Investigating the Ecological Drivers of Agricultural Yield in the Ecuadorian and Peruvian Andes

Investigating the Ecological Drivers of Agricultural Yield in the Ecuadorian and Peruvian Andes

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In submitting this thesis to the Harvard John A. Paulson School of Engineering and Applied Sciences in partial fulfillment of the requirements for the degree with honors of Bachelor of Arts, I affirm my awareness of the standards of the Harvard College Honor Code.

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List of Contributions

Following previous investigations of the effects of soil moisture, temperature, and vegetation activity on crop yields in different regions across the globe by other members of the research group, this current research project was jointly designed by T. Jiménez and Prof. Huybers. Spatial data for the ecological variables were provided by A. Rigden. All statistical analyses were done independently by T. Jiménez. Data and results were interpreted by T. Jiménez with assistance and guidance from Prof. Huybers.

Abstract

Climate change threatens the future of food and water security across the globe. In the tropical Andes, where there is still high uncertainty around how shifting environmental conditions will affect the crop yields, climate change is expected to inequitably hurt already vulnerable small-scale farmers. In this study, we aim to quantify the sensitivity of the annual yield of key crops to changing climatic conditions across different elevation ranges in Ecuador and Peru. To do this, we spatially aggregated monthly-average soil moisture, maximum temperature, and SIF observations of croplands with the reported national annual yields from 2007-2018. We then ran linear regressions to model the relationship between crop yield and these ecological parameters. Our findings show that the variability in Peruvian, high elevation crop yields is attributable to the variations in soil moisture, temperature, and SIF observations during the twelve year time period. Crop yields are found to have a higher sensitivity to variations in soil moisture rather than variations in temperature. Our results suggest that high elevation croplands are more susceptible to climate variability than low elevation croplands, and that adaptation strategies to conserve soil moisture in these croplands can help to offset the increasing temperatures from climate change.

Resumén

El cambio climático amenaza el futuro de la seguridad alimentaria y del agua en todo el mundo. En los Andes tropicales, donde todavía existe una gran incertidumbre sobre cómo las condiciones ambientales cambiantes afectarán los rendimientos de los cultivos, se espera que el cambio climático perjudique de manera desigual a los pequeños agricultores ya vulnerables. En este estudio, nuestro objetivo es cuantificar la sensibilidad del rendimiento anual de cultivos clave a las condiciones climáticas cambiantes en diferentes rangos de elevación en Ecuador y Perú. Para hacer esto, agregamos espacialmente la humedad del suelo promedio mensual, la

temperatura máxima y las observaciones del SIF de las tierras de cultivo con los rendimientos anuales nacionales informados de 2007-2018. Luego realizamos regresiones lineales para modelar la relación entre el rendimiento del cultivo y estos parámetros ecológicos. Nuestros hallazgos muestran que la variabilidad en los rendimientos de los cultivos peruanos a gran altitud es atribuible a las variaciones en la humedad del suelo, la temperatura y las observaciones del SIF durante el período de doce años. Se encuentra que los rendimientos de los cultivos tienen una mayor sensibilidad a las variaciones en la humedad del suelo que a las variaciones de temperatura. Nuestros resultados sugieren que las tierras de cultivo a gran altitud son más susceptibles a la variabilidad climática que las tierras de cultivo a baja altitud, y que las estrategias de adaptación para conservar la humedad del suelo en estas tierras de cultivo pueden ayudar a compensar el aumento de las temperaturas debido al cambio climático.

Introduction

Over the past century, the significant increase in greenhouse gas emissions has led to increased variability and severity in global climate patterns [1], [2]. Increased greenhouse gas emissions, including chemical compounds such as CO_2, has led to increased climate forcing and a shifting of the radiative balance, essentially keeping energy within the Earth's atmosphere and warming the planet [3]. The current threats around anthropogenic climate change remain ominous as these effects can vary significantly across the world. In some regions, it has led to impacts including, but not limited to, the increased severity of weather, increased temperature, and shifting of the average seasonal patterns [4]. These shifts are expected to affect the diversity and distribution of vegetation across different regions [5], [6]. With so much uncertainty surrounding the future effects of climate on vegetation and ecological conditions, there has been increasing concern about the future of food and water insecurity. Climate change has already affected food insecurity through increasing temperatures and changing precipitation patterns [7]. As described in Myers et al., global food production is likely to be altered through many climate change-related pathways that can impact growing seasons, temperatures, water availability, pest accessibility, and many more [8]. These pathways are not only limited to the direct land-climate interactions, but include the impact on farmers not being able to predict or plan for the next growing season conditions for their crops. This can have a stronger impact on small-scale farmers who do not have access to a safety net for a low production year.

Besides impacting the net production of food, climate change is expected to affect global nutrition and the equitable distribution of food across populations. With an increasing unpredictability of annual food supply, simulations predict that there will be heightened economic pressure on food access globally [8]. The International Food Policy Research Institute

currently predicts the price of staple grains to inflate 31-106% by 2050, dependent on the combination of population, income distribution, and climate change impacts [9]. This inflation can further exacerbate food insecurity for vulnerable populations. As seen in the economic recession of 2007-2008, the rise in the price of staple foods led to widespread hunger and increased conflict in over 20 countries worldwide [10], [11]. With climate change expected to further threaten the adequate production of crops with a growing population, global food security is considered as the "link between the ecological and economic crises affecting the planet" [10]. Investigating the effect of regional and global climate variability on crop yield has been a growing concern of researchers across the scientific and socioeconomic realms. While climate change is expected to alter crop yields and food security on a global scale, there is still high uncertainty around what regional impacts farmers should expect to encounter. This uncertainty is intensified around regions of high ecological diversity, such as the northwestern Andes.

Though climate change has and will continue to affect every region across the globe, the equatorial region across South America is extremely vulnerable to climate variability due to its unique ecological characteristics. First, being located across the equator provides higher levels of direct incoming solar radiation throughout the year, which has led to some of the most productive areas globally, including the "lungs of the world," the Amazon rainforest. However, the presence of drastic topographic features has shaped a wide range of unique ecosystems across this region. On the western side of the continent spans the Andes, the longest continental mountain range in the world. Across the equatorial line alone, the elevation reaches up to 5,790 meters at Mount Cayambe in Ecuador. In accordance with the ideal gas law and atmospheric lapse rate, which describes the negative relationship between temperature and altitude, the sharp change of elevation allows for a large range of surface temperatures to exist across the equatorial

region. This range of temperature combined with shifts in soil characteristics provides the unique opportunity for a large range of ecosystems to exist across the Andes.

However, elevation is not the only influential factor in determining the type of ecosystem present in this area. The Andes is also characterized by distinct rain-shadow effects that carry an uneven distribution of precipitation over the mountain range. Across the region, the easterly trade winds bring precipitation over the eastern Andes through orographic uplift [12]. Orographic uplift occurs when an air parcel is forced to rise due to a topographic feature, effectively cooling the air parcel and causing it to condense and precipitate under ideal humid and temperature conditions [13]. In northern Ecuador and Colombia, a second rain-shadow effect occurs on the western side of the Andes from tropical Pacific winds driven by the warm sea surface temperatures influenced by the El Niño–Southern Oscillation (ENSO) [14]. These rain-shadow effects, combined with the influences of direct solar radiation, stark changes in elevation, and temperature shifts create a wide variety of microclimates across the Andes; ranging from the Amazon rainforest, to coastal deserts, to mountainous cloud forests, dry Andean valleys, and tropical glacial peaks.

The wide range of microclimates across the Andes contribute to a higher uncertainty around the effect of climate change across these different regions. In the past 50-60 years, the tropical Andes has experienced increases in temperature averaging to about 0.1°C per decade [15]. Modeled projections of climate change indicate enhanced temperature increases at higher elevations than at the lower elevations. These increases in temperature have already had tangible impacts, with notable rapid glacial retreats across the tropical high Andes [16]. This rapid decline has temporarily increased water supply and soil moisture downstream, however, the continued glacial retreat raises concerns for a future of water scarcity and dry conditions in the highlands.

In addition to this, climate change is expected to impact the natural variability and intensity of ENSO, having regionally diverse impacts on precipitation and temperatures across South America [4], [17]. Climate change is expected to more strongly affect the high elevation, tropical mountain ranges than the surrounding lowlands [18]. These shifting temperature and precipitation levels are expected to shift the distribution of vegetation across these regions, especially within these microclimate regions where endemic, biodiverse species have thrived from the specific climatic conditions [6]. This has raised concerns around the future of agriculture in the Andes.

Agriculture has historically been a central part to the cultural, nutritional, and economic wellbeing of Andean communities [19]. Many of these communities consist of small-scale farmers who rely on traditional agricultural practices and local ecological knowledge to predict the following season's weather patterns and prepare for the next harvest [20]. With this region already experiencing increasing temperatures and weather variability, these small-scale farmers have already felt impacts on their crop yields. While increasing temperatures do pose a threat on the long-term future of Andean agriculture, the increasing year-to-year climatic variation and unpredictability has already had a detrimental effect on these communities. Farmers have noted that while their techniques for predicting the conditions of the next growing season used to be reliable, the accuracy has declined significantly in recent years. With increasing temperatures, there's been a lack of water availability for crops and an increase of pests and plagues that used to exist at lower elevations. These small-scale farmers are less able to cope with the threats posed by climate change because they have far fewer options in their agricultural system to adjust to year-to-year variations, and are economically reliant on their crop yield from year-to-year [21].

With decreasing crop yields and lack of governmental support, many of these communities have fallen into poverty, or have been forced to migrate.

In order to support these communities, it would be beneficial to quantify the effects of shifting seasonality, temperature, and water availability on crops across the Andean region. Measuring the sensitivity of crop yield to different ecological shifts and variations can help farmers better prepare their croplands for these expected environmental changes. In an effort to do this on the field, Tito et al. investigated the sensitivity of maize and potato varieties in the Peruvian Andes to increasing temperatures by planting these crop varieties at lower elevations to simulate different warming scenarios [22]. This was done to explore the possibility of countering increasing temperatures by shifting crops to higher elevations with more suitable climates. They found that maize and potato production was reduced by over 87% under warmer conditions, mostly attributable to the larger presence of pests. While this study argued for the infeasibility of adjusting to climatic conditions by changing the cultivation location, the necessity of effective management strategies, and the urgency of the threat of climate change to Andean agriculture, the derived sensitivity of these crops to temperature was limited to the conditions present within the experimental region. It could be advantageous to quantify the sensitivity of Andean crops to shifting ecological conditions across a more widespread area. In this study, we aim to quantify the large-scale sensitivity of crop yield to shifting climatic conditions through satellite-derived observations. This would allow us to measure the response of agriculture to increasing temperatures and a changing hydrologic cycle across widespread regions.

Past studies have used satellite-derived observations to quantify the large scale predictions of shifting crop yields in response to climate change in different regions. In Rigden et al., the sensitivity of Kenyan tea yields to water and heat stress were predicted by defining

solar-induced fluorescence as a spatial proxy for interannual variability in yield, and creating a spatial and temporal linear regression model. They found that while rising temperatures would decrease tea yields by about 10%, the increase of soil moisture would offset that loss. A similar study was performed in Australia, where solar-induced fluorescence and climate data were combined and analyzed with machine learning methods to quantify the predicted wheat yield [23]. In their study, they found that combining satellite and climate data provided high performance in crop predictions. Satellite-based solar-induced fluorescence has been further confirmed to function well in predicting interannual crop yield production in maize and soybean yields over the U.S. Midwest in 2018 [24]. With high resolution solar-induced fluorescence proven to be highly sensitive to climate variability, we aim to take on a similar approach of tying satellite and climate data of the Andes to national annual yields to analyze the widespread effect of climate change. [25].

In this thesis, we aim to quantify the response of Ecuadorian and Peruvian crop yields to shifting climatic and environmental conditions across the Andes. We hope to better understand the relationship between the predominant ecological drivers and changing crop yields in the northwestern Andes to potentially help plan specific adaptation strategies for these communities. In order to do this, we will 1) identify and quantify the national and regional annual agricultural yield of crops of interest; 2) identify the croplands and their corresponding elevation across Ecuador and Peru; 3) spatially-aggregate the geographical distribution of croplands with the maximum temperature, soil moisture, and vegetation activity levels for the years of interest; and 4) quantify the sensitivity of yield to the interannual variations in these conditions.

Methodology

Identifying Crops of Interest

In order to accurately model and compare the effects of climate change-induced temperature and water availability shifts on Ecuadorian and Peruvian croplands, both spatial and temporal data regarding the soil moisture, temperature, vegetation activity, and national crop yields were collected. To first collect data regarding the annual national crop yield of each country of interest, the Food and Agricultural Organization of the United Nations (FAO) was referenced [26]. This site provides data on the national annual yield of a variety of crops (in units hg ha^{-1}) and the estimated area harvested (ha). Both of these metrics were utilized to calculate the average annual yield of each country. Because the goal of this study is to determine the effect of changing ecological conditions on crop yields at different elevations, key crops of each country were chosen to represent low and high elevation crops. This was done to better reflect how a changing climate will affect the crops that are critical to the economic and nutritional wellbeing of the people of these nations. The crops of interest were determined based on annual reports given from the Ecuadorian and Peruvian governmental sectors regarding the agricultural yield, geographical location, and harvested area of the crops considered to be of importance to the nation. For Ecuador, the Encuesta de Superficie y Producción Agropecuaria Continua (ESPAC), or the Survey of Area and Continuous Agricultural Production, produced by the Ecuadorian National Institute of Statistics and Censuses, was referenced [27]. For Peru, data given by the Ministerio de Agricultura, or Ministry of Agriculture, from the National Institute of Statistics and Informatics (INEI) was referenced [28]. After reviewing these reports to determine the importance of each crop in terms of economic value, nutritional significance, and its elevation range, six crops were identified for each country. Maize, potatoes, and rice were identified as key crops in each country, in addition to barley, sugar cane, and palm oil in Ecuador and quinoa,

cocoa and coffee in Peru. Each of these crops was also categorized as either a low elevation crop or high elevation crop.

