Investigating the Impact of Environmental Suitability on Production of Global Top Crops

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Abstract

Changes in cropland suitability for the world's top crops have significant implications for sustaining future production and meeting global demand. Gaining a deeper understanding of past changes in suitability and the key factors that influence them is crucial to predicting future changes and implementing effective interventions to maintain sustainable levels of production. Previous work has examined specific crops and suitability in localized regions. We focus both on a broader scale by examining suitability for asian rice (*oryza sativa*), sugar (*saccharum officinarum*), maize (*zea mays*), wheat (*triticum aestivum*), and arabica coffee (*coffea arabica*) on a global scale as well as conducting case studies on specific crops. This allows for both intra-regional comparison as well as analysis of global shifts of cropland suitability. Our analysis consists of (1) expanding on an existing environmental suitability model from prior ecology research by running the model for the top produced crops listed above, (2) creating a new method for calculating each country's composite environmental suitability, (3) analyzing feature importance of bioclimatic variables, and (4) conducting regional crop case studies.

1 Introduction/Motivation

Food is a vital resource on which the human population depends and is increasingly threatened by the changing climate. Previous research has done extensive studies on forecasting how the climate is expected to change with increasing greenhouse gas emissions, but does not fully capture the expected impact on growing crops. In addition, most countries are not fully self-sustainable and rely on trade with other countries for crops and commodities. As the population is expected to grow to 10.4 billion by the mid-2080s (14), there will be additional stress on having a larger food supply available. Our research question is: how will climate-driven changes in environmental suitability for the world's top crops reshape global trade dynamics?

Originally, our project was on arabica coffee alone. We later switched to include asian rice, sugar, maize, and wheat to expand the scope of our project. These four are the top produced crops by metric tons, globally. We also chose to continue including coffee (even though it was not in the top produced crops) because coffee is a rapidly growing industry that can only be grown in a limited geographic band.

Our first hypothesis is that due to climate change, the environmental suitability for most regions to grow specific crops will decrease. Conversely, the environmental suitability of some regions to grow crops will increase. If this previous hypothesis is true, then we can also expect to see respective shifts in the top global producers of crops and commodities as well.

Our hypotheses are based on climate change research and the suggested impacts on global climate. From our ecology research on growing crops, we found that crops need a certain set of conditions to be met to be viable to grow in a specific environment. Additionally, some crops are more sensitive than others to climate and environmental conditions. For example, the two main species of coffee are arabica and robusta. Although robusta coffee is less sensitive to environmental conditions, robusta does not taste as good, so approximately 60-70% of coffee grown is arabica (13). If crops grow in a certain set of climate conditions and the climate is expected to change in different regions of the world, then we can also expect to see some regions lose the ability to grow specific crops and other regions to gain the ability to grow specific crops. Subsequently, this will also impact crop production yields and trade dynamics.

2 Dataset description

We used three main types of datasets: bioclimatic variables, crop presence points, and the USDA commodities datasets. The bioclimatic variables and crop presence points serve as input for the environmental suitability model (ESM). We utilize the USDA commodities dataset to validate the ESM output of environmental suitability scores by comparing them to production values for each country (see §4.3). There was no required preprocessing of the datasets.

2.1 Bioclimatic Variables

The bioclimatic variables are from WorldClim (9) and include a combination of historical aggregated climate data and future forecasted climate data. This dataset includes 19 bioclimatic variables, such as annual temperature, annual precipitation, mean temperature of wettest/driest quarter, and more. The historical data is aggregated over 1970-2000. The forecasted climate data is aggregated over 2021-2040, 2041-2060, and 2061-2080 and is considered on three different socioeconomic pathways that correspond to how well climate change is addressed.

There are various bioclimatic variables datasets, so we explored a variety of options. One dataset from CHELSA was higher quality and contained 48 bioclimatic variables. For some background context, the files for these bioclimatic variables are tiffs. A higher quality dataset was a much larger size and required more memory to train the model. Due to memory constraints and the shorter scope of the capstone project, we decided to go back to the WorldClim dataset.

2.2 Crop Presence Points

The crop presence points were sourced from the GBIF occurrence records database. We used observations of crops with the exact scientific name to ensure our model learns species specific features rather than using higher level class or genus. The exact query parameters are linked below (10).

