100.00	-82.70	-82.70	42000.00	-36.70
Paraguay	0	0	-	100.00	-100.00	-100.00	300.00	-100.00
Rwanda	858792	108725	-573378	89.08	-66.80	-54.10	41762.00	-9.20
Saudi Arabia	802649	1111	-768697	99.03	-95.80	-95.60	0.00	0.00
South Sudan	140253	5615	-110543	93.32	-78.80	-74.80		0.00
Solomon Islands	44906	5927	-44870	100.00	-99.90	-86.70		0.00
Sierra Leone	0	0	-	100.00	-100.00	-100.00	14000.00	-100.00
El Salvador	88234	11743	-59752	90.19	-67.70	-54.40	139958.00	-33.90
Somaliland	535507	10985	-533484	99.92	-99.60	-97.60		0.00
Somalia	94467	4137	-94467	95.80	-100.00	-95.60		-100.00
S„o TomÈ and Principe	22915	0	-16475	100.00	-71.90	-71.90	250.00	0.00
Swaziland	94563	8035	-79389	78.66	-84.00	-75.50		0.00
Thailand	236767	0	-236761	100.00	-100.00	-100.00	52000.00	-100.00
Timor-Leste	201630	15264	-161490	99.85	-80.10	-72.50	55000.00	-12.10
Taiwan	17859	45193	-17859	85.53	-100.00	153.00	0.00	-100.00
Tanzania	10120904	1745435	-8474385	96.69	-83.70	-66.50	127335.00	-21.80
Uganda	5007871	67539	-4767946	99.69	-95.20	-93.90	310000.00	-60.20
United States	457497	20861	-400461	98.97	-87.50	-83.00	2550.00	-85.70
Venezuela	5232487	259415	-3729513	96.81	-71.30	-66.30	182000.00	-3.70
Vietnam	1469106	73643	-1256133	98.44	-85.50	-80.50	574314.36	-1.90
Vanuatu	14532	0	-14417	90.77	-99.20	-99.20	65.00	0.00
Yemen	2949889	16273	-2137856	98.63	-72.50	-71.90	34987.00	-27.40
South Africa	2635760	760688	-2252927	98.86	-85.50	-56.60		0.00
Zambia	4406514	13720	-4193830	95.68	-95.20	-94.90	7000.00	-34.40
Zimbabwe	398934	6065	-390551	99.82	-97.90	-96.40	5397.00	-31.40

Robusta Changes, Baseline - 2050, RCP 8.5

	Suitable Areas						Harvested Areas	
Country	Baseline (Ha)	Increase (Ha)	Decrease (Ha)	Conf. (%)	Loss (%)	Chng. (%)	Harvest (Ha)	H. Loss (%)
Angola	5150021	5959656	-2805429	85.92	-54.50	61.20	31000.00	-17.80
Argentina	1286056	2105318	-1114987	91.68	-86.70	77.00		0.00
American Samoa	0	0	0	100.00				0.00
Antigua and Barbuda	0	0	0	100.00				0.00
Australia	170410	3414649	-114523	93.17	-67.20			0.00
Burundi	494565	145247	-284285	92.28	-57.50	-28.10	27000.00	-14.20
Bangladesh	0	561488	0	15.07				0.00
Bahamas	0	0	0	50.00				0.00
Belize	0	885404	0	82.07	0.00		47.00	0.00
Bolivia	2038575	8924087	-962916	65.29	-47.20	390.50	30000.00	-0.10
Brazil	8450738	35586649	-2304340	72.03	-27.30	393.80	2120080.00	-14.00
Barbados	0	12	0	100.00				0.00
Brunei Darussalam	0	13	0	100.00				0.00
Bhutan	0	104353	0	99.09				0.00
Botswana	405172	2386421	-405166	62.82	-100.00	489.00		-100.00
Central African Republic	198116	3599572	-33401	84.84	-16.90		14000.00	-0.00
Chile	12937	6	-12937	99.95	-100.00	-100.00		-100.00
China	3768742	550157	-3466649	98.36	-92.00	-77.40	62000.00	-7.20
CÙte d'Ivoire	7815	1220362	-296	94.34	-3.80		160000.00	-0.10
Cameroon	1324883	5991635	-175708	96.84	-13.30	439.00	210000.00	-1.60
Democratic Republic of the Congo	9668515	16006969	-6745133	82.72	-69.80	95.80	86000.00	-0.70
Republic of Congo	570588	2522891	-354354	92.87	-62.10	380.10	10500.00	-6.70
Colombia	4831268	6170063	-2722280	78.40	-56.30	71.40	778084.00	-8.40
Comoros	1083	41001	0	78.33	0.00		885.00	0.00
Cape Verde	47599	10128	-17921	84.26	-37.70	-16.40	0.00	0.00
Costa Rica	563486	158883	-271265	80.43	-48.10	-19.90	93774.00	-7.90
Cuba	188896	1498809	-375	83.71	-0.20	793.30	28000.00	-0.00
Cayman Islands	0	15092	0	100.00				0.00
Djibouti	0	0	0	88.23				0.00
Dominica	0	18146	0	100.00			610.00	0.00
Dominican Republic	249043	1195690	-73639	92.28	-29.60	450.50	133342.00	-0.70
Ecuador	2266507	1056561	-1267955	90.67	-55.90	-9.30	78709.71	-1.70
Eritrea	606180	92476	-303872	96.16	-50.10	-34.90		0.00
Spain	0	54557	0	79.99				0.00
Ethiopia	9630697	2589937	-5991843	90.52	-62.20	-35.30	528571.00	-27.30
Fiji	31202	215943	-1686	91.50	-5.40	686.70	30.00	0.00
France	87221	96079	-14879	99.72	-17.10	93.10	120.00	0.00
Gabon	31063	5413957	-9317	99.52	-30.00		310.00	-0.00
Ghana	0	196263	0	98.17			4000.00	0.00
Guinea	433521	831493	-243442	87.70	-56.20	135.60	66000.00	-6.90
Equatorial Guinea	1050	318762	-11	99.57	-1.10		12500.00	-0.10
Grenada	0	23207	0	97.94				0.00
Guatemala	1428221	2652766	-876418	82.59	-61.40	124.40	250000.00	-31.40
Guyana	510369	419814	-48270	78.66	-9.50	72.80	360.00	-0.40