Annual Agricultural Yield

After identifying each of these crops, the calculated annual yield for each crop (hg ha^{-1}) was extracted from the FAO for 12 years of interest: from 2007 through 2018. The annual yield of each crop given by the FAO was cross-referenced with the annual yield provided by the Ecuadorian and Peruvian governments, and disparities in the reported maize yield were identified. While looking at the data given by the FAO, Peru had two classes of maize: Maize and Maize (Green). However, Ecuador only accounted for Maize. When cross-comparing the FAO data and that given by the Peruvian government, it was noted that the Maize and Maize (Green) varieties applied to what Peru recognized as Maize Seco and Maize Choclo, respectively. Maize Seco is more commonly grown for exports and feed, and tends to be grown at lower elevations. However, Maize Choclo, also known as Peruvian Corn, is grown in the high Andes and is a staple to the diet of the people who live across the Andean region. To account for the importance of each of these maize varieties along with their differences in annual yield and necessary environmental conditions, the two FAO classifications of maize for Peru were considered as two separate crops in this analysis and sorted into their respective low elevation and high elevation crop categories. For Ecuador, the FAO Maize data accounted for the Maize Seco annual yields reported by the Ecuadorian government as well, reported as “Maize” in this study. To incorporate this same classification scheme in Ecuador, yield and area harvested calculations for Maize Choclo from the ESPAC were combined with the FAO data, and further classified as “Maize (Green)” for this study.

Country of Interest	Crop	Geographical Distribution	Area Harvested 2017 (ha)
Ecuador	Maize	Low Elevation	3.59E+05
	Maize (Green)	High Elevation	2.62E+04
	Potatoes	High Elevation	2.95E+04
	Barley	High Elevation	1.12E+04
	Rice	Low Elevation	3.58E+05
	Sugar Cane	Low Elevation	1.11E+05
	Palm Oil	Low Elevation	2.60E+05
Peru	Maize	Low Elevation	4.46E+05
	Maize (Green)	High Elevation	4.00E+04
	Potatoes	High Elevation	3.10E+05
	Quinoa	High Elevation	6.17E+04
	Rice	Low Elevation	4.22E+05
	Cocoa	Low Elevation	1.43E+05
	Coffee	Low Elevation	4.24E+05

Table 1: List of crops of interest in each country along with their geographical distribution and estimation of area harvested in 2017.

To calculate the total annual yield of all crops for each region that also aligned with the study's other spatially aggregated data, the spatial distribution of these crops were considered. Rather than simply summing the yield of each crop for each year, the yield of each crop was weighted by the fraction of land the crop covered in comparison to the other crops of interest. To do this, the Area Harvested quantifications from the 2017 FAO statistics were utilized, as there was no significant change in the fraction of land each crop covered in comparison to the others over the twelve year period. The weight for each crop was calculated for each country and the high elevation and low elevation regions within each country, by:

$$fraction_A HA = \frac{HA(crop, 2017)}{HA(regional\ crop\ sum)}$$

After calculating the fraction of space each crop represented within each country and region, the total annual yield was estimated by summing the yield of each crop of interest weighted by its corresponding fraction of cropland for each year.

$$Annual\ Yield_{Region\ \alpha} = (fraction_A\ HA)(Yield_A) + \ldots + (fraction_N\ HA)(Yield_N)$$

This estimate was calculated for each country, Ecuador and Peru, and for the low elevation and high elevation regions within each country. A total of six annual yield time series were evaluated using this technique.

	Ecuador			Peru		
Year	Total Yield	Low Elevation Yield	High Elevation Yield	Total Yield	Low Elevation Yield	High Elevation Yield
2007	1.34E+05	1.40E+05	3.70E+04	4.74E+04	3.11E+04	1.05E+05
2008	1.47E+05	1.54E+05	3.25E+04	5.00E+04	3.37E+04	1.07E+05
2009	1.23E+05	1.28E+05	3.09E+04	5.10E+04	3.38E+04	1.11E+05
2010	1.31E+05	1.36E+05	4.37E+04	5.07E+04	3.39E+04	1.09E+05
2012	1.35E+05	1.41E+05	3.96E+04	5.23E+04	3.47E+04	1.13E+05
2013	1.28E+05	1.34E+05	4.13E+04	5.46E+04	3.65E+04	1.18E+05
2014	1.13E+05	1.18E+05	3.74E+04	5.40E+04	3.55E+04	1.19E+05
2015	1.37E+05	1.41E+05	6.54E+04	5.43E+04	3.47E+04	1.22E+05
2016	1.58E+05	1.64E+05	6.73E+04	5.58E+04	3.65E+04	1.23E+05
2017	1.34E+05	1.38E+05	7.64E+04	5.42E+04	3.53E+04	1.20E+05
2018	1.32E+05	1.36E+05	7.12E+04	5.58E+04	3.53E+04	1.27E+05

Table 2: Annually-Estimated Crop Yields (hg ha^{-1}) for Ecuador and Peru on the regional and national scale.

Application to Ecological Factors

To measure the effects of shifting temperatures and water availability on the productivity of land and agricultural yield in Ecuador and Peru, spatially-distributed satellite measurements of the maximum temperature, soil moisture, and Solar-Induced Chlorophyll Fluorescence were extracted. These datasets were aggregated to monthly-averaged measurements from 2007-2018

at 0.25-degree resolution across both of the countries. The soil moisture measurements were provided by the European Space Agency Climate Change Initiative's Soil Moisture Combined data product [29], and the maximum temperature measurements were provided by the National Oceanic and Atmospheric Administration's Climate Prediction Center [30]. This data was simplified to monthly averages in order to better identify and compare the overall shifts in climatic conditions during the growing season, which usually ranges to a few months of the year. Solar-Induced Chlorophyll Fluorescence, from here on referred to as SIF, observations were provided from the Global Ozone Monitoring Experiment-2 (GOME-2) instrument on the Metop-A satellite. SIF observations, considered a measure of vegetation activity and productivity through measurements of photosynthesis [31],[32], were also collected to function as a spatial proxy for crop yield across these regions. Past literature suggests that SIF measurements are comparable to gross primary productivity rates and have the ability to capture shifts in crop yield and productivity in response to shifting ecological conditions [11],[34]. These SIF observations were collected in an effort to show that these measurements are comparable to our calculated yield parameter for each of our regions of interest, as demonstrated in past literature [35].

Land Cover Classification

However, in order to compare these ecological measurements directly to the agricultural yield of the croplands of these regions, spatial land cover data of both Ecuador and Peru were obtained from the Land Processes Distributed Active Archive Center (LP DAAC)'s Terra and Aqua Combined Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover data product, MCD12Q1 Version 6 [36]. The MODIS observations provide global annual land cover classifications at a 500m resolution. The International Geosphere-Biosphere Programme (IGBP)

Classification Layer was utilized. The locations with either the *Croplands* classification (class 12) or the *Cropland/Natural Vegetation Mosaics* classification (class 14) were identified for analysis. According to the MODIS documentation, the *Cropland* classification was given to a 500m grid where at least 60% of the area is cultivated cropland, while the *Cropland/Natural Vegetation Mosaic* contained mosaics for small-scale cultivation of 40-60% croplands with natural tree, shrub, or herbaceous vegetation [37]. Both of these were of interest to the study as we would like to measure the changing environmental effects on small farms as well, especially since they are more common in the high Andes. In an effort to capture the changing climatic effects on all croplands that have existed within the time frame of interest, the locations of all croplands identified over the twelve year period were aggregated.

Due to the fact that past studies have questioned the validity of the MODIS Land Cover Product classifications, the croplands identified for this study were visually compared to other Land Cover references in order to confirm their accuracy [38]–[40]. The MODIS classifications were first compared with the NASA Making Earth System Data Records for Use in Research Environments' (MEaSUREs) Global Food Security-Support Analysis Data (GFSAD) Cropland Extent Product at 30m resolution for South America [41]. This product was found to have an overall accuracy of 92.4-96.8% for cropland classifications. The MODIS classifications for both Ecuador and Peru were further compared to each of their respective government's spatial cropland distribution maps; given by the Ecuadorian Ministerio de Agricultura y Ganadería (Ministry of Agriculture and Livestock) and Peruvian Ministerio de Desarrollo Agrario y Riego (Ministry of Agricultural Development and Irrigation) [42], [43]. After confirming the reliability of the MODIS Land Cover Product, the study proceeded using this classification method. The MODIS product was preferred to the GFSAD product, considering that these cropland areas

would eventually be upscaled to the 0.25-degree spatial resolution grid. The coordinates of each of these 500m gridded cropland areas from these twelve years were recorded to later align with the 0.25-degree grid.

Application of elevation measurements

To deepen the analysis of the effect of changing ecological conditions on crop yields in different regions, and to identify the regions with different crop varieties growing in Ecuador and Peru, the elevation of each cropland area was acquired. NASA's MEaSUREs' Shuttle Radar Topography Mission (SRTM) global 3 arc second, version 3 was applied in this study [44]. This near-global digital elevation model (GDEM) was generated through the STS-99 mission of the Space Shuttle Endeavour. The SRTM dataset was selected as it has fewer altimetry errors in comparison to other GDEM options in South America, and has filled its own data voids with information from other popular GDEMs [45], [46]. SRTM provides elevation information in a 90m-grid format, so the elevation information was upscaled to the 500m-grid croplands. The elevation data was first smoothed across all locations in the 90m-grid, and was then interpolated with the locations of the croplands to create a new dataset containing the approximated elevation at the coordinates of the 500m-grid.

Sensitivity Analyses

After obtaining the elevation, land cover, temperature, soil moisture, SIF, and crop yield information of Ecuador and Peru, it was then possible to calculate the spatial and temporal effects of changing climatic conditions on agriculture at different elevations in the Northwestern Andean Region. With each 500m cropland plot now identified and given an elevation metric,

croplands were split into two regions in each country to correspond to the low elevation crop yield and the high elevation crop yield calculated from the information given by the FAO and the Ecuadorian and Peruvian governments. To split the spatially-aggregated data into these two regions, a histogram illustrating the distribution of elevation of croplands was created to identify if there was a clear break between low elevation croplands and high elevation croplands. The distribution of SIF observations and corresponding elevations for each of these croplands will also be investigated to determine if a break between low elevation and high elevation crops should be determined through clusters of SIF and elevation correlations. After splitting these countries into two regions each, there was a total of six regions of interest: Ecuadorian Croplands, Ecuadorian Low Elevation Croplands, Ecuadorian High Elevation Croplands, Peruvian Croplands, Peruvian Low Elevation Croplands, and Peruvian High Elevation Croplands.

After identifying each region of interest, each 500m cropland plot was then coupled to its corresponding 0.25-degree resolution ecological grid. The fraction of 500m identified cropland plots within each larger 0.25-degree grid was calculated to investigate the proportion of crops grown at lower elevations versus higher elevations, and the spatial distribution of cropland intensity in each country. The growing season of each region was then determined in an effort to narrow our analyses to the critical months for crop growth, and to investigate how climatic changes are shifting the ecological conditions within these months. To do this, the SIF measurements were first averaged across the region of interest over the twelve year period to show the monthly trend in photosynthetic productivity. The growing season was estimated with the assumption that the growing season occurs during the months with the highest SIF observations. After approximating the months with the highest SIF observations in each region,

the growing season was confirmed by running linear regressions of how the seasonal SIF measurements, or the SIF averaged over the growing season within a region for each year, described the calculated yield response for that respective region. The growing season for each region was then established as the collection of months surrounding the peak average monthly SIF that returned the highest statistical significance (lowest p-value) of describing the calculated crop annual yield.

After identifying the growing season, detrended seasonal SIF measurements were compared to the detrended calculated agricultural yield, to determine whether there was a correlation between the two metrics for each region. If there was a high correlation between these two, then SIF measurements could be assumed to work as a proxy for agricultural yield. This would allow a spatial analysis of the way that maximum temperatures and soil moisture are affecting agricultural yield across the regions. If not, then these spatial analyses could still be used to determine how the vegetation across each region is responding to shifting temperature and water availability.

Both temporal and spatial linear regression models were then produced to investigate the effect of soil moisture and temperature on seasonal SIF values for each region of interest. For the temporal regressions, the maximum temperature, soil moisture, and SIF observations were averaged over the seasonal months of each region of interest to create an annual time series estimate for each variable. The temporal relationship between the ecological covariates and the seasonal SIF across the twelve year time period was then determined. The spatial effects of changing climatic conditions were then quantified by running a cross-sectional regression of SIF observations on soil moisture and maximum temperature measurements. For each region, each variable was averaged over seasonal months and years. Finally, the temporal and spatial effects

of these ecological variables on SIF observations were evaluated. This regression was expected to have the lowest level of uncertainty in comparison to previous spatially-averaged and temporally-averaged regression models. This panel model was done by averaging the variables over the seasonal months, but maintaining the annual and spatial features to have a time series for each grid box of interest. Each of these regressions gave a different perspective to contribute to understanding the effect of these predictors on vegetation.

These same ecological covariates were then compared to the calculated annual crop yield over a spatially-averaged regression model for each region. Linear regressions to describe SIF observations were previously utilized in an effort to spatially describe the effect of changing environmental factors on crop yields, however, the calculated crop yield can also be directly compared to temperature and soil moisture as well. For each region, the spatially-averaged temperature, soil moisture, and SIF observations were detrended and compared to the detrended calculated crop yield for that respective region. This was done to determine whether the seasonal variations in maximum temperature, soil moisture, or SIF can explain the annual variations of the agricultural yield of the key crops of each region. The sensitivity coefficient of each variable, the predicted linear model, adjusted R^2, confidence interval (at 95%), and p-value were recorded for each of these relationships of interest. Each of these parameters was then analyzed to determine whether these relationships were significant.

The sensitivity of agricultural yield to each of these ecological variables was quantified in an effort to describe the response of yield to shifting climatic conditions. If a regression was statistically significant, the equation was analyzed as a possible predictor of the future of agricultural yield for its respective region.

Results

Ecuadorian Analyses

First, the representative crop yields of Ecuador and of its lower and higher elevation regions were calculated in order to later compare to changing SIF, soil moisture, and temperature observations. Each crop was weighted by the percentage of harvested area it covered relative to the other crops of interest within each region. In Ecuador, we found that the low elevation annual crop yield was substantially greater than the high elevation annual crop yield. There was a jump in crop yield in both regions after 2013, and there seems to be a general upward trend of crop yield at high elevations. When we compare the detrended crop yields, we find similarities across all of the regions. There were dips in crop yield across each region during 2009, 2013, and 2018. The detrended crop yields indicate larger variations in crop yield at the lower elevations.