For each crop of interest, there is a corresponding presence points dataset that contains geographic coordinates for where each specific crop occurs (see figure 11). This data is gathered through a combination of field surveys, literature review, and dataset records. The ESM only requires a presence points dataset with where the crop occurs and not where the crop is absent. One limitation is that if the crop presence points dataset is low quality and does not contain a lot of datapoints on where the crop occurs, the ESM accuracy decreases.

2.3 USDA Commodities Dataset

Data on where the crop grows and which regions are more suitable to grow that crop do not explicitly highlight trade dynamics. USDA has datasets on the world's top crops and commodities that capture these trade dynamics (15). For example, fields in this dataset include country of yield, year, month, production count, import/export yield, and more. We used this dataset to evaluate the ESM output as well as discuss how trade dynamics might shift due to changes in environmental suitability.

3 Analytical Approach

3.1 Environmental Suitability Model

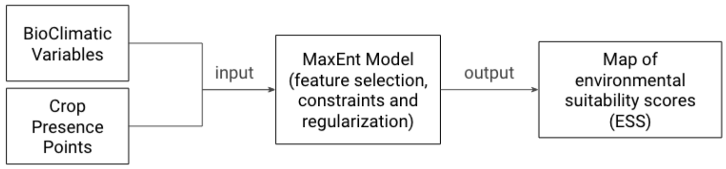


Figure 1: Environmental Suitability Model (ESM) input, training, and output diagram.

We turned our hypothesis into a concrete analysis by first determining how to calculate environmental suitability. From prior ecology research, we found a MaxEnt Environmental Suitability Model (ESM) that produces an Environmental Suitability Score (ESS) on a global grid landscape (see figure 1). The ESS is a proxy for how suitable an environment is at a specific location for producing a crop. The MaxEnt ESM takes the bioclimatic variables and crop presence points as input. The MaxEnt ESM then outputs feature importance and a map of environmental suitability scores (ESS).

3.2 Overall Steps

First, for each crop, we trained the ESM to determine historical and future environmental suitability. As the ESM output is on a pixel-by-pixel basis, we calculated the aggregated ESS for each country. This value is utilized for validating the ESS construct by comparing each country's aggregated ESS to its historical production for a specific crop. Next, we ran further analysis on overlap in environmental suitability for crops and top global producers. We lastly ran case studies for individual crops and a global case study to better understand the underlying trends in the data.

3.3 Model Limitations and Alternatives

One limitation of the model is the input and output time frame. The ESM takes bioclimatic variables that are aggregated over a 20-30 year range. Thus, the ESM outputs an environmental suitability forecast over a similar large year range. One way to evaluate the model was to forecast environmental suitability to the current year and compare the results with current events. However, one limitation with the model is that it cannot forecast environmental suitability on a granular temporal scale (i.e., predict environmental suitability for arabica coffee in 2024 instead of 2021-2040). The only way to predict on a granular scale would be to switch to a different model, such as a neural network. As we discovered this around the midpoint of the project and this would require developing a different model with different datasets, we decided to continue with the MaxEnt ESM. However, our focus was originally on arabica coffee alone. To answer a more exploratory and complex research question, we decided to expand our scope to the top imported and exported crops and forecast their environmental suitability.

3.4 Country-Specific Environmental Suitability Score Aggregation

MaxEnt ESM output is on a pixel level for the global grid landscape. To analyze the relationship between global production per country, we needed to devise a way to aggregate suitability scores for all pixels of a country into a single value for all 5 crops. This allows us to compare production data and MaxEnt ESM output on a country-by-country basis.

We initially explored using a thresholded average approach to normalize scores across countries of different sizes. This method was intended to prevent larger countries from disproportionately influencing the overall average, ensuring a more balanced representation of the data. However, further exploration of the results revealed flaws in this approach. While the generated scores adequately reflected suitability for smaller highly suited countries for a crop, they failed for larger countries with smaller suitable areas, producing disproportionately lower scores and failed our validation test of a nonzero production value country having an ESS of zero. This indicated the possibility that the selected thresholds were masking important points. We also reconsidered taking the mean since the motivation of doing so was to normalize the scores for each country. But realistically, bigger countries like Brazil can naturally have a higher suitability with more land, and that should not be ignored. Similarly, countries such as Colombia are smaller yet extremely suitable regions. Amount of land and level suitability is captured should therefore be captured in ESS and either one cannot be ignored

We considered the Minimum Training Presence (MTP) for evaluating a threshold based on an individual crop by taking the minimum pixel-based ESS of all crop presence points. A similar technique is cited by other ecology studies(2). Doing this yielded a threshold of near zero for all five crops of interest. Thus, the final approach of non-threhsholded sum was finalized as the best way to aggregate Environmental Suitability on a per country basis. This approach also passed our internal validation checks.