Robusta Changes, Baseline - 2050, RCP 8.5

	Suitable Areas						Harvested Areas	
Country	Baseline (Ha)	Increase (Ha)	Decrease (Ha)	Conf. (%)	Loss (%)	Chng. (%)	Harvest (Ha)	H. Loss (%)
Hong Kong	0	14612	0	74.94				0.00
Honduras	2594743	2282517	-702365	91.15	-27.10	60.90	266000.00	-10.60
Haiti	434375	779343	-28904	92.06	-6.70	172.80	92000.00	-0.50
Indonesia	5364764	19407103	-1702290	93.03	-31.70	330.00	1233900.00	-4.60
India	191152	2193510	-84498	92.31	-44.20		368687.00	-1.80
Jamaica	6010	61053	0	92.30	0.00		7500.00	0.00
Kenya	4190724	1238752	-2507363	91.06	-59.80	-30.30	160000.00	-6.90
Cambodia	175055	427216	-24262	57.23	-13.90	230.20	430.00	-0.00
Saint Kitts and Nevis	0	0	0	100.00				0.00
Lao PDR	666770	1268847	-273633	66.60	-41.00	149.30	56875.00	-2.60
Liberia	0	1323785	0	99.43			2800.00	0.00
Saint Lucia	0	104	0	100.00			0.00	0.00
Sri Lanka	53824	44149	-36806	87.67	-68.40	13.60	8460.00	-0.10
Morocco	0	1953628	0	87.06				0.00
Madagascar	579295	5905617	-430242	93.92	-74.30	945.20	138000.00	-21.80
Mexico	20342425	9564738	-16492118	94.79	-81.10	-34.10	695350.00	-24.90
Myanmar	782366	972653	-693545	93.04	-88.60	35.70	12000.00	-0.00
Mozambique	1196437	8105709	-466356	86.79	-39.00	638.50	980.00	-8.60
Mauritania	0	9144	0	99.83				0.00
Montserrat	0	0	0	88.23				0.00
Mauritius	34422	107428	0	89.97	-0.00	312.10	0.00	0.00
Malawi	652634	1158706	-259512	82.41	-39.80	137.80	2580.00	-14.10
Malaysia	552660	2165838	-28576	95.38	-5.20	386.70	19300.00	-0.10
Namibia	1325792	192435	-1300052	98.90	-98.10	-83.50		0.00
New Caledonia	39667	596897	-1088	99.88	-2.70		95.00	0.00
Nigeria	22291	127003	-2176	89.15	-9.80	560.00	2200.00	-0.20
Nicaragua	680281	1773570	-53620	96.00	-7.90	252.80	123000.00	-0.00
Nepal	0	0	0	100.00			1780.00	0.00
Oman	0	82194	0	90.57	0.00			0.00
Panama	385527	538364	-163103	83.74	-42.30	97.30	30000.00	-9.50
Peru	6609345	6578036	-4375019	80.81	-66.20	33.30	312251.00	-10.40
Philippines	1200467	2966352	-368050	88.92	-30.70	216.40	119999.00	-5.60
Papua New Guinea	2390681	4469796	-1276059	91.17	-53.40	133.60	73000.00	-11.90
Puerto Rico	105939	352303	0	98.38	0.00	332.60	42000.00	0.00
Paraguay	0	2483538	0	84.98	-100.00		300.00	-100.00
Rwanda	667299	8125	-512784	92.74	-76.80	-75.60	41762.00	-36.00
Western Sahara	0	31668	0	99.03				0.00
Saudi Arabia	828878	46020	-300087	100.00	-36.20	-30.70	0.00	0.00
Sudan	0	19421	0	97.53				0.00
South Sudan	81932	306289	-31559	60.11	-38.50	335.30		0.00
Senegal	0	0	0	100.00				0.00
Solomon Islands	39621	378509	-61	98.42	-0.20	955.10		0.00
Sierra Leone	2290	483628	-2288	88.83	-99.90		14000.00	-0.00
El Salvador	178283	112387	-59934	62.25	-33.60	29.40	139958.00	-4.10