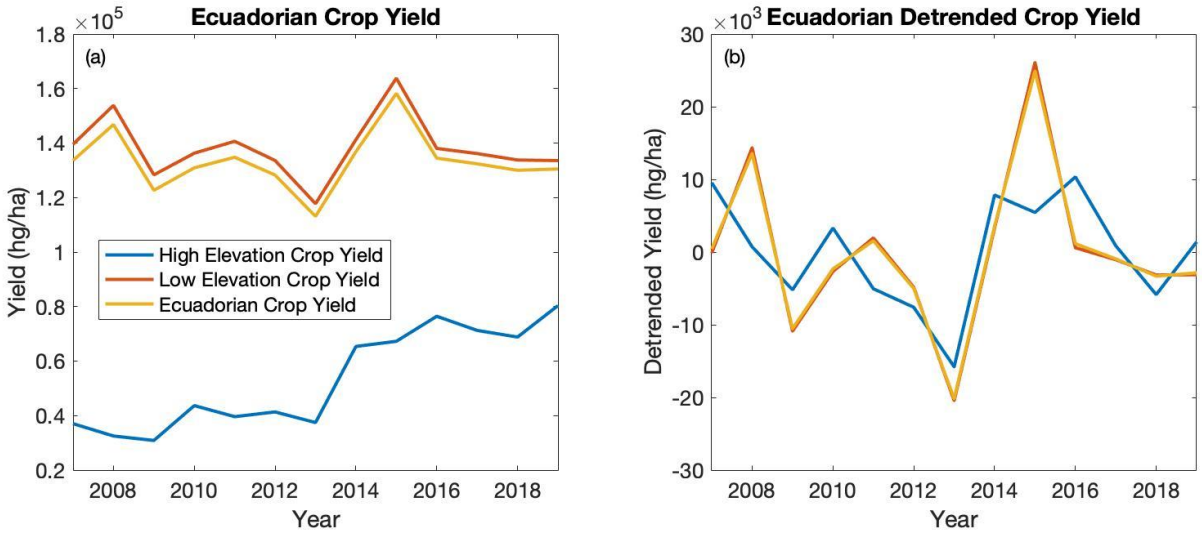

Figure 1: The Ecuadorian calculated annual yield of key crops at both the national and regional scale. The overall calculated yield for each region (a), and the detrended calculated yield (b) for each region from 2007-2019.

After calculating the annual crop yield for each region of interest for this study, the spatial ecological characteristics of Ecuador were analyzed. We spatially aggregated monthly average maximum temperature, monthly average SIF, and monthly average soil moisture with

elevation. Each of these ecological variables were then annually averaged and plotted with elevation to illustrate the differences of environmental conditions across Ecuador. Notably, each of the conditions were driven in part by the topography of the region. The average SIF observations generally decreased as elevation increased. However, both the highest and the lowest SIF observations in Ecuador were found at the lowest elevation. As we expected, the highest SIF values were located on the eastern side of the Andes, over the Ecuadorian Amazon Rainforest. The data also indicates a trend of higher levels of SIF on the northwestern side of the Andes as well, aligning with the cloud forest environments enforced by Ecuador's double rain-shadow effect and high water availability [14]. The lowest levels of SIF observations are located along the western coast of Ecuador where there tends to be desert conditions. We found that the SIF measurements produced are consistent with the general type of ecosystem in each region.

The maximum temperature observations were most strongly correlated with elevation. Located along the Equator, there tends to be high temperature conditions across Ecuador at low elevations. However, in accordance with the environmental lapse rate, as altitude increases the temperature decreases. The highest elevation points of Ecuador were found to have the lowest annual average maximum temperature.

There were many gaps in the soil moisture data available in Ecuador for the time period of interest. The soil moisture measurements were only obtainable in Southwestern Ecuador, a low elevation area that features high temperatures and low SIF measurements. After plotting the spatial annually-averaged climatology of the country, we investigated which region had higher levels of agricultural intensity.

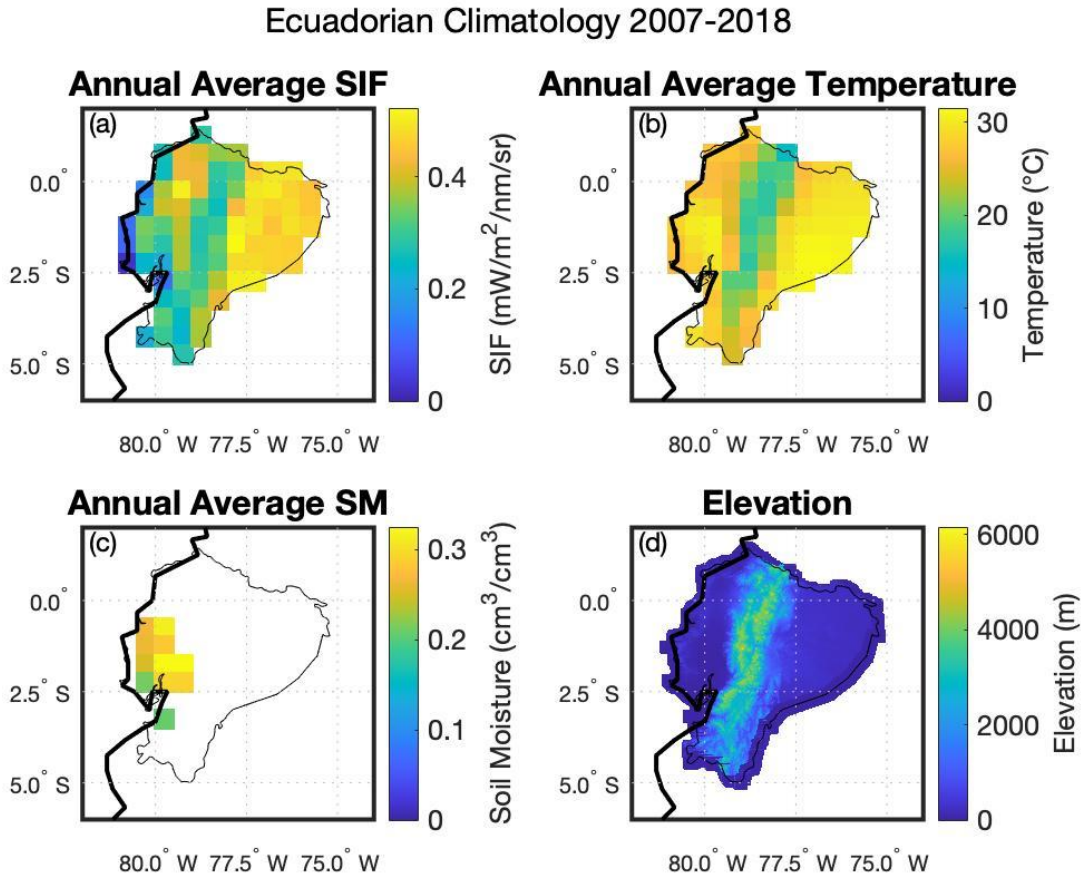

Figure 2: Ecuadorian Spatial Climatology from 2007-2018. The annual average SIF observations (a), annual average maximum temperature (b), annual average soil moisture at 0.25-degree resolution (c), and average elevation at 500m-grid resolution(d).

To illustrate the levels of agricultural intensity across different regions in Ecuador, the fraction of 500m croplands for each 0.25-degree grid was calculated. The highest fraction of cropland was found to be located in the southwestern region, with a maximum of 51% agricultural coverage within a grid. Though agriculture is also present across the upper Andean region, the fraction of cropland was significantly lower than the western region. No cropland was detected in Eastern Ecuador.

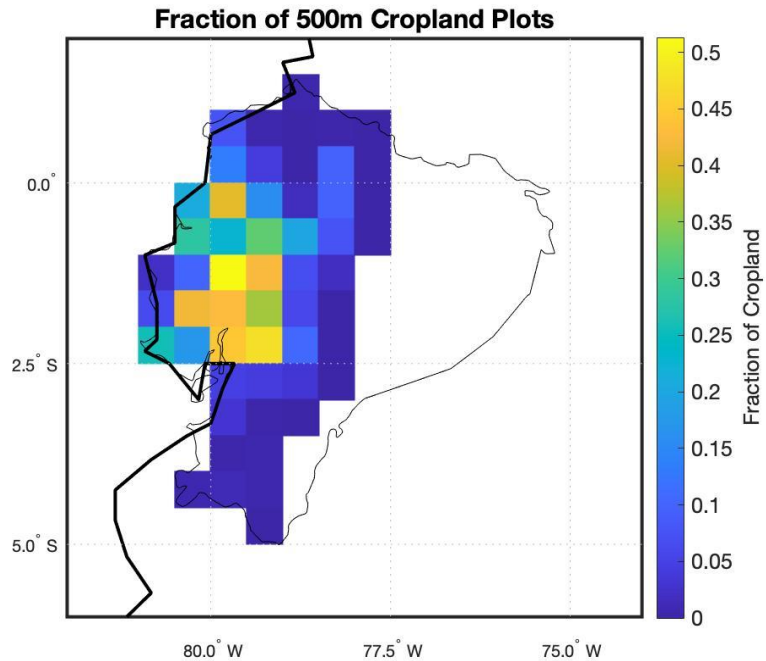

Figure 3: The fraction of 500m-gridded cropland within each 0.25 degree grid.

After finding the relative distribution of croplands in Ecuador, we split the croplands into two elevation-based regions for analysis. To do so, we first referenced the distribution of croplands across different elevations with a histogram. We noticed a transition between low elevation croplands and high elevation croplands, as there was a bimodal distribution between all the croplands. The regions were split at the trough between these two peaks, at around 2000m. All croplands below 2000m were assigned to the low elevation group, while all croplands above 2000m were assigned to the high elevation group. Each of these groups was then compared to their respective calculated regional crop yield. The high elevation croplands and low elevation croplands were both plotted on a map of Ecuador, to better visualize the spatial distribution of these croplands.

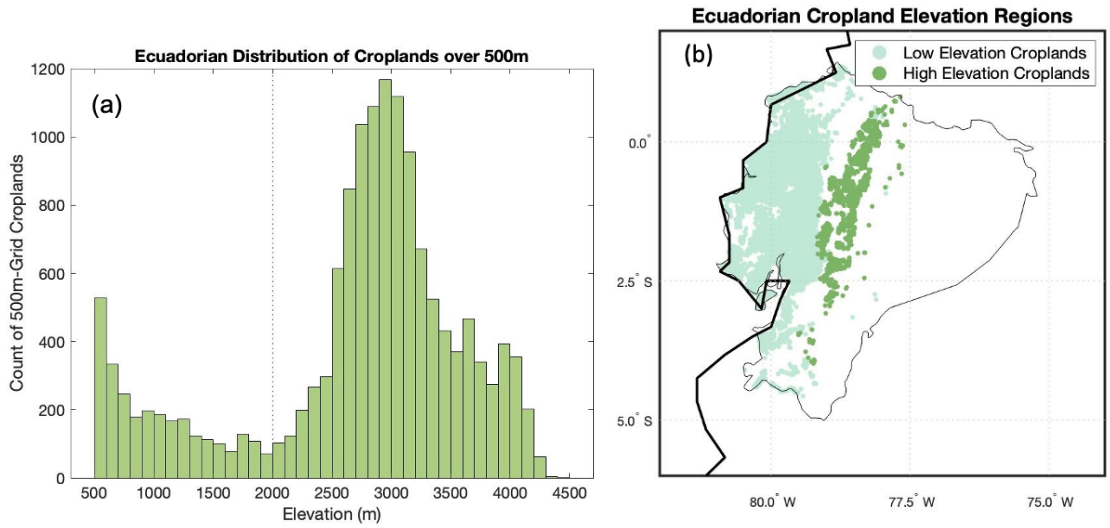

Figure 4: The elevation distribution of Ecuadorian croplands. (a) The numerical distribution of Ecuadorian croplands over an altitude of 500m. All croplands below an altitude of 500m were omitted from this distribution to better visualize the transition from low elevation croplands to high elevation croplands. In our analysis, all croplands below an altitude of 2000m were included in the low elevation region, while all croplands above an altitude of 2000m were included in the high elevation region. (b) The spatial distribution of each cropland region in Ecuador.

Once the cropland regions of interest were spatially identified, we explored the growing season by plotting the monthly-averaged SIF observations for each region. It was assumed that the months during the growing season would contain the highest observed levels of SIF. The low elevation cropland regions contained the highest averages of SIF, at about 0.38 $mW/m^2/nm/sr$. All regions had two peaks, February to April and September to November; however, the first peak for the lower elevation regions was more distinguished than the second peak. Upon first glance, the monthly-averaged SIF levels in the lower elevation region was observed to have a growing season from February to April, while the higher elevation region was observed to include both SIF peaks, from February to April and September to November. In order to confirm this hypothesis, we ran a linear regression between the annually-calculated yield value and the seasonal SIF observations for the twelve year time period.

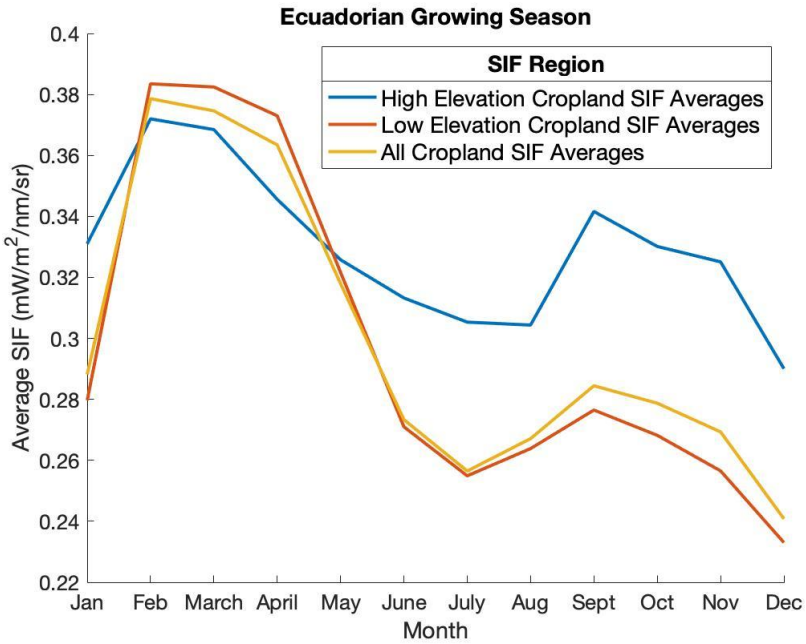

Figure 5: Monthly-averaged SIF observations for each region of interest, averaged across the twelve years of interest.

The growing season of each region was determined by finding the monthly SIF observations that best described the respective calculated annual yield through a linear regression. This analysis indicated that the growing season for all croplands in Ecuador was from January to April; the growing season for the low elevation croplands were from January to April; and the growing season for the high elevation croplands were from January to April and September to December. This moderately aligns with the rainy season in Ecuador, where there tends to be a heavier rainfall season in February to May, and a lighter rainfall season from October to late November [47]. We postulate that the atmospheric lapse rate can describe the importance of the second rainfall season at the higher elevations, as there is a greater chance for the formation of clouds and precipitation at higher altitudes.