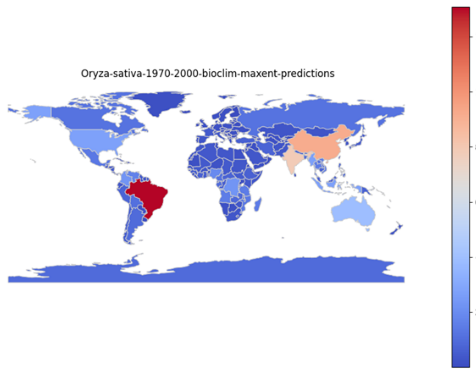


Figure 2: Global Oryza-sativa (Rice) ESS for years 1970 - 2000

3.5 Evaluation: Validation and Correlation

To validate that our ESM and environmental suitability scores effectively measure how conducive an area is for growing specific crops, we examined expected trends and established validation methods in ecological suitability modeling. For the ESM, we observed that high suitability scores often coincide with crop presence, while zero suitability (determining an area as completely unsuitable) aligns with the absence of the crop. Similarly, for ESS, countries with high scores for a particular crop tend to produce that crop in larger quantities, while countries with an ESS of 0 are observed to have no production.

Using crop presence data, we evaluated the suitability assigned to each coordinate by the ESM. Our analysis showed that most crop presence occurs on land with relatively high suitability scores: across all crops, 60–83% of crop presence was observed on land with a suitability score of at least 0.5. Furthermore, for each crop, the suitability score at which crop presence was most frequent ranged between 0.9 and 1. Importantly, no instances of crop presence were found on land classified as completely unsuitable, confirming the model's consistency.

For ESS validation, we compared each country's aggregated environmental suitability scores with its crop production levels. As seen in Figure 5, countries with high ESS values for a crop generally produce more of it. For example, Brazil, with high summed ESS for arabica coffee and sugarcane, was the leading producer of these crops between 1970 and 2000. Although Brazil also has high ESS for rice and maize, it produces less of these crops, possibly due to greater economic incentives for higher-value crops. Despite this, Brazil still ranked among the top nine producers of rice and maize during the studied time-frame, maintaining the expected trend.

China provides another example: while its summed ESS for wheat and maize is moderate relative to other countries, it outperforms others in production, likely by maximizing land use efficiency. Conversely, countries with near-zero ESS scores generally produce minimal quantities of a crop. However, there are exceptions, such as Cuba, which produces sugarcane despite having a near-zero ESS. This anomaly may be due to limitations in the sugarcane presence point dataset, which had fewer data points and lower quality, potentially leading to less accurate ESS scores.

Our findings are based on the relationship between environmental suitability and trade dynamics, examined specifically through production, which we validate with correlation analysis. We computed the Pearson correlation coefficient between the ESS for a country and the average production of each crop during the time interval 1970–2000. The results are as follows:

Table 1: Pearson Correlation Results for Different Crops

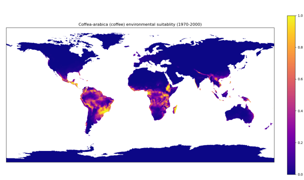
Crop	Pearson Correlation (r)	p-value
Coffee	0.88	1.53×10^{-17}
Maize	0.58	5.74×10^{-12}
Rice	0.65	5.68×10^{-15}
Sugar	0.65	8.10×10^{-19}
Wheat	0.70	2.21×10^{-18}

While these correlations support the validity of our approach, we acknowledge that some selection effects may not be fully captured. Factors such as labor availability, land reclamation, and agronomic practices—beyond the scope of our bioclimatic variables—can also influence production. For instance, crops like coffee and maize are sometimes grown for purposes like land reclamation, which may not align strictly with their suitability scores (8).