Robusta Changes, Baseline - 2050, RCP 8.5

	Suitable Areas						Harvested Areas	
Country	Baseline (Ha)	Increase (Ha)	Decrease (Ha)	Conf. (%)	Loss (%)	Chng. (%)	Harvest (Ha)	H. Loss (%)
Somaliland	510372	402411	-161477	83.59	-31.60	47.20		0.00
Somalia	0	57573	0	45.79	-100.00			-100.00
S„o TomÈ and Principe	7584	11738	-174	98.88	-2.30	152.50	250.00	0.00
Suriname	0	6728	0	31.93			488.00	0.00
Swaziland	16051	15316	-16051	100.00	-100.00	-4.60		-100.00
Togo	0	100627	0	100.00			27000.00	0.00
Thailand	221535	640290	-70468	80.08	-31.80	257.20	52000.00	-0.00
Timor-Leste	24148	145298	-8755	93.06	-36.30	565.40	55000.00	-2.20
Tonga	0	7290	0	96.30			10.00	0.00
Trinidad and Tobago	0	32	0	50.01			350.00	0.00
Taiwan	6208	256909	0	90.01	-0.00		0.00	0.00
Tanzania	14434260	5551037	-8871902	85.55	-61.50	-23.00	127335.00	-13.80
Uganda	6944190	1159159	-5756638	80.92	-82.90	-66.20	310000.00	-60.40
United States	129750	359497	-29880	88.00	-23.00	254.00	2550.00	-26.80
Saint Vincent and the Grenadines	0	72	0	100.00				0.00
Venezuela	3515842	2313894	-2227300	78.01	-63.40	2.50	182000.00	-2.50
United States Virgin Islands	0	0	0	100.00				0.00
Vietnam	1883848	4343466	-92368	88.85	-4.90	225.70	574314.36	-0.40
Vanuatu	63133	327533	-1013	96.96	-1.60	517.20	65.00	0.00
Samoa	0	11403	0	58.88			35.00	0.00
Yemen	2748339	2130013	-985741	91.92	-35.90	41.60	34987.00	-18.50
South Africa	4799951	713212	-4627116	100.00	-96.40	-81.50		0.00
Zambia	1625781	704492	-1063716	86.34	-65.40	-22.10	7000.00	-51.40
Zimbabwe	962921	347792	-955963	95.36	-99.30	-63.20	5397.00	-20.90

References

Alves, M. d. C., de Carvalho, L., Pozza, E., Sanches, L., and Maia, J. d. S. (2011). Ecological zoning of soybean rust, coffee rust and banana black sigatoka based on brazilian climate changes. *Procedia Environmental Sciences*, 6:35–49.

Arbenz, P. (2013). Bayesian copulae distributions, with application to operational risk management—some comments. *Methodology and Computing in Applied Probability*, 15(1):105–108.

Bunn, C., Läderach, P., Rivera, O. O., and Kirschke, D. (2015). A bitter cup: climate change profile of global production of arabica and robusta coffee. *Climatic Change*, 129(1-2):89–101.