Once the growing season was determined for each region, seasonal SIF averages were calculated by averaging the months of the growing season for each year. This seasonal average

was then detrended and compared to the detrended calculated crop yield for each region. The Pearson correlation coefficient between the detrended values for SIF and yield was evaluated for each Ecuadorian region. The higher elevation region had the highest correlation coefficient, at about 0.41. The lower elevation region followed at 0.26, and all croplands had a correlation of 0.20. However, if the detrended calculated yield were compared to the annually-averaged SIF observations rather than the seasonally-averaged SIF observations, the correlation increased to about 0.44 for high elevations, 0.38 for low elevations, and 0.36 for all of Ecuador. Nevertheless, the previously determined growing seasons for SIF were utilized in the linear regressions in comparing temperature and soil moisture variations to agricultural yield, as they characterized the strongest model of describing the calculated annual yield.

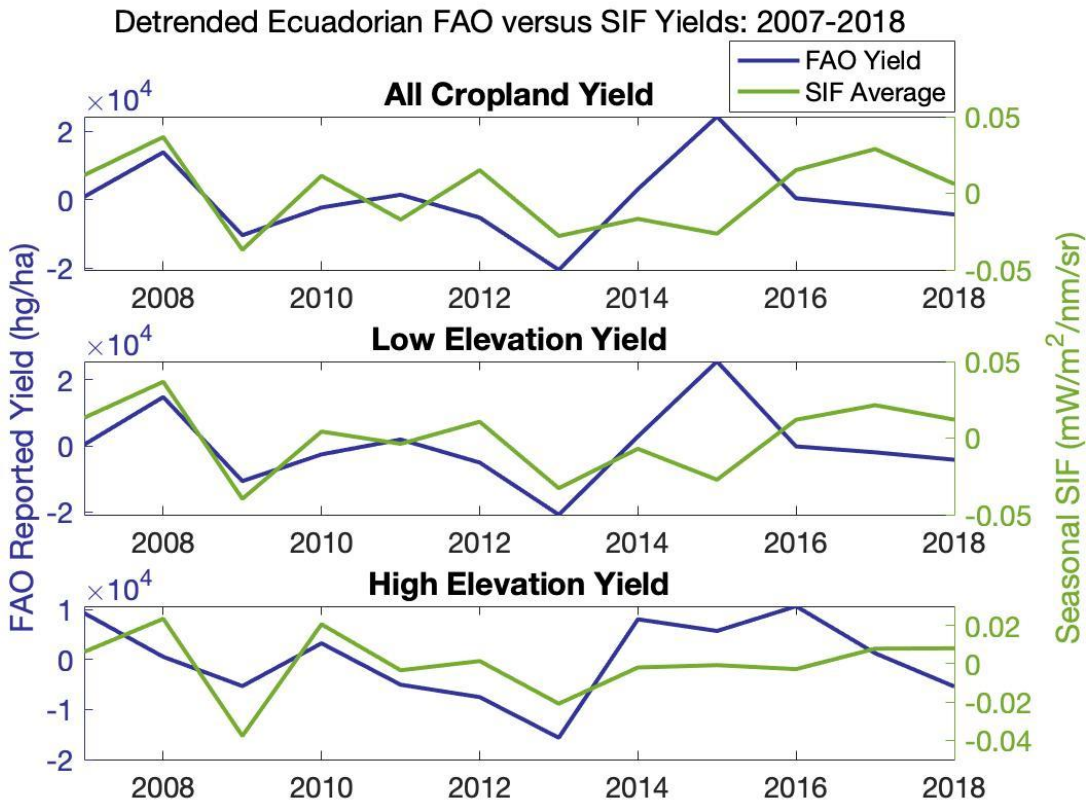

Figure 6: The detrended annual agricultural yield compared to the detrended seasonal SIF observations within each region during the twelve year period.

Determining the growing season of each region allowed us to further calculate whether the temperature and soil moisture variations could describe the variations of agricultural yield within each region. Though our findings did not find a strong relationship between seasonal SIF observations and crop yield as was found in Rigden et al., the spatial and temporal effect of soil moisture and temperature on SIF were analyzed as a way to further investigate how changing climatic conditions are affecting the Andes [35]. We first seasonally averaged the maximum temperature, soil moisture, and SIF observations over the growing season for the twelve year period. To better visualize the temporal shifts of each of these statistics over each region, the detrended temperature, soil moisture, and SIF of each region were plotted against each other. While higher elevations generally have lower temperatures, soil moisture, and SIF observations,

the variations in temperature are fairly correlated across regions. Of note, the peaks in seasonal temperatures in 2013 and 2016 align with the annual drops in Ecuadorian crop yields across all the regions of those same years. The seasonal average SIF observations also decrease over the twelve year time period across the regions.

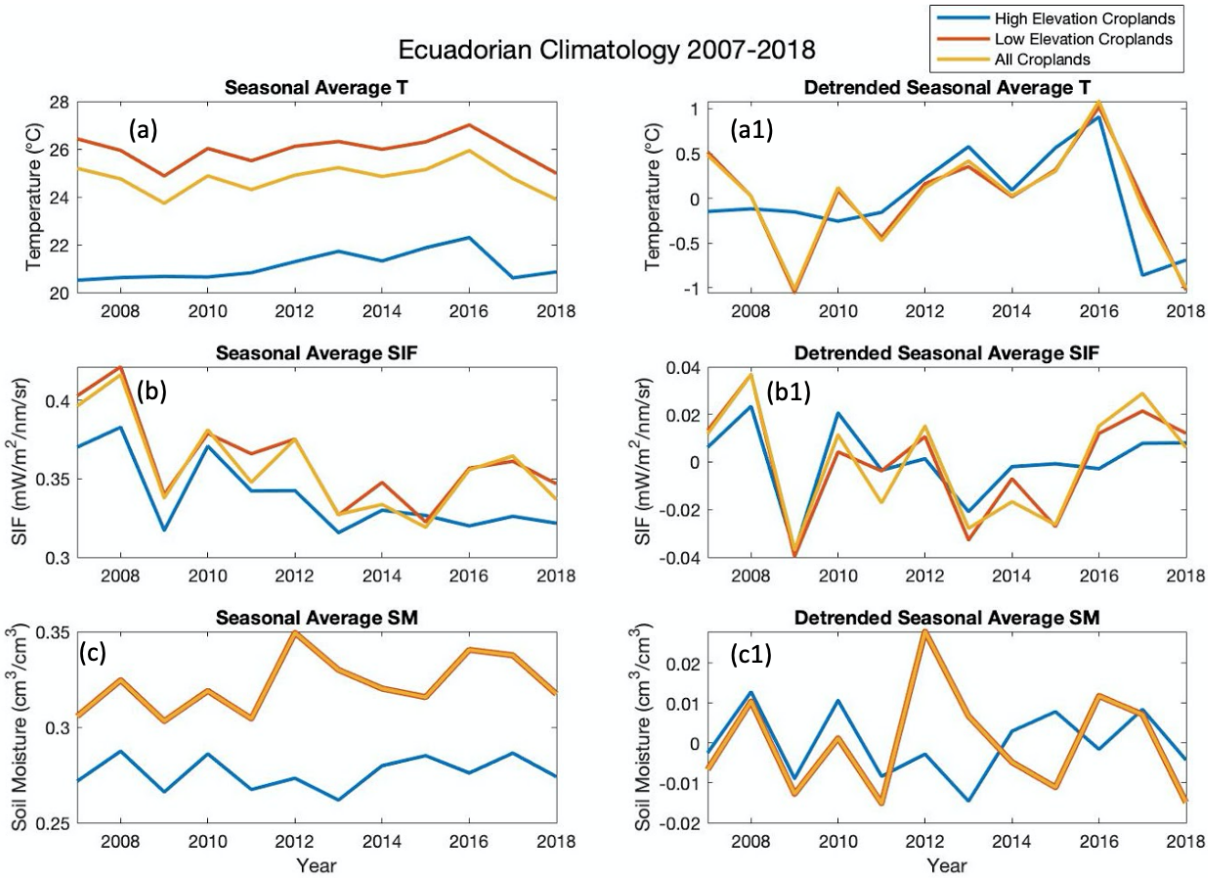

Figure 7: The Ecuadorian seasonal average maximum temperature (a), SIF (b), and soil moisture observations during the twelve year period (c). Each of these ecological factors were detrended to visualize the variations from the mean for each season. The variations in seasonal average maximum temperature (a1), seasonal average SIF (b1), and seasonal average soil moisture (c1) are shown above.

We explored the spatial and temporal effect of seasonal soil moisture and temperature on seasonal SIF observations by performing multivariate linear regressions at each regional scale. The temporal linear regressions that focused on the relationship between soil moisture and SIF observations over time were found to be significant, with a p-value below 0.05; however, this

finding is questionable due to the lack of soil moisture available in Ecuador. The only significant temporal linear relationship between temperature and SIF was found to be in the high elevation croplands, but the p-value regarding the sensitivity coefficient was not significant (0.33). The spatial linear regressions were all found to be insignificant. However, the regressions found to have the strongest statistical significance were those that measured the temporal and spatial variations of seasonal temperature and soil moisture with SIF observations through the panel estimate model. This could be attributed to the large amount of data available to analyze across the whole spatial and temporal range.

Though not many of these relationships were statistically significant, it is important to note the sensitivity coefficients found across all of these regressions. As we observed in *Figure 7*, SIF observations are expected to decrease over time, aligning with the negative sensitivity coefficient given to the year in our temporal regressions. The sensitivity coefficient of soil moisture was consistently positive, while the sensitivity coefficient of temperature had more variability depending on the model. From this we can assume that increasing soil moisture can lead to an increase of crop yields, however the confidence intervals do not confirm this assumption.

The confidence intervals of both soil moisture and temperature show that even though there may be some consistency in the predicted sensitivity coefficients, it's possible that each of these variables could have a positive or negative influence on SIF observations--temporally and spatially. Overall, these regressions did not find a reliable linear model to describe the relationship between seasonal SIF, temperature, and soil moisture.

Ecuadorian Croplands							
All Croplands	Linear Regression	α	β	Equation Predicted	Adj. R^2	Conf. Interval	P-Value
temporal variation	SIF ~ αSM + βYr	1.009	-0.007	SIF = 13.538 + 1.0089*SM* - 0.0067*Yr*	0.451	SM: -0.1265 2.1443	0.03
	SIF ~ αTMax + βYr	0.011	-0.005	SIF = 10.265 + 0.011*TMax* - 0.005*Yr*	0.262	Tmax: -0.0183 0.0399	0.10
	SIF ~ αSM + βTMax + Yr	1.048	-0.002	SIF = 13.656 + 1.048*SM* - 0.0016*TMax* - 0.0068*Yr*	0.384	SM: -0.4039 2.4998 TMax: -0.0337 0.0305	0.08
spatial variation	SIF ~ αSM + βTMax	0.330	0.018	SIF = -0.025 + 0.33*SM* + 0.018*TMax*	0.01	SM: -0.9203 1.5825 TMax: -0.0152 0.0518	0.39
temporal + spatial variation	SIF ~ αSM + βTMax + Yr + Pixels	0.280	0.025	*Equation Omitted*	0.259	SM: -0.8233 1.3882 TMax: -0.0026 0.0522	3.9E-06
Low Elevation Croplands							
temporal variation	SIF ~ αSM + βYr	0.720	-0.006	SIF = 12.792 + 0.72*SM* - 0.0063*Yr*	0.37	SM: -0.4751 1.9141	0.05
	SIF ~ αTMax + βYr	0.008	-0.005	SIF = 10.33 + 0.0083T*Max* - 0.0051*Yr*	0.275	TMax: -0.0202 0.0368	0.10
	SIF ~ αSM + βTMax + Yr	0.734	-0.001	SIF = 12.844 + 0.73*SM* - 0.00058*TMax* - 0.0063*Yr*	0.291	SM: -0.8075 2.2751 TMax: -0.0349 0.0337	0.13
spatial variation	SIF ~ αSM + βTMax	0.330	0.018	SIF = -0.25 + 0.33*SM* + 0.018*TMax*	0.01	SM: -0.9203 1.5825 TMax: -0.0152 0.0518	0.39
temporal + spatial variation	SIF ~ αSM + βTMax + Yr + Pixels	0.280	0.025	*Equation Omitted*	0.26	SM: -0.8233 1.3882 TMax: -0.0026 0.0522	3.9E-06
High Elevation Croplands							
temporal variation	SIF ~ αSM + βYr	1.460	-0.005	SIF = 10.26 + 1.46*SM* - 0.0051*Yr*	0.74	SM: 0.5194 2.4029	9.3E-04
	SIF ~ αTMax + βYr	-0.010	-0.004	SIF = 8.09 - 0.01*TMax* - 0.0037*Yr*	0.45	TMax: -0.0334 0.0128	0.03
	SIF ~ αSM + βTMax + Yr	1.390	-0.005	SIF = 9.53 + 1.39*SM* - 0.0049*TMax* - 0.0047*Yr*	0.72	SM: 0.3740 2.4137 TMax: -0.0220 0.0123	3.7E-03
spatial variation	SIF ~ αSM + βTMax	1.980	0.120	SIF = -3.42 + 1.98*SM* - 0.12*TMax*	NaN		NaN
temporal + spatial variation	SIF ~ αSM + βTMax + Yr + Pixels	3.820	0.017	*Equation Omitted*	0.393	SM: 1.1367 6.5118 TMax: -0.0281 0.0628	9.9E-04

Table 3: The Ecuadorian spatial and temporal sensitivity estimates of temperature and soil moisture on SIF observations.

After conducting linear regressions on the spatial and temporal effects of soil moisture and maximum temperature on SIF, the relationship between variations of soil moisture, maximum temperature, and SIF observations with the variations in annual crop yield were then

analyzed for each region. Each ecological feature was averaged over the croplands and growing season for each region to be compared on the annual scale with its respective calculated crop yield. To compare the variations of each ecological factor with the variations in yield, each variable was detrended over the twelve year time period and then compared.

Across the regional analyses, each of the linear models were not found to be quantitatively statistically significant, except for the relationship with soil moisture variation at high elevation yield. However, this is doubtful due to the lack of soil moisture data available in this region. The sensitivity coefficients were also not reliable, as they each had a confidence interval reflecting they could create either a positive or negative response to variations in yield. Each of these linear models to describe Ecuadorian crop yield, either via an annual crop yield route or through spatial measurement of productivity, proved to be unreliable with the data available.