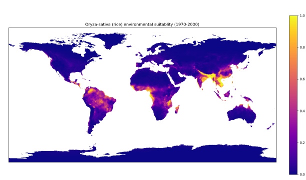
In terms of external validity, our research spans a broad geographic scale, making it generalizable to global suitability and trade dynamics across countries. At the same time, our findings are applicable at a regional level, allowing us to address shifts within specific areas of countries. For instance, anomaly maps in our case studies, which illustrate differences in past and future environmental suitability for crops, highlight regional changes in crop demand. However, some environmental suitability studies have focused on even finer granularity, such as local or farm-level analyses, leveraging detailed farm-specific data (8). While these studies may offer more precise insights at a local level, our findings are not intended to apply at such scales.

4 Results

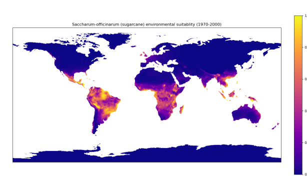
4.1 Model Output



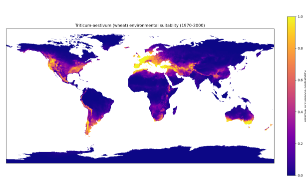
(a) *Coffea arabica*



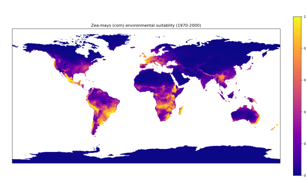
(b) *Oryza sativa*



(c) *Saccharum officinarum*



(d) *Triticum aestivum*



(e) *Zea mays*

Figure 3: MaxEnt environmental suitability models from 1970-2000

The model output world plot (Figure 3) uses color to indicate environmental suitability scores per pixel, where yellow and purple correspond to a high and low probabilities of suitable conditions for the crop species respectively. Individual plots identify the spatial divide of growth regions. For example, the Himalayan mountain range can be seen as a divide in all five plots. Note that this output is dependent on the bioclimatic variables and crop presence points (Figure 11) .

4.2 Feature Importance

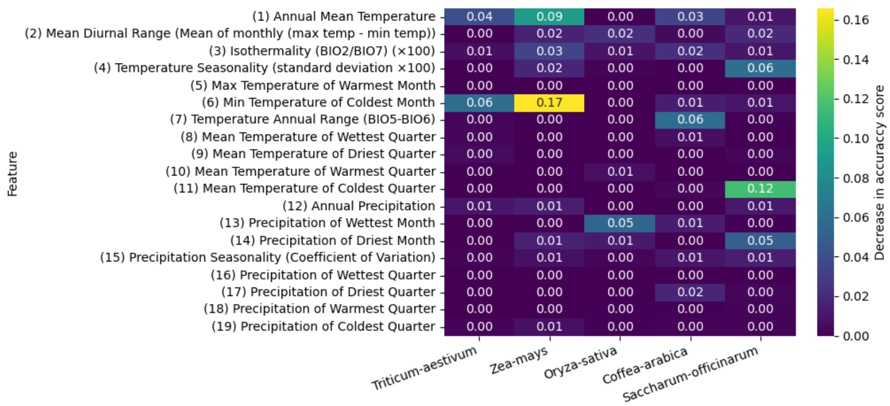


Figure 4: Permutation importance scores for each trained MaxEnt model

We also analyzed the permutation importance scores for each of crops trained models (Figure 4). We can see that corn has a high sensitivity to BIO6 (min temperature of coldest month). This matches studies on crop growth which find that corn is particularly sensitive to frost in early stages of seeding (1). In particular air temperatures below 28°F can be fatal. We also see that asian rice weighted BIO13 (precipitation of wettest month) highly. This also lines up with research on rice growth which states: "More than 92% of rice in China is cultivated in the southern humid regions (Mao, 2002), and rice cultivation consumes more than 65% of the available agricultural irrigation water (Li et al., 2016)." (11).

Overall, we can see that all crops have a mix of temperature related features that are used for the ESM even if annual mean temperature does not have highest percentage. This means that the various changes in temperature due to climate change will affect all of the crops in this study.