CIAT (2010). Climate adaptation and mitigation in the kenyan coffee sector. Technical report, International Center for Tropical Agirculture, Cali, Colombia.

Davis, A. P., Gole, T. W., Baena, S., and 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.

Eitzinger, A., Läderach, P., Carmona, S., Navarro, C., and Collet, L. (2013). Prediction of the impact of climate change on coffee and mango growing areas in haiti. Technical report, Full Technical Report. Centro Internacional de Agricultura Tropical (CIAT), Cali, Colombia. http://dapa. ciat. cgiar. org/wp-content/uploads/2014/03/CC_impact_coffeemango_Haiti_CRS-CIAT_final. pdf.

FAO/IIASA/ISRIC/ISSCAS/JRC (2012). Harmonized world soil database (hwsd). *FAO, Rome, Italy and IIASA, Laxenburg, Austria*.

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., Jarvis, A., et al. (2005). Very high resolution interpolated climate surfaces for global land areas. *International journal of climatology*, 25(15):1965–1978.

Jaramillo, J. (2013). Coffee under threat. In *Coffee: A Comprehensive Guide to the Bean, the Beverage, and the Industry*.

Jaramillo, J., Muchugu, E., Vega, F. E., Davis, A., Borgemeister, C., and Chabi-Olaye, A. (2011). Some like it hot: the influence and implications of climate change on coffee berry borer (hypothenemus hampei) and coffee production in east africa. *PLoS One*, 6(9):e24528.

Jarvis, A., Reuter, H. I., Nelson, A., and Guevara, E. (2008). Hole-filled srtm for the globe version 4. *available from the CGIAR-CSI SRTM 90m Database (http://srtm. csi. cgiar. org)*.

Jassogne, L., Lderach, P., and van Asten, P. (2013). The impact of climate change on coffee in uganda: Lessons from a case study in the rwenzori mountains. *Oxfam Policy and Practice: Climate Change and Resilience*, 9(1):51–66.

Kutywayo, D., Chemura, A., Kusena, W., Chidoko, P., and Mahoya, C. (2013). The impact of climate change on the potential distribution of agricultural pests: the case of the coffee white stem borer (monochamus leuconotus p.) in zimbabwe. *PloS one*, 8(8):e73432.

Laderach, P., Lundy, M., Jarvis, A., Ramirez, J., Portilla, E. P., Schepp, K., and Eitzinger, A. (2009). *Predicted impact of climate change on coffee supply chains*. na.

Nelsen, R. B. (2013). *An introduction to copulas*, volume 139. Springer Science & Business Media.

Nzeyimana, I., Hartemink, A. E., and Geissen, V. (2014). Gis-based multi-criteria analysis for arabica coffee expansion in rwanda. *PloS one*, 9(10):e107449.

Ovalle-Rivera, O., Läderach, P., Bunn, C., Obersteiner, M., and Schroth, G. (2015). Projected shifts in coffea arabica suitability among major global producing regions due to climate change.

Schneider, A., Friedl, M., Woodcock, C. E., et al. (2003). Mapping urban areas by fusing multiple sources of coarse resolution remotely sensed data. In *Geoscience and Remote Sensing Symposium, 2003. IGARSS'03. Proceedings. 2003 IEEE International*, volume 4, pages 2623–2625. IEEE.

Schroth, G., Läderach, P., Cuero, D. S. B., Neilson, J., and Bunn, C. (2014). Winner or loser of climate change? a modeling study of current and future climatic suitability of arabica coffee in indonesia. *Regional Environmental Change*, pages 1–10.

Thurston, R. W., Morris, J., and Steiman, S. (2013). *Coffee: A Comprehensive Guide to the Bean, the Beverage, and the Industry.* Rowman & Littlefield Publishers.

WDPA Consortium (2004). World database on protected areas. *World Conservation Union and UNEP-World Conservation Monitoring Centre, New York, New York, USA*.

Acknowledgments

We would like to thank **Walter Baethgen** at the International Research Institute for Climate and Society for his thoughtful reviews of the work here and all of his comments and suggestions.

Many thanks also to:

Andrea Illy, illycaffè S.p.A., Chairman/CEO

Mario Cerutti, Lavazza S.p.A., Corporate Relations

Belay Begashaw, Columbia Global Centers, Director

Mauricio Galindo, International Coffee Organization, Head of Operations

Alexandra Tunistra, Root Capital, Advisory Services

Amir Jina, University of Chicago, Economics

Joann de Zegher, Stanford University, Environment and Resources

Marion Dumas, Columbia University, School of International and Public Affairs