Ecuadorian Yield						
Total Yield	Linear Regression	α	Equation Predicted	Adj. R^2	Conf. Interval	P-Value
	Detrended Yield ~ α (Detrended SM)	-1.38E+05	DYield = -6.4679E-12 - 1.3776E5(DSM)	-0.071	1.0e+05 * DSM: -7.2473 4.4920	0.61
	Detrended Yield ~ α (Detrended TMax)	3.42E+03	DYield = 3.9579E-11 + 3422.1(DTMax)	-0.063	1.0e+04 * DTMax: -0.9509 1.6353	0.57
	Detrended Yield ~ α (Detrended SIF)	9.13E+04	DYield = 8.6899E-13 + 91328(DSIF)	-0.058	1.0e+05 * DSIF: -2.3055 4.1320	0.54
Low Elevation Yield						
	Detrended Yield ~ α (Detrended SM)	-1.43E+05	DYield = -9.07E-12 - 1.43E5(DSM)	-0.071	1.0e+05 * DSM: -7.5022 4.6485	0.61
	Detrended Yield ~ α (Detrended TMax)	3.79E+03	DYield = 1.16E-11 + 3786.5(DTMax)	-0.058	1.0e+04 * DTMax: -0.9644 1.7217	0.54
	Detrended Yield ~ α (Detrended SIF)	1.32E+05	DYield = 2.07E-11 + 1.32E5(DSIF)	-0.025	1.0e+05 * DSIF: -2.0993 4.7314	0.41
High Elevation Yield						
	Detrended Yield ~ α (Detrended SM)	5.42E+05	DYield = 6.50E-11 + 5.42E5(DSM)	0.280	1.0e+06 * DSM: 0.0163 1.0670	0.04
	Detrended Yield ~ α (Detrended TMax)	1.70E+03	DYield = -1.29E-11 + 1697.5(DTMax)	-0.087	1.0e+04 * DTMax: -0.9150 1.2545	0.74
	Detrended Yield ~ α (Detrended SIF)	1.94E+05	DYield = -2.78E-12 + 1.94E5(DSIF)	0.081	1.0e+05 * DSIF: -1.1462 5.0309	0.19

Table 4: The sensitivity of Ecuadorian yield variability to the variability of maximum seasonal temperature, seasonal soil moisture, and seasonal SIF observations.

Though the estimated linear models of variations in environmental factors to describe Ecuadorian yield were not found to be significant, the variations of crop yield, temperature, soil moisture, and SIF observations were still plotted along with their respective linear models to visualize the relationship. As we can see in *Figure 8*, with each marker representing a year during the twelve year period, there was no visible trend across regions and variables. With the given data, there was no relationship found across these factors during the time period of interest.

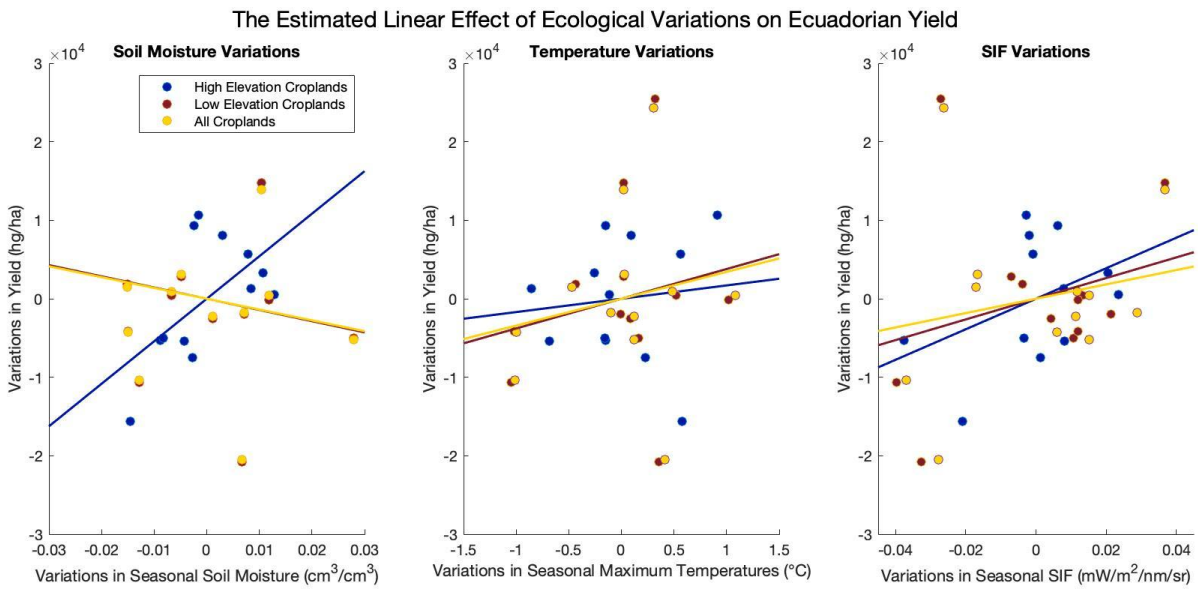

Figure 8: The estimated linear model of ecological variations describing variations in Ecuadorian agricultural yield. These models were not found to be statistically significant.

Peruvian Analyses

After concluding our analyses regarding Ecuadorian agricultural trends and variations, we then began the same process to evaluate whether Peruvian croplands at different elevations had similar results. First, the representative crop yield for all Peruvian croplands, low elevation Peruvian croplands, and high elevation Peruvian croplands were calculated based on the identified key crops in each region. Unlike Ecuador, we found that the high elevation annual crop yield was significantly greater than the low elevation annual crop yield. Similar to Ecuador, while the yield of low elevation crops tended to be fairly stagnant, the high elevation crop yields steadily increased across the time period. When analyzing the detrended crop yields of each region, there has not been as much variation in yield year-to-year in Peru as compared to Ecuador. There are dips in crop yield across each region in 2010 and 2016, but there is also a shared peak of higher crop yields in 2012. After quantifying the annual crop yield of each Peruvian region, we then investigated the spatial ecological characteristics of Peru.

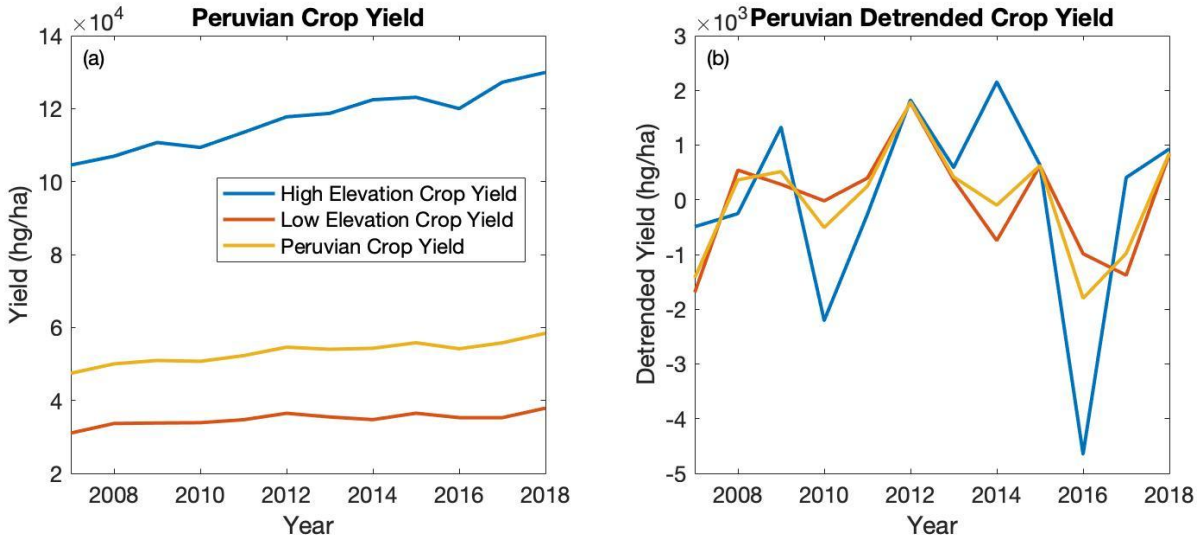

Figure 9: The Peruvian calculated annual yield of key crops at both the national and regional scale. The overall calculated yield for each region (a), and the detrended calculated yield for each region (b) from 2007-2018.

We analyzed the climatology of Peru from 2007 to 2018 by finding the annual average of the maximum temperature, soil moisture, and SIF observations in each 0.25-degree grid. This data was plotted with elevation to illustrate the different ecosystems present across Peru. Similar to Ecuador, we find that each of the ecological factors correlate with the topography of the region. The lowest temperatures present in Peru are located at the highest elevations, again in accordance with the environmental lapse rate. However, annually-averaged SIF measurements differed significantly between the western and eastern side of the Andes. Due to the singular rain-shadow effect from the east, there are higher levels of SIF from the Peruvian Amazon Rainforest to the eastern side of the Andes [12]. On the western side of the Andes, SIF measurements are lower, corresponding to the dry conditions on the Peruvian coast.

Unlike Ecuador, there was a substantially higher availability of soil moisture measurements in Peru. The Andean region was noted to have higher levels of soil moisture than the western coast of Peru. Soil moisture measurements were mostly missing from the Amazonian region, however, the few that were recorded featured the highest levels of soil moisture. Generally, each of these ecological measurements aligned with the type of environment of each region. After examining the spatial distribution of elevation along with annual average SIF, maximum temperature, and soil moisture, we investigated the distribution of croplands throughout these regions.

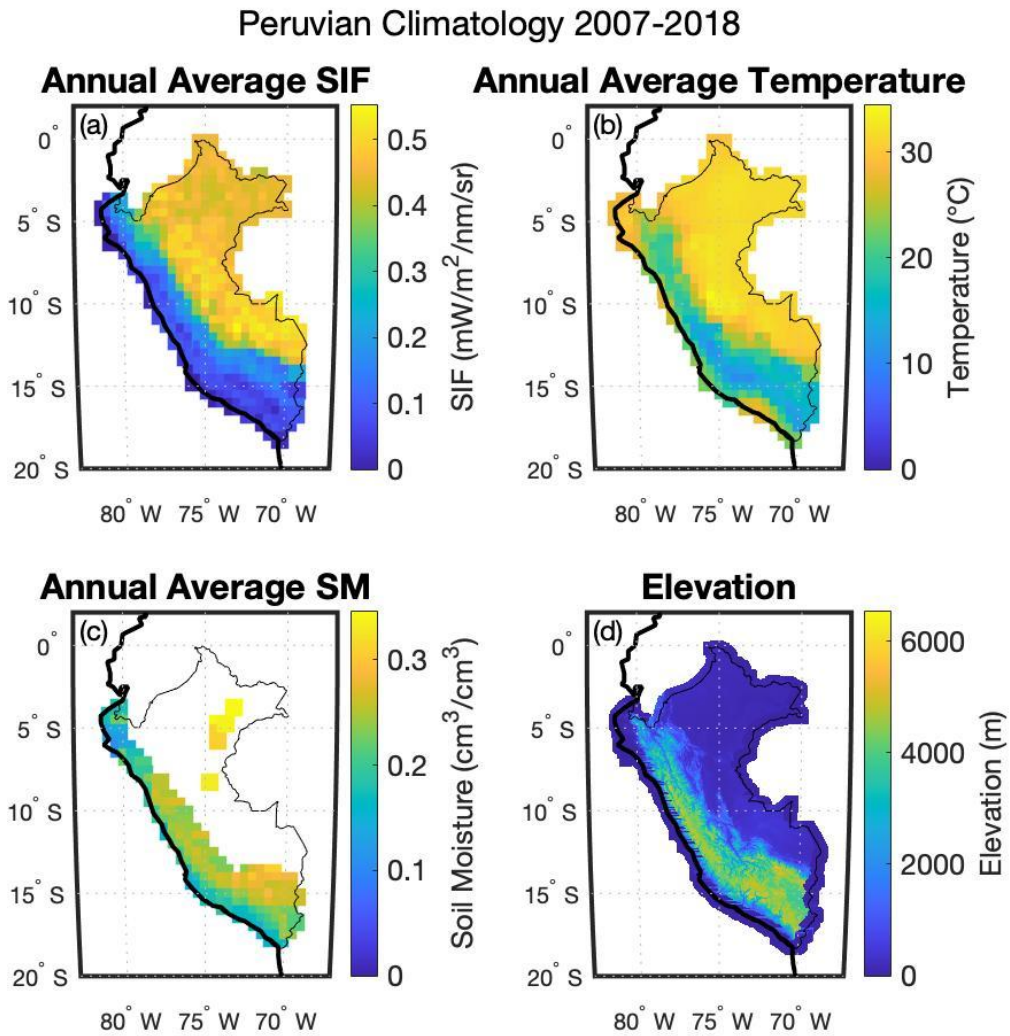

Figure 10: Peruvian Spatial Climatology from 2007-2018. The annual average SIF observations (a), annual average maximum temperature (b), annual average soil moisture at 0.25-degree resolution (c), and average elevation at 500m-grid resolution(d).

When calculating the fraction of 500m croplands within each 0.25-degree grid, we found that cropland tended to be fairly evenly distributed across different environments in Peru. However, the grids with the highest fraction of croplands were located in Northwestern Peru, along the coast, and Southeastern Peru, near Lake Titicaca. There were also higher fractions of cropland found dispersed across the high Andes. None of these fractions were quite as high as

the highest fraction found in Ecuador, showing that agricultural intensity tends to be lower and more dispersed across the country.

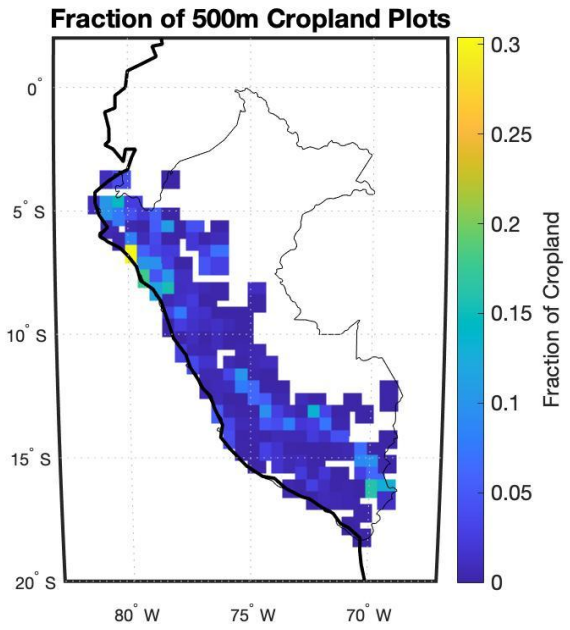

Figure 11: The fraction of 500m-gridded cropland within each 0.25 degree grid.