4.3 ESS Scores vs Production

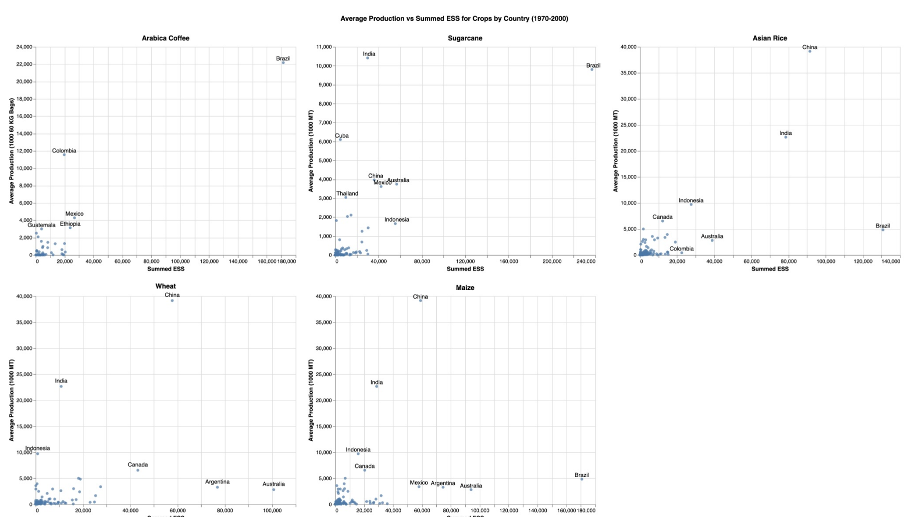


Figure 5: Each of the subgraphs correspond to one of the five crops. The average production of the crop versus the summed ESS over 1970-2000 for all the geographic locations in a country is plotted.

One way that we evaluated our approach is through checking construct validity. The environmental suitability score is a proxy for how suitable an environment is for producing a crop. One way to validate this is by comparing a country's aggregated environmental suitability scores with that country's production of the crop. So, as you can see in the plots (in Figure 5), countries that have

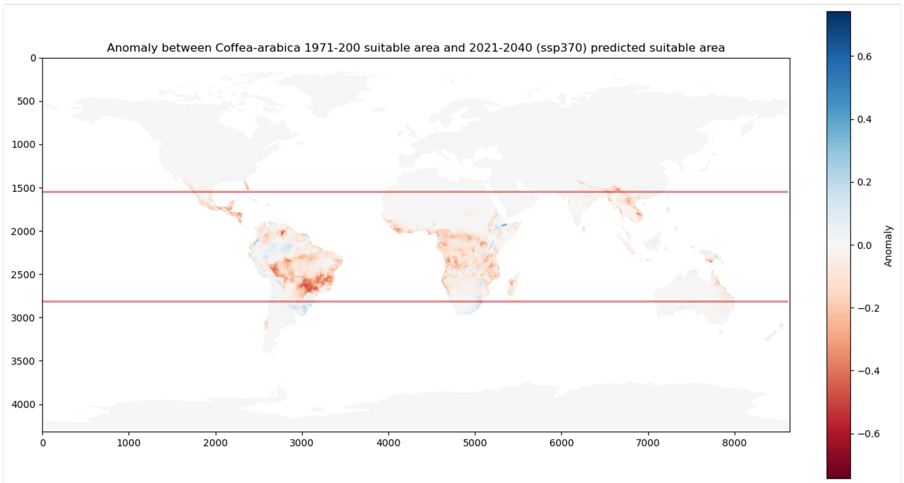


Figure 6: Anomaly between suitability for *coffee arabica* between 1970-2000 and 2021-2040. Blue (positive anomaly) means the region will gain suitability. Red (negative anomaly) means the region will lose suitability. Grey (zero anomaly) means the region will stay unsuitable or stay suitable. The light red lines represent an approximation of the "coffee belt" where a majority of the world's coffee is currently grown.

a high ESS for a crop tend to produce more of it. For example, Brazil has a high summed ESS for arabica coffee and sugarcane and also produces the most of that crop in the time range from 1970-2000.

5 Discussion

5.1 Coffee Case Study

Focusing in on the ESM output for arabica coffee (*coffea arabica*), we see that the model had a test AUC score of 0.981. This accuracy is perhaps higher than expected, however there are few coffee producing regions and we have a considerable number of presence points in all of those regions. So the model is able to successfully identify the conditions that can produce *coffee arabica*. The trend of suitable regions for coffee arabica seen in Figure 3 also matches with the expected “bean belt” where a majority of the world's coffee is currently grown. We also accounted for spatial autocorrelation in the data by using a checkerboard train test split. Next, let's examine the anomaly between the predicted suitable growth area in 1970-2000 versus 2021-2040. The future climate data was using the NOAA GFDL-ESM4.1 (6) climate model under SSP 370 (12).

When we zoom in on South America, we see that Brazil, the largest producer of arabica coffee, has the largest decrease in suitability. Colombia is similarly losing suitability in the center and northern regions. This might be alarming for Colombia as coffee production accounts for 7-8% of their GDP. However, there is one small region that is predicted to become more suitable and that is a mountainous region (within Andes mountain range) that has strong environmental and geographic conditions. This is consistent with prior research that found that the ideal growth altitudes for arabica coffee ranges from 1,000 to 2,000 meters above sea level. This altitude can even be extended to above 2,000 meters in regions like Ethiopia (3). Arabica coffee is even often referred to as "mountain coffee".

Due to the sensitivity of *coffea arabica* to temperature, much of the coffee belt is expected to face increased challenges in coffee cultivation. Brazil, the largest producer of*coffea arabica*, is projected to experience the greatest decrease in suitability. In contrast, Colombia is comparatively less affected and includes regions around the Andes mountain range that may become more suitable for coffee production.

In light of these anticipated changes, recent studies have identified rare coffee species that are more resilient to temperature changes while maintaining a flavor profile similar to *coffea arabica*. These include *Coffea stenophylla* and *C. affinis*, historically cultivated in West Africa (5).

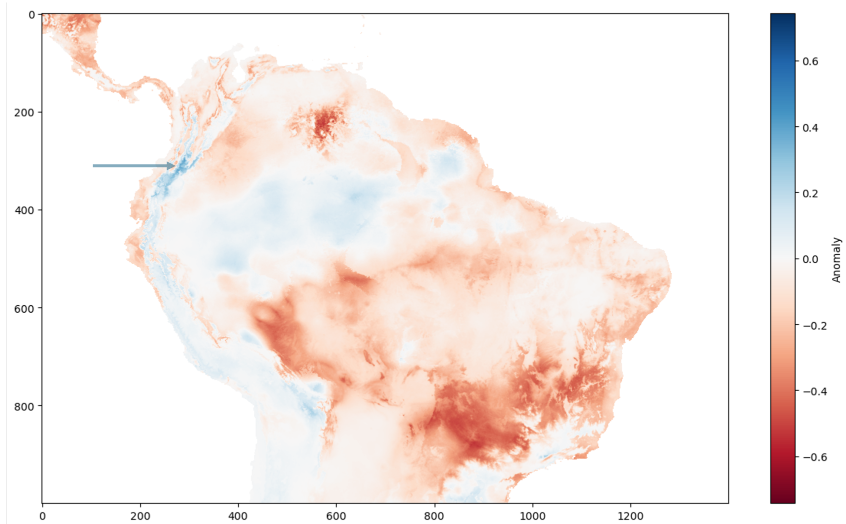


Figure 7: Anomaly between suitability for *coffee arabica* in 1970-2000 and 2021-2040 for South America. The blue arrow points to a region of Columbia where suitability is predicted to increase. Blue (positive anomaly) means the region will gain suitability. Red (negative anomaly) means the region will lose suitability. Grey (zero anomaly) means the region will stay unsuitable or stay suitable

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5.2 Sugarcane Case Study

Next, we conduct a case study on sugarcane. Figure 8 shows sugarcane suitability from the 1970 to 2000 range and the predicted suitability for the 2021 to 2040 range. To further examine the changes in suitability, Figure 9 shows the level of change and whether it is in the positive or negative direction. The top sugarcane producers are India, Brazil, Cuba, China, Australia, Mexico, and Thailand. In the Brazil region, we can see that there are some areas that are blue, which indicates a predicted increase in suitability in the future. However, most of the other countries that have historically been a top producer of sugarcane have lower predicted suitability.

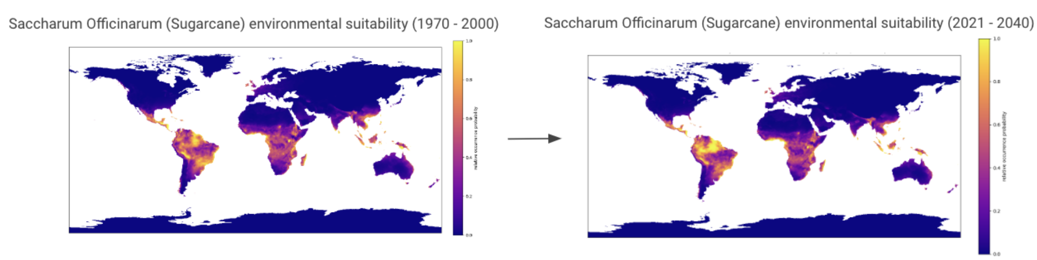

Figure 8: Global sugarcane suitability for years 1970 - 2000 and 2021 - 2041.