After finding that croplands tend to be relatively evenly distributed across Peru, we sought out to split the croplands into two regions based on elevation. While in Ecuador, we were able to split the cropland regions at 2000m, in Peru we determined the 2000-2500m range to be a "transition" area between the lowlands and highlands. We did this to accommodate the fact that coffee, a key "lowlands" crop, can reach an elevation around or slightly above 2000m [48]. The low elevation croplands were identified to be all croplands below an elevation of 2500m, while the high elevation croplands were above an elevation of 2000m. We later confirmed this split that accounted for the transition area by comparing the annual average SIF of each cropland region to their respective calculated regional crop yield. The higher elevation croplands, lower elevation croplands, and transitory croplands were all plotted on a map of Peru to illustrate the spatial distribution of these croplands.

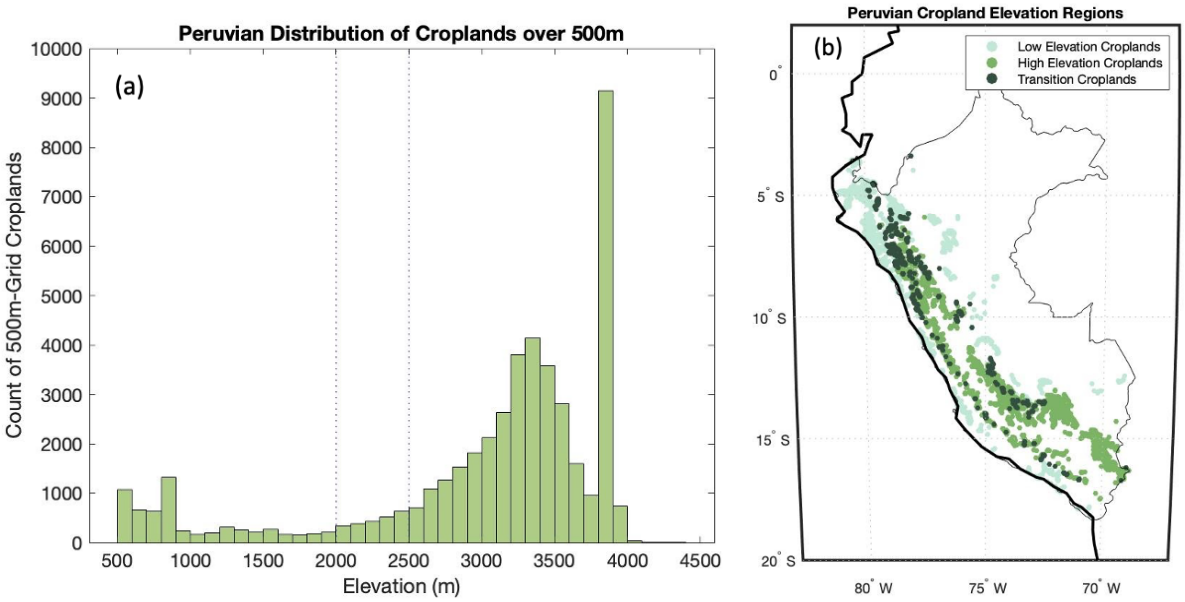

Figure 12: The elevation distribution of Peruvian croplands. (a) The numerical distribution of Peruvian croplands over an altitude of 500m. All croplands below an altitude of 500m were omitted from this distribution to better visualize the transition from low elevation croplands to high elevation croplands. In our analysis, all croplands below an altitude of 2500m were included in the low elevation region, while all croplands above an altitude of 2000m were included in the high elevation region. (b) The spatial distribution of each cropland region in Peru.

After splitting the croplands into their respective elevation groups, we defined the growing season for each region by plotting the monthly-averaged SIF observations over the twelve year period. Generally, we found that SIF observations were lower than those found in Ecuador, with the maximum reaching about 0.26 mW/m^2/nm/sr. Furthermore, unlike Ecuadorian croplands, the lowlands seemed to have two peaks in SIF measurements while the highlands had one distinct growing season. There were peaks in SIF across all regions from February to April, and the lowlands seemed to have a second from October to November. To confirm the growing season for each of these regions, we ran a series of linear regressions to determine which permutation of different months would create a seasonal SIF value that best described the annually calculated crop yield in each region.

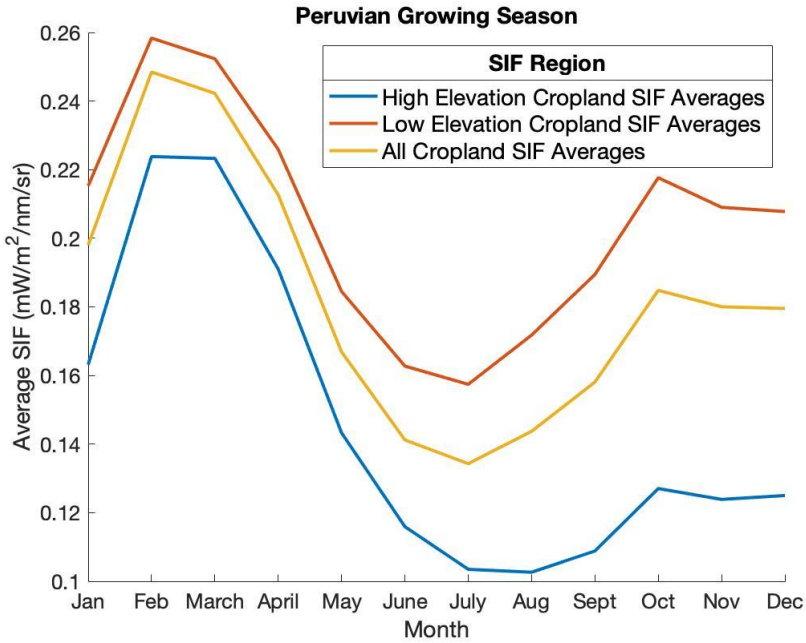

Figure 13: Monthly-averaged SIF observations for each region of interest, averaged across the twelve years of interest.

After running the linear regression, the growing season was determined to be from January to April for all regions across Peru. This growing season aligns with the rainy season in Peru, with the wettest months also being from January to April [49]. Determining the growing season allowed us to then identify the seasonal SIF, maximum temperature, and soil moisture observations by averaging the months of the growing season for each year. The seasonal SIF observations were then detrended and compared to the detrended crop yield calculated for each region. Interestingly, each of the regions had a negative correlation between the variations in seasonal SIF averages and the variations in the calculated annual yield for each respective region. The Pearson correlation coefficient for all croplands was the highest at -0.71, with the high elevation croplands following at -0.57 and the low elevation croplands at -0.49.

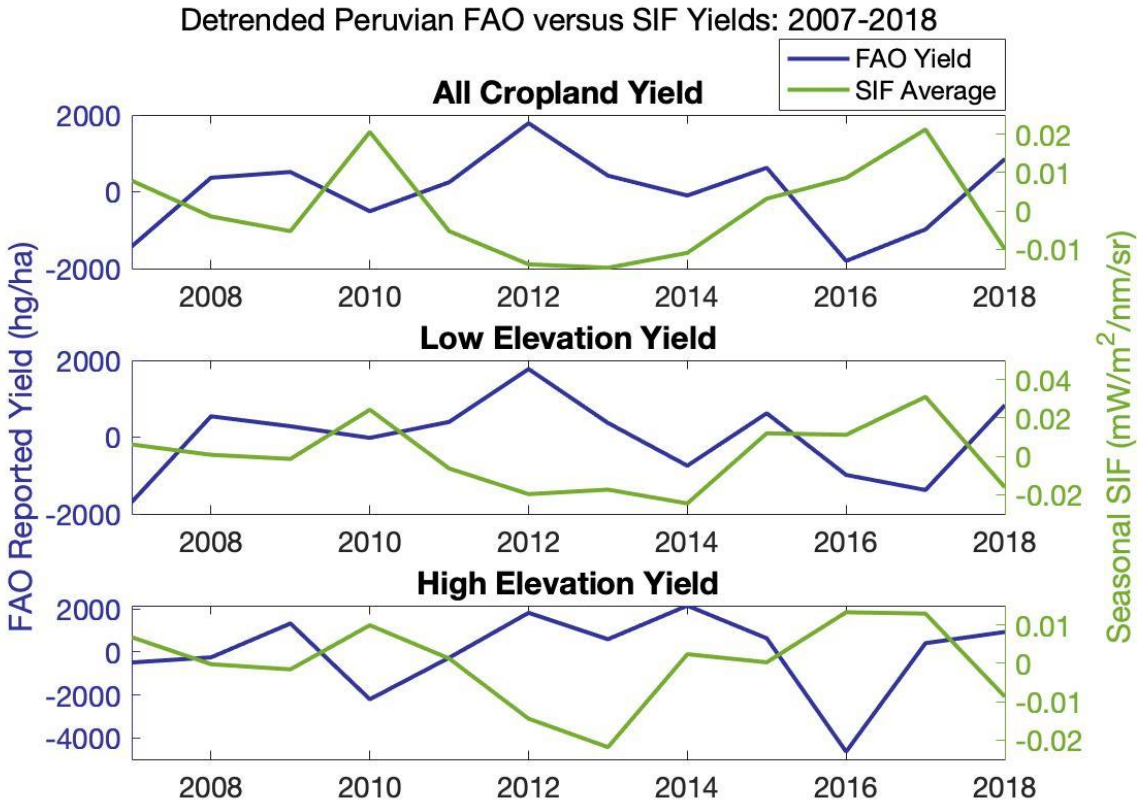

Figure 14: The detrended annual agricultural yield compared to the detrended seasonal SIF observations within each region during the twelve year period.

Though our findings did not find a positive relationship between seasonal SIF observations and crop yield, the seasonal maximum temperature, soil moisture, and SIF observations were still calculated to compare across regions. As we expected, the high elevation croplands had the lowest seasonal temperatures and SIF observations in comparison to the other regions across the twelve year period. However, the highlands also experienced the highest levels of soil moisture. The lowlands experienced the highest seasonal average temperature and the lowest levels of seasonal soil moisture in comparison to the other regions.

Despite each region being very distinct in it's average climatic and vegetation characteristics, the same variations across the time series are apparent across all regions for each ecological factor. When analyzing the detrended plots, each region is nearly overlapping with the

other when describing variations from their respective seasonal average temperature and soil moisture measurements. Though the variations in SIF are not quite as similar, correlations are still discernible between the regions. We see similar variations of seasonal average temperature between Peru and Ecuador, where there are peaks during 2010, 2013, and 2016. These peaks in temperature also align with the years containing drops in Peruvian seasonal average soil moisture and crop yields. We see that across the regions, seasonal average SIF seems to have been decreasing from 2010 until around 2014, before increasing again to 2017 and after decreasing. While the variations in temperature and soil moisture seem to range from year to year, the variations in SIF seem to extend over longer periods of time.

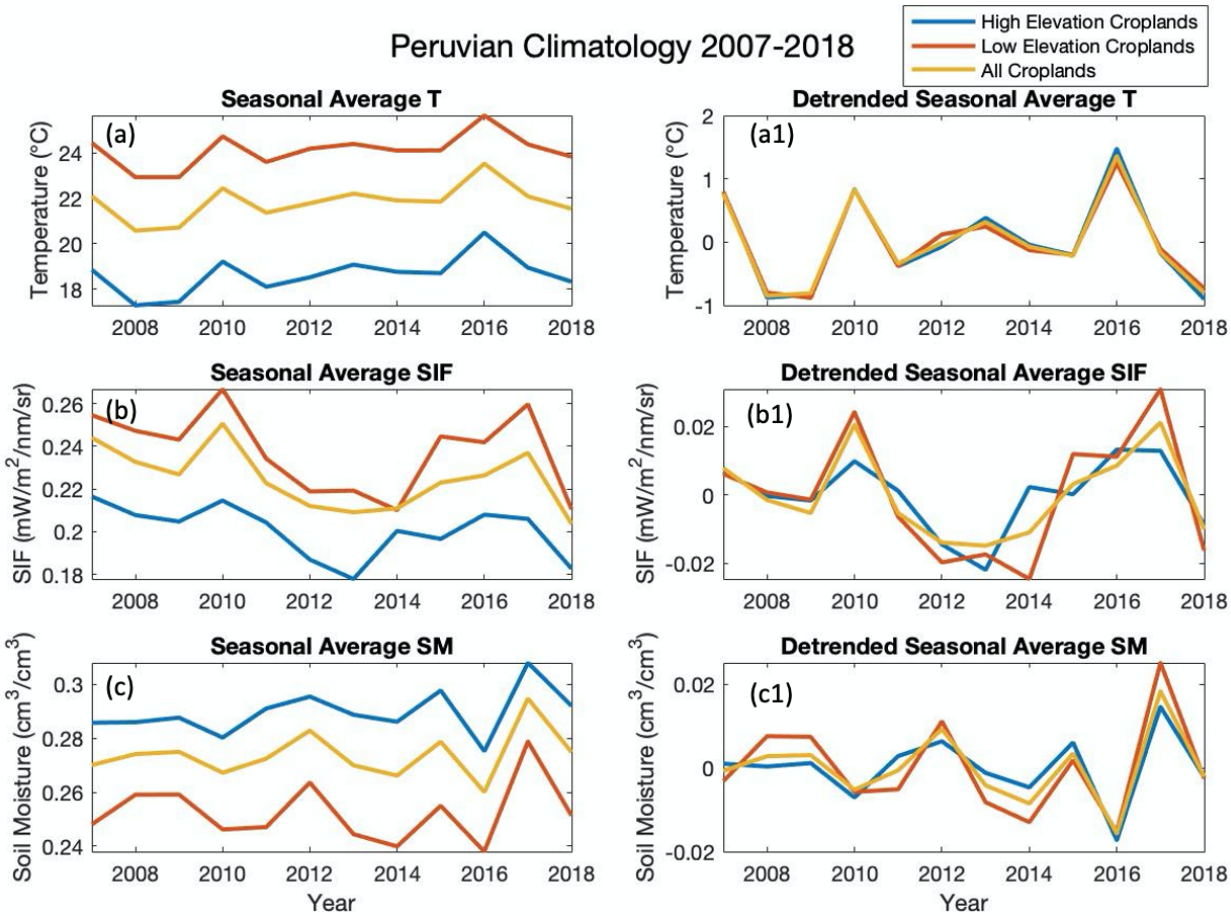

Figure 15: The Peruvian seasonal average maximum temperature (a), SIF (b), and soil moisture observations during the twelve year period (c). Each of these ecological factors were detrended to visualize the variations from the mean for each season. The variations in seasonal average

maximum temperature (a1), seasonal average SIF (b1), and seasonal average soil moisture (c1) are shown above.