Looking more closely at the region in South America in Figure 10 with higher predicted suitability in the future, we see that this region overlaps significantly with the Amazon Rainforest. Since Brazil was the only one of the top sugarcane producing countries that showed a promising increase in predicted suitability, this is especially concerning as the expansion of sugarcane production into the Amazon Rainforest leads to deforestation and many other adverse effects on its fragile and bio-diverse ecosystem.

However, there is potential for future sugarcane production in lower suitability regions using developments in precision agriculture. For example, Louisiana has had success in sugarcane production despite having temperate climate and shorter growing seasons. This has been possible due to developments such as new sugarcane varieties that produce sugar in shorter time frame and variable-rate application of lime to sugarcane fields to correct acid soil conditions. We also see moderate levels of

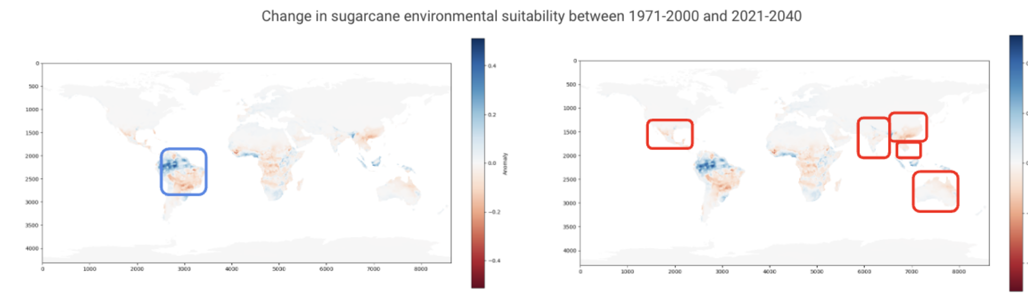

Figure 9: Predicted global change in sugarcane suitability from years 1970 - 2000 to 2021 - 2040. Boxes show the highest sugarcane producers: India, Brazil, Cuba, China, Australia, Mexico, and Thailand. A blue box indicates an increase in predicted suitability and a red box indicates a decrease in predicted suitability.

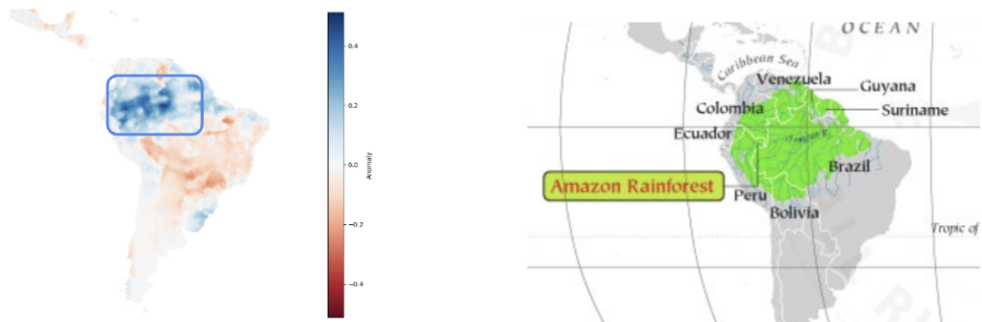

Figure 10: Comparison of region with predicted sugarcane suitability increase between 1970 - 2000 and 2021 - 2041 (left) and the Amazon Rainforest in South America (right).

production in regions with lower suitability such as the EU, which indicates there is a possibility of increasing production by focusing on factors outside of environmental suitability scores alone.

6 Related Work

In *Modeling Coffee (coffea arabica) climate suitability under current and future scenario in Jimma Zone, Ethiopia*, Benti et al. (2022) research which procedures should be suggested to protect arabica coffee production based on forecasted environmental suitability zones in Ethiopia (4). For background context, one-third of the country's export income is from coffee, so coffee plays a major role in the financial and social life of Ethiopia. The choice of a MaxEnt ESM in this paper prompted us to further investigate the use of the MaxEnt model in our own project. While we utilized a similar MaxEnt ESM approach, our research question examined a more global focus and we also looked at top global crops.