After visualizing the trends and variability of each ecological factor over the twelve year period, we performed the same spatial and temporal multivariate linear regressions of seasonal soil moisture and temperature on seasonal SIF observations at the regional scale. Similar to the Ecuadorian tests, the temporal models were found to be statistically insignificant, while both the spatial, and the spatial and temporal, tests were found to be statistically significant.

While the confidence intervals of the time series sensitivity estimates were found to not be reliable for either soil moisture or temperature, with the prediction ranging from a negative to a positive impact on SIF observations, soil moisture proved to have a higher confidence of having a positive relationship with SIF. Across both the low elevation cropland group and the total cropland group, the time series sensitivity coefficient of soil moisture was positive, with a confidence interval spanning from a negative to a positive influence. However, across all regions the cross-sectional and panel soil moisture sensitivity estimate and its corresponding confidence interval was positive--further justifying that an increase of soil moisture would increase the SIF observations of a region. Temperature was more variable in its effect on SIF, with smaller sensitivity coefficients and a confidence interval that ranged between a negative or positive influence on SIF observations. In comparison to the sensitivity coefficient of soil moisture, the sensitivity of SIF to temperature was nearly three magnitudes lower across all regions. In the panel estimates, where the sensitivity coefficient of soil moisture became more certainly positive, the sensitivity to temperature remained fluctuant.

While the linear models produced may not have been statistically significant as a whole, it still gave us insight into the sensitivity of seasonal SIF observations to changing temperatures and shifting soil moisture. These suggest that soil moisture could be the driving force behind

changes in productivity relative to temperature. We proceeded to test the temporal linear relationship between variations in soil moisture, temperature, and annual crop yield to see whether we would find similar results across the same regions.

Peruvian Croplands							
All Croplands	Linear Regression	α	β	Equation Predicted	Adj. R^2	Conf. Interval	P-Value
temporal variation	SIF ~ αSM + βYr	0.220	-0.002	SIF = 4.53 + 0.22*SM* - 0.0022*Yr*	0.116	SM: -0.8553 1.2962	0.232
	SIF ~ αTMax + βYr	0.008	-0.003	SIF = 5.6 + 0.0077*TMax* - 0.0028*Yr*	0.27	TMax: -0.0043 0.0198	0.100
	SIF ~ αSM + βTMax + Yr	0.730	0.012	SIF = 6.96 + 0.73*SM* + 0.012*TMax* - 0.0036*Yr*	0.369	SM: -0.3469 1.8047 TMax: -0.0009 0.0255	0.087
spatial variation	SIF ~ αSM + βTMax	1.990	0.010	SIF = -0.58 + 1.99*SM* + 0.0099*TMax*	0.434	SM: 1.5355 2.4398 TMax: 0.0062 0.0136	2.15E-13
temporal + spatial variation	SIF ~ αSM + βTMax + Yr + Pixels	0.960	0.004	*Equation Omitted*	0.551	SM: 0.6144 1.3078 TMax: -0.0022 0.0096	4.69E-151
Low Elevation Croplands							
temporal variation	SIF ~ αSM + βYr	0.550	-0.002	SIF = 4.33 + 0.55*SM* - 0.002*Yr*	0.078	SM: -0.5513 1.6497	0.281
	SIF ~ αTMax + βYr	0.009	-0.003	SIF = 5.46 + 0.0087*TMax* - 0.0027*Yr*	0.066	TMax: -0.0097 0.0272	0.298
	SIF ~ αSM + βTMax + Yr	0.960	0.016	SIF = 6.70 + 0.96*SM* + 0.016*TMax* - 0.0035*Yr*	0.314	SM: -0.1128 2.0394 TMax: -0.0022 0.0337	0.118
spatial variation	SIF ~ αSM + βTMax	1.760	0.009	SIF = -0.52 + 1.76*SM* + 0.0093*TMax*	0.405	SM: 1.2104 2.3119 TMax: 0.0045 0.0140	1.83E-07
temporal + spatial variation	SIF ~ αSM + βTMax + Yr + Pixels	1.150	0.003	*Equation Omitted*	0.628	SM: 0.8048 1.5027 TMax: -0.0041 0.0101	3.27E-112
High Elevation Croplands							
temporal variation	SIF ~ αSM + βYr	-0.230	-0.002	SIF = 3.22 - 0.23*SM* - 0.0015*Yr*	0.098	SM: -1.2470 0.7795	0.255
	SIF ~ αTMax + βYr	0.005	-0.002	SIF = 4.58 + 0.0053*TMax* - 0.0022*Yr*	0.196	TMax: -0.0048 0.0153	0.151
	SIF ~ αSM + βTMax + Yr	0.060	0.006	SIF = 4.74 + 0.061*SM* + 0.0056*TMax* - 0.0023*Yr*	0.096	SM: -1.1761 1.2978 TMax: -0.0074 0.0186	0.313
spatial variation	SIF ~ αSM + βTMax	1.940	0.007	SIF = -0.52 + 1.94*SM* + 0.0072*TMax*	0.214	SM: 1.1420 2.7375 TMax: 0.0018 0.0127	2.11E-05
temporal + spatial variation	SIF ~ αSM + βTMax + Yr + Pixels	0.740	0.004	*Equation Omitted*	0.436	SM: 0.2595 1.2258 TMax: -0.0023 0.0111	1.09E-83

Table 5: The Peruvian spatial and temporal sensitivity estimates of temperature and soil moisture on SIF observations.

To finally measure the relationship of the soil moisture, SIF, and maximum temperature observations to the crop yield of each region, these spatial covariates were averaged over the

growing season over all croplands of each respective region to create an annual time series comparable to the calculated crop yield of each region. Each of these variables were then detrended, in order to determine whether variations in ecological factors could describe the variations in agricultural yield from year-to-year.

After running these three linear regressions across each of our regions of interest, we found that the linear models produced for the high elevation region were statistically significant for each ecological factor. Across all the regions, the sensitivity coefficient of soil moisture was positive, while the coefficients of maximum temperature and SIF were negative. However, just as SIF had a higher sensitivity to changes in soil moisture, agricultural yields were found to be more sensitive to changes in soil moisture than temperature by an order of two magnitudes across each of the regions.

While each of the linear models were statistically significant at the higher elevation regions, the relationships between both detrended temperature and detrended SIF observations with the detrended yield were statistically significant across the all croplands group in Peru. Each of these show a negative relationship with crop yield, with each of the confidence intervals being negative. This further implies that, while the variations of soil moisture are more uncertain and can have a larger influence on crop yields, the increases of temperature and SIF measurements away from the mean will have an almost certain negative impact on crop yields.

Peruvian Yield						
Total Yield	Linear Regression	α	Equation Predicted	Adj. R^2	Conf. Interval	P-Value
	Detrended Yield ~ α (Detrended SM)	3.96E+04	DYield = -1.8201E-11 + 39645(DSM)	0.024	1.0e+05 * DSM: -0.3876 1.1805	0.29
	Detrended Yield ~ α (Detrended TMax)	-9.77E+02	DYield = -2.8781E-11 - 977.13(DTMax)	0.399	1.0e+03 * DTMax: -1.7322 -0.2221	0.02
	Detrended Yield ~ α (Detrended SIF)	-5.79E+04	DYield = -2.2974E-11 - 57927(DSIF)	0.451	1.0e+04 * DSIF: -9.8653 -1.7200	0.01
Low Elevation Yield						
	Detrended Yield ~ α (Detrended SM)	1.09E+04	DYield = -4.3313E-12 + 10944(DSM)	-0.083	1.0e+04 * DSM: -5.1113 7.3000	0.70
	Detrended Yield ~ α (Detrended TMax)	-7.05E+02	DYield = -4.7823E-12 - 705.14(DTMax)	0.151	1.0e+03 * DTMax: -1.6201 0.2098	0.12
	Detrended Yield ~ α (Detrended SIF)	-2.79E+04	DYield = -7.2789E-12 - 27879(DSIF)	0.164	1.0e+04 * DSIF: -6.2842 0.7083	0.11
High Elevation Yield						
	Detrended Yield ~ α (Detrended SM)	1.55E+05	DYield = -1.7242E-11 + 1.546E5(DSM)	0.364	1.0e+05 * DSM: 0.2713 2.8207	0.02
	Detrended Yield ~ α (Detrended TMax)	-1.77E+03	DYield = -4.3979E-11 - 1772.6(DTMax)	0.454	1.0e+03 * DTMax: -3.0125 -0.5328	0.01
	Detrended Yield ~ α (Detrended SIF)	-1.00E+05	DYield = -4.2311E-11 - 1.0013E5(DSIF)	0.262	1.0e+05 * DSIF: -2.0081 0.0055	0.05

Table 6: The sensitivity of Peruvian yield variability to the variability of maximum seasonal temperature, seasonal soil moisture, and seasonal SIF observations.

We aim to highlight these relationships below to better visualize the comparison of these linear models to the year-to-year variation of each environmental factor to Peruvian yield. Each of the regressions for the higher elevation croplands were found to be statistically significant, along with the temperature and SIF models across all croplands. Across all regions, crop yield has a negative relationship with increasing temperature and SIF and a positive relationship with soil moisture. The high elevation croplands are more susceptible to changes in these ecological factors, as we note with the higher sensitivity coefficient for each of the environmental factors in this region.

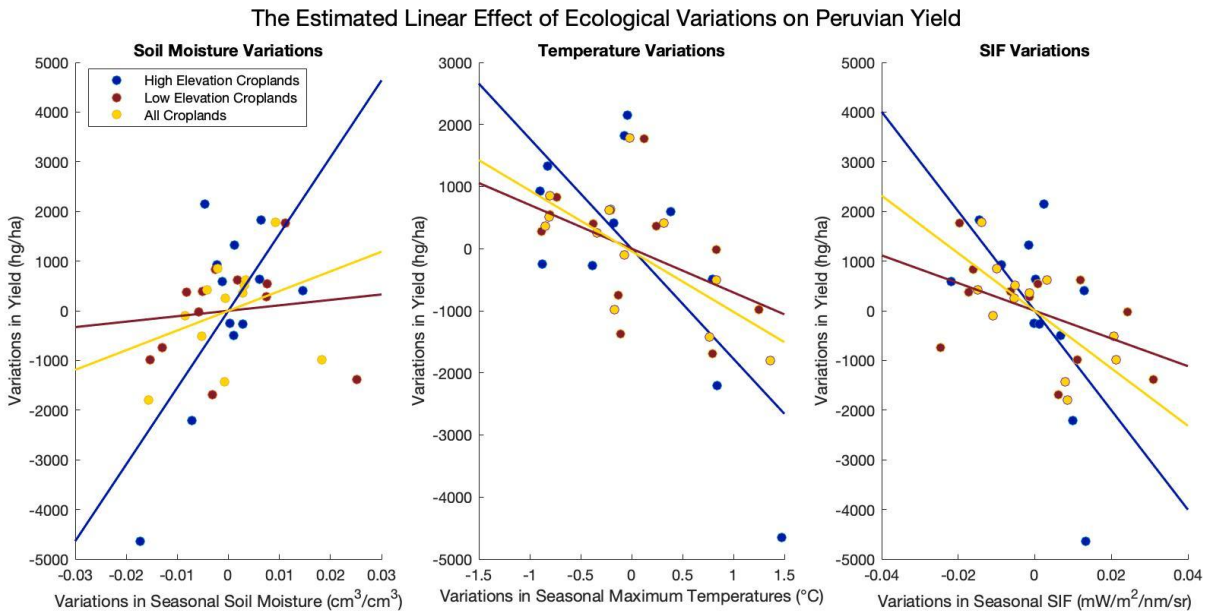

Figure 16: The estimated linear model of ecological variations describing variations in Peruvian agricultural yield. Many of these models were found to be statistically significant.

Discussion

Calculated Agricultural Yield

While the calculated annual crop yield was not a complete picture of agriculture in Ecuador and Peru, we sought out to achieve a strong representation of the most nutritionally and

economically critical crops within each of these regions. Maize, potatoes, and rice were selected for both of these regions, as they are each highly produced and a staple to most Ecuadorian and Peruvian diets. However, despite the overlap of these key crops between Peru and Ecuador, the calculated annual yield for each region differed significantly between these countries.

We found that in Ecuador, lower elevation croplands had a significantly higher level of annual yield than the crops grown at higher elevations (*Figure 1*). Meanwhile, in Peru, the higher elevation croplands were found to have a higher annual yield than the lower elevation croplands (*Figure 8)*. Based on the way we calculated yield in our study, we know that two factors could have contributed to this difference between these countries. To calculate the yield, the measured annual yield of each crop (hg ha^{-1}) was weighted by the fraction of cropland it covered in relation to the other crops of interest (ha) before being summed. This was done in an effort to account for the spatial distribution of each crop to better align and compare our annual yield to our spatial ecological data. So, some crops could have had a higher influence on this calculated yield if it covered more surface area, but was not as productive within each hectare. This allows large-scale farming to have a higher influence on the calculated crop yields of each region, even if most of the crops produced are meant for exports rather than for the communities around the farmland. We notice the effect from the weighing of each crop through our total calculated crop yield for each country, as even in Peru where high elevation croplands have a larger annual yield, the total cropland yield remains more closely to the low elevation crop yield calculation, similar to Ecuador. This can limit our evaluation of the effect of climatic changes to smaller, high elevation croplands when analyzing the total annual crop yield. With this in mind, it is more beneficial to compare and analyze the effect of shifting temperatures and water availability to the high elevation crop yield and the low elevation crop yield as two separate regions, rather than to the

country as a whole, to correctly quantify the impact of climatic changes on each of these critical croplands.

While the differences between our high elevation and low elevation crop yields could be due to our choice of key crops in our analysis, we believe that the weighting of each crop by its spatial distribution had a high impact on our calculated crop yield--suggesting differences in the regions of agricultural intensity between Ecuador and Peru.

Spatial Distribution of Croplands

The differences between low elevation and high elevation crop yields allude to the fact that these countries have a higher agricultural intensity within different elevation regions. After finding the fraction of 500m-grid croplands within each 0.25-degree grid, we observed that Ecuador invests in high-intensity agricultural farming with a maximum fraction of 51% in the coastal Southwest (*Figure 3)*. While Peru doesn't have a grid with quite the same agricultural intensity of Ecuador, its maximum fraction lies at about 30% (*Figure 10)*. While Ecuador seems to have more concentrated farmland locations, we note that in Peru there tends to be agriculture speckled throughout the high Andes. The areas with the highest agricultural intensity are in the coastal Northeast, through the Andes around Cusco, and in the Southeast nearby Lake Titicaca.

Furthermore, in each of our histograms of the distribution of croplands at different elevations, there tends to be two main peaks of cropland elevations, corresponding to the low and high elevation croplands we analyzed. However in Peru, we noticed a high count of croplands in regions at an elevation of over 3500m. This count is attributed to the agricultural region between Cusco and Lake Titicaca, recognized as a Globally Important Agricultural Heritage Systems (GIAHS) by the FAO [50]. Our spatial distribution results show that while agriculture exists at

all elevations in each of these countries, in Ecuador there tends to be higher levels of agricultural intensity centered at the lower elevations while the Peruvian agricultural centers are more distributed across the Andes. With high elevation croplands more representative in Peru, along with higher availability of soil moisture data across the region, we can presume that Peru will offer more opportunities to analyze and deduce the effect of changing climatic conditions on croplands across the Andes.

It is also critical to consider the environment of the lowland agricultural regions in both Ecuador and Peru. We noticed that between both countries, the higher fractions of low elevation croplands were apparent in hotter and drier regions of the countries, both on the western coastal side of the Andes. The presence of higher intensity agriculture in a typically hot and dry region suggests that it's possible that there are high levels of irrigation into these cropland regions. The control of water availability over a region could decrease the effect of changing climate conditions on these croplands, as they may not suffer from the effects of a dry year if irrigation is consistent, and they are already accustomed to high temperatures. This could impact our future analyses by showing a weak relationship between climate conditions and crop yields.

Either way, this distribution of croplands allowed us to draw a clear elevation distinction between the two regions of cropland across both of these countries. We then hoped to find a commonality between the seasonal SIF observations and the agricultural yields of the crops growing between these respective regions.

Comparing Seasonal SIF Averages to Calculated Agricultural Yield

Past studies have related seasonal SIF observations to reported national yields by spatially downscaling the SIF measurements to the region of agricultural production [23], [35].

However, after identifying the growing season and downscaling the regional vegetation activity to an annual average, we found that the regional yields in neither Ecuador nor Peru had a strong relationship to their corresponding observed SIF measurements. In Ecuador, the strongest correlation was 0.41 at higher elevations, while in Peru, each of the regions had a negative correlation with the highest being at -0.71 across all croplands.

We can postulate that there is a weak correlation between the final harvested yield and the observed SIF measurements of the corresponding cropland because the measurement of vegetation activity may not parallel with the actual growth of the product to be harvested. While SIF is considered a measurement of the photosynthetic processes that occur in vegetation, in our crops of interest, photosynthesis will be occurring in the leaves and stems of these plants rather than through the product itself; unlike the case with Kenyan tea yields where the product harvested are the photosynthetic leaves [35]. Because the products from most of our crops of interest are not involved with photosynthesis, we can note that there wouldn't be a strong relationship between the harvested product quantity and the measured vegetation activity in these croplands. While past studies have shown high correlation between SIF observations and maize yield, our crop yield estimates combine several different types of crops with varying photosynthetic properties [24]. This combination can further contribute to the disparities between SIF observations and the measured annual yield. It is possible that comparing the yield of each crop in isolation with its corresponding cropland SIF observations would offer a higher correlation between the two.

However, it was still unexpected for the variations in SIF observations to have a negative correlation with the variations in annual crop yield. While SIF may not be able to directly measure the growth of the product to be harvested, we would expect it to still document the

growth of the crop itself. We hypothesize that the negative SIF correlation in Peru could be attributed to the fact that croplands may not reflect the vegetation activity of areas surrounding the farm. In periods of lower SIF observations, when we can assume different ecological conditions are decreasing the productivity of a region, the cropland could still be productive with controlled conditions such as irrigation. Our SIF observations were collected at a 0.25-degree scale, so the measurement offers more information about the surrounding vegetation productivity rather than for the croplands themselves. This disparity can simply be showing the inconsistency between the productivity of croplands and their corresponding region.

Despite the lack of strong positive correlations between observed seasonal SIF and annual yield, the growing season found was still utilized in our sensitivity analyses of SIF and annual yield to shifting maximum temperatures and soil moisture. The growing season determined corresponded to the wet season and the overall productivity of a region, so it was safe to assume that the conditions present during those months would highly influence the crop yields for each year.

SIF Sensitivity Analyses

Upon first running our linear regressions on the spatial and temporal effects of maximum temperature and soil moisture on SIF observations, we found that only our panel estimates were found to be statistically significant across both countries. We expected our uncertainties to be lower for our panel estimates, as those offer significantly larger amounts of observations for analysis. Across these panel regressions, the sensitivity estimate of soil moisture and temperature suggested a positive impact on yield, however the time-series and cross-sectional sensitivity estimates did not always align with these approximations.

In Ecuador, the temporal model of soil moisture describing SIF observations initially peaked our interest by returning as statistically significant across all regions. However, further analysis showed this model to be unreliable, as there were large gaps in the soil moisture observations available across each of the regions. While the model itself is not a reliable representation of the effect of soil moisture on SIF observations, the sensitivity coefficient of soil moisture was found to be positive and a magnitude larger than the coefficient of temperature across all regions and all regressions in Ecuador. This aligned with our panel estimate, and can suggest that water availability may play a larger role in the productivity of a region rather than temperature itself.

When analyzing the Peruvian SIF response to soil moisture and temperature, the temporal models were similarly found to not be statistically significant. However, the sensitivity of SIF to soil moisture were similar to the Ecuadorian findings, with a positive coefficient in all but the temporal models for high elevation croplands. This further implies that increasing soil moisture can have a positive effect on the productivity of a region, but also highlights the uncertainty of the effect of soil moisture in the highlands. With increasing temperatures, glaciers in the upper Andes have been and are expected to continue melting over the next few decades. This melting can lead to the increase of soil moisture and water availability in the highlands via infiltration during this time period [15]. However, the uncertainty in the model about the sensitivity of SIF to increasing soil moisture at higher elevations is concerning, as those regions will be the first to receive an increase in soil moisture.

Furthermore, while it seems that temperature will not have as significant of an impact on the SIF observations of a region in comparison to soil moisture, it's critical to note that soil moisture and temperature are not independent of each other. An increase in temperature can

effectively decrease the water available to crops through higher levels of evapotranspiration, decreasing the surface level soil moisture. Due to the fact that our soil moisture sensitivity estimates are determined by satellite-based surface-level soil moisture estimates, the measurements of each of these ecological inputs to our model are tightly connected.

Overall, these linear models were not found to be reliable in predicting the effect of changing temperature and soil moisture on SIF observations over time. The only statistically significant models found were through the panel estimates, and even those showed a wide confidence interval range for both the soil moisture and temperature sensitivity coefficients. Though the soil moisture sensitivity estimate was more often found to be positive, there was still uncertainty across the different models. The sensitivity of SIF observations to temperature was even more variable than that of soil moisture. Though these analyses were inconclusive to the effect of soil moisture and temperature on SIF observations, as we discussed in the last analysis, the low correlation between the SIF observations and annual yield variations showed that these values were not interchangeable. So, the direct comparison between the variations in annual yield and seasonal variations of these ecological measures was also necessary to consider.

Yield Sensitivity Analyses

We analyzed each of the individual effects of variations in soil moisture, temperature, and SIF observations on variations to yield by running temporal linear regressions between each of these detrended factors. The soil moisture, temperature, and SIF observations were each averaged over each elevation region and its respective growing season for each country, to create a time series comparable to the annual crop yields of each region.

When first running these regressions across each region in Ecuador, we found that these models were not successful in describing a relationship between the detrended ecological factors and the detrended yield for each region. None of the models found were statistically significant, except for the model comparing variations of soil moisture and yield at high elevation croplands. This finding is misleading, as there was a very limited availability of soil moisture data at this high elevation region. Each of the sensitivity coefficients have a 95% confidence interval that ranges from a negative to a positive impact on detrended yield, further showing that there's high uncertainty in each of these models produced. In *Figure 8,* we notice that there is no trend across all the regions for each of these ecological variables.

However, our findings for Peru showed a strong relationship between these detrended variables with yield. Each of the models at the higher elevation croplands were found to be statistically significant, which p-values all below 0.05. Variations in SIF and temperature were also found to be very descriptive of the effect on variations in yield across all croplands in Peru. At the high elevation croplands, higher levels of soil moisture were found to have a positive impact on the crop yields, while the variations in temperature and SIF observations were found to have a negative impact. The confidence intervals for soil moisture and temperature confirmed their net impact on variations in yield. Is it important to note that these models found a higher sensitivity to variations in soil moisture than to temperature, further suggesting the idea that crops are more limited by water availability, as the SIF sensitivity analyses found.

Upon analyzing these results, we suggest that the success of the Peruvian model in describing variations in annual yield by variations in soil moisture, SIF, and temperature is directly attributable to the availability of data throughout the country. It was difficult to find a relationship between Ecuadorian croplands and ecological factors, as there were large pieces of

soil moisture data missing across both the low elevation and high elevation regions. The availability of data in Peru led to a higher reliability of our models. With this higher reliability, we can analyze our Peruvian models as a proxy for the high Andean region crop response to climate variability.

Furthermore, with the variation of high elevation crop yield showing a statistically significant relationship to the variation of these ecological conditions during these twelve years, we can conclude that the high elevation croplands will have a higher susceptibility to the effects of climate change. In *Figure 16*, we can see that while there is a response in each region to shifts in environmental conditions, the high elevation croplands continuously illustrated a higher sensitivity to these shifts. The low elevation croplands had the lowest sensitivity, further contributing to the idea that climate change is already affecting the high elevation mountain regions at a higher intensity than the surrounding lowlands [18].

Implications

While our seasonal SIF observations were not directly comparable to the interannual variations in crop yield, the sensitivity of each of these measurements to soil moisture was continuously predicted to be positive and have a larger influence on crop yields in comparison to the effect of temperature and SIF variations. This illustrates that while rising temperatures are expected to have a negative effect on these crop regions, these losses in yield can be offset by the implementation of an irrigation system to control the soil moisture of croplands. However, while this finding can be helpful to plan for future climatic conditions in the Andes, installing an irrigation system for small-scale Andean farmers can be expensive and unrealistic in their economic situation. Furthermore, while high elevation crop yields have been shown to be

increasing in current years, these findings can be explained by how the current melting and recession of glaciers has been increasing the soil moisture of these regions, and have possibly offset the effects of increasing temperatures in the highlands. Based on these models, we can predict that there will be significant decreases in crop yield following the recession of these glaciers, and water availability in these highlands will become more reliant on seasonal precipitation. At that point, the combination of increasing temperatures with the high variability in soil moisture will harm the future of Andean agricultural practices.

With high elevation crops at a higher susceptibility to climate change, and many of these Andean communities relying on the interannual crop production, these findings insinuate that there will be an increased vulnerability for these communities as the effects of climate change increase. Our results recommend the implementation of support systems to expand adaptation strategies to better conserve soil moisture for these high Andean farmers to better prepare for the increased variability in climate to come.

Limitations

As we found early on in our spatial analysis, there was a lack of soil moisture data available across both countries of interest. The gaps in the soil moisture data available are mostly attributable to the dense vegetation present across these regions. As we see in Peru, where there was more soil moisture data available in comparison to Ecuador, the soil moisture observations are cut abruptly where the Peruvian Andes transitions into the Peruvian Amazon. For microwave remote sensing techniques, the soil moisture signal can be hard to retrieve through dense vegetation, explaining the missing information on the Eastern sides of both Ecuador and Peru. We can assume that the double-rain shadow effect in Ecuador, which increases the probability of

dense cloud forests around the Andes, increases the dense vegetation and thus decreases the opportunity for satellites to collect soil moisture data. We notice that there tends to be higher levels of annual average SIF in the high Ecuadorian Andes at about 0.3 $mW/m^2/nm/sr$, further implying this speculation.

However, this absence of observations was detrimental to our analyses in Ecuador, where soil moisture data was only available in the southwestern region. While this is a region of high agricultural intensity, we were unable to create a reliable model of how soil moisture and yield interact across the different ecosystems that exist in Ecuador. As for Peru, while we were able to create a reliable model with the higher availability of spatial soil moisture data, satellite-based measurements of soil moisture are a fairly recent development, and there isn't as much temporal data available for these measurements. Due to this, we are unable to quantify the long term effect of soil moisture on crop yields.

Furthermore, the satellite-based data reports the ecological measurements across a 0.25-degree resolution plot. With croplands at a 500m gridded scale, this study generalized the average large scale ecological measurements to apply to all the croplands within that region. Not only does this not account for the variety of microclimates that may persist within short distances, but it also accounts for the ecological data of regions with not much cropland within them. It would be helpful to have these measurements on a smaller spatial scale to better estimate the relationships between these ecological factors and crop yields.

Future Research

After completing this analysis, it is clear that there are many opportunities for future research in this realm. While in this project, the MODIS land cover data product was utilized to

define croplands across Ecuador and Peru, it could be beneficial to reproduce the same analyses with the reference to the GFSAD croplands dataset. While this dataset has significantly higher accuracy levels of defining croplands in comparison to MODIS, the smaller resolution can also allow a more reliable aligning of croplands with their respective elevation from the SRTM dataset, which is also available at 30m resolution. It could also be interesting to directly quantify the accuracy of the MODIS land cover croplands classification with the GFSAD classification.

However, even with a higher resolution of croplands and their respective elevation, the spatial data available for maximum temperature, soil moisture, and SIF remain at lower resolutions. Downscaling these ecological measurements with accuracy can further help to identify the response of crop yields to these climatic shifts. The analysis of daily-averaged maximum temperature, soil moisture, and SIF observations rather than monthly-averaged can also account for more of the variability increasing in these factors over time.

Another possible route of future research can be to investigate the disparities apparent between seasonal SIF measurements and crop yield. Reapplying these analyses to one crop, such as those done with Kenyan tea yields, Australian wheat, or Midwestern maize, would be interesting to show if there would be a higher correlation between these two measurements when only one crop is analyzed [23], [34], [35].

Overall, there is much room for future research around the impact of climate change on crop yields globally. In this study, we hoped to explore the effect of increased variability of ecological factors in the Andes, a region known for its high diversity of ecosystems and range of extreme conditions. While this project quantified the sensitivity of crop yields to changing ecological factors in the high Peruvian Andes, there is much more research to be done for this topic. We hope that this project can contribute to the scientific community's current

understanding of the future shifts and effects of climate change on agricultural production and food security.

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