In *A statistical explanation of Maxent for ecologists*, Elith et al. (2010) discusses how MaxEnt models species distribution from a statistical perspective (7). We utilized this paper to inform our MaxEnt implementation and better understand the theoretical basis of the model.

In *Modeling land suitability for Coffea Arabica L. in Central America*, Estrada et al. (2017) investigates the development and validation of a Bayesian network model designed to aid agricultural planning for coffee production through determining land suitability at a more local level (8). It addresses the challenges of uncertainty and lack of information in land evaluation when using suitability functions at a broader scale, and incorporates more detailed, farm-level data. This research provided valuable methodologies for validating our own environmental suitability models and offered insights into additional factors that could explain discrepancies between crop yields and suitability scores.

In *The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6*, O'Neill et al. (2016) sought to understand the interaction between the changing environment and land use potential to develop effective mitigation and adaption strategies (12). While both our approach and the one in this paper forecast agricultural potential based on changing environmental factors, the key difference is that this paper focuses on different types of land while our project focuses on the environmental suitability of major crops. This paper also provided us with background context on how the bioclimatic variables dataset are forecasted on three different socioeconomic pathways.

7 Conclusion

This study provides an analysis of the impact of environmental suitability on the production of the world's top crops, specifically focusing on asian rice (*oryza sativa*), sugar (*saccharum officinarum*), maize (*zea mays*), wheat (*triticum aestivum*), and arabica coffee (*coffea arabica*). We ran a MaxEnt model analysis and found that the output results were consistent with global trends and events. A study of this nature on multiple crop strains with a global lens provided unique insight into understanding current and future global agricultural trade. Our study supported our hypothesis that some regions will lose the ability to grow certain crops while other regions will gain the ability to grow certain crops. Our findings are crucial to inform effective agricultural strategies and policies to sustain our growing population's food demands midst of a changing climate. Additionally, our research adds to the broader discussion on food security and environmental sustainability, highlighting the importance of adaptive strategies that address both regional and global agricultural changes.

8 Ethical Considerations

Our findings carry ethical risks related to their potential misuse in economic decision-making, particularly in reallocating farming to new regions without considering broader environmental and social contexts. For example, our sugarcane case study highlights declining suitability in parts of central and southern Brazil and increasing suitability in the Amazon. This finding aligns with ongoing policy debates about farming in the Amazon, a region of great ecological importance. If used without contextual information, our findings could inadvertently encourage agricultural expansion into the Amazon, leading to deforestation, biodiversity loss, and disruptions to a critical ecosystem that plays a key role in stabilizing carbon dioxide levels. To mitigate these risks, it is essential to emphasize that our results are not prescriptive but rather one component of a holistic decision-making process. Decisions about reallocating crop production should incorporate additional factors such as conservation priorities, socioeconomic impacts, and long-term sustainability goals. By framing our findings as part of a broader context, we can help ensure they are used responsibly to support sustainable agricultural practices rather than exacerbate environmental harm.

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A Appendix

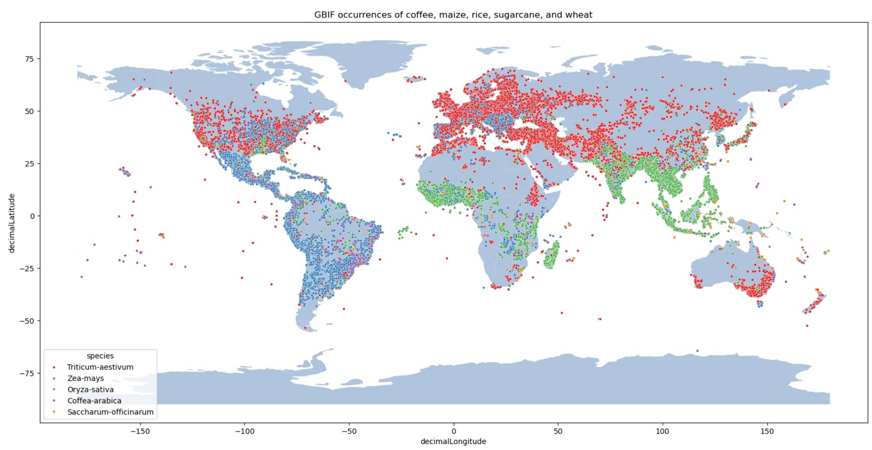

Figure 11: This map shows the GBIF input presence points for wheat (red), maize (blue), asian rice (green), arabica coffee (purple), and sugarcane (orange)