Predicted Climate Hazard for California Agriculture

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It is well understood that climate change will impact agricultural productivity in California, but it is difficult to know which regions are more at risk due to climate hazard, exposure and vulnerability. Here, we create an agricultural climate hazard index and assess the regions of high hazard with respect to the overlap with current agriculture, the number of farmworkers employed, and the market value of agricultural products sold, on a county-level scale. We find that Monterey, Stanislaus, Merced, and San Joaquin Counties are particularly at risk due to climate change, and we recommend mitigation efforts be directed to these regions.

Introduction

With the scientific certainty of a warming world, the future of agriculture is a major concern as it is at the nexus of climate, food security, and the global economy. California is in a unique position as potentially the most important agricultural region in the country that faces a future with extreme drought and higher temperatures[1], as well as policy changes that may limit capacity for agricultural adaptation[2]. Competing demands for increased agricultural production, conservation, and enhanced socioeconomic equity makes it difficult to assess risk and make decisions about resource allocation for mitigation.

California agriculture accounts for 13% of the total United States agricultural production value, supplying approximately two thirds of the country's nuts and fruits and over one third of the country's vegetables[3]. It is consistently the leading agricultural earner in the U.S., with 69,900 farms and ranches spanning 24.3 million acres and generating $50.1 billion in revenue in 2019[4]. With such extensive operations, California is also the largest employer of farmworkers; roughly 500,000-800,000 farmworkers, or one third to one half of all the farmworkers in the country[5].

Recent research on California climate change focuses on temperature[1,6], precipitation and water availability[1,7], drought[8,9], and wildfires[10]. Impacts on California agriculture have also been studied with respect to crop yields[11,12], irrigation water requirements[13], and economy[14,15]. Over the next century, climate change in California is expected to impact agriculture both directly and indirectly[13]. Direct impacts on crop yields occur through plant production due to changes in temperature, precipitation, and atmospheric CO_2 concentrations. Indirect impacts will occur due to changes in the supply of water for irrigation, including policy changes such as the Sustainable Groundwater Management Act (SGMA) which requires the adoption of groundwater sustainability plans for critically over drafted groundwater basins in California[2]. Therefore, the ability to identify regions that will experience significant changes in weather is critical for climate change mitigation planning.

Concerns for agricultural systems go beyond impacts on crop yield and market value[16], and the severity of impacts from climate change depends on vulnerability and exposure to these events[17]. Vulnerability may be thought of as a region's capacity to be restored post-disaster or to adapt to changes, and is often discussed with respect to socioeconomic makeup, sensitivity and resilience. Exposure is typically defined as a region's physical location and whether that intersects with climate change hazard. In some literature, vulnerability is a function of exposure[18,19]. Previous work has researched the impacts of climate change on farm workers in terms of heat stress on the body and the negative effects on farmworker health[31]. In this paper, we infer vulnerability due to loss of wages earned from farm work. Our causal model showed that significant climate change hazard decreases crop yield, which will require either a shift in crop type or abandonment of the farmland. This will change the need for hired farmworkers and impact the livelihoods of thousands of workers.

Previous work has identified a climate vulnerability index based on recent historical climate data[18], but does not account for predicted climate change. In this paper, we confirm a relationship between crop yield and three climate variables using a causal model. Next, we use those climate variables to calculate an Agricultural Climate Hazard Index (ACHI) for agricultural regions in California under two Representative Concentration Pathways (RCP) based on the Fifth Assessment Report (AR5) of the IPCC. We use 30-year average climate variables predicted to year 2100 in RCP 4.5 and 8.5 to calculate the index on current agricultural land. We then assess the vulnerability of California agricultural regions to climate change. We consider the number of migrant workers and total farm workers employed per county, as well as market value of products sold to identify priority regions for mitigation.

Results

California cropland ACHI values range from 0 to 9.96 with an average of 3.61 in the more intermediate scenario RCP 4.5, and from 0 to 9.99 with an average of 4.99 in the high emission scenario RCP 8.5 (Figure 1). The RCP 8.5 ACHI values predict that approximately 36,584 km^2 of California agricultural land will have a hazard index value greater than 5 in 2100, representing 64.5% of the total agricultural land, and 1,125 km^2 will have a hazard index value greater than 8, representing 2% of the total agricultural land. In the more moderate RCP 4.5, approximately 2,191 km^2 will have a hazard index value greater than 5 (3.9% of the total agricultural land), and 311.8km^2 will have a hazard index greater than 8 (0.5% of the total agricultural land).

The counties with cropland that display the highest normalized average ACHI values are listed in Table 1 and displayed in Figure 1. In both RCP scenarios, Sutter, San Juaquin, Merced, Stanislaus, Kings, San Benito, Yolo, and Monterey Counties experience moderate to high ACHI values over a large area of cropland. RCP 4.5 predicts Alameda County will experience high hazard values relative to the area of cropland, while RCP 8.5 predicts Madera County is more at risk of climate change.

In RCP 4.5, emissions are expected to peak around 2040, then decline to roughly half the levels of 2050 by 2100[20]. It is considered an intermediate emission scenario in the Fifth IPCC report. In this scenario, the length of an annual dry spell is expected to increase by up to 13 days in San Joaquin, San Benito, and Alameda counties (Figure 2). The more northern counties of Colusa, Yolo and Sutter are expected to experience only 8-9 more days per dry spell. The number of extreme heat days is expected to increase by approximately 50 in Kings, Merced, and Sutter counties, and by 40-45 in Colusa, San Joaquin, and Stanislaus counties. With warming temperatures, we expect KBDI values to increase, since higher values indicate drier soil conditions. In RCP 4.5, we see increases of up to 65 (on a scale of 800) in San Joaquin, Stanislaus, Merced, and San Benito counties.

The RCP 8.5 scenario is characterized by little to no mitigation efforts to curb global emissions of CO_2 and other greenhouse gasses, and therefore results in high radiative forcing by 2100[21]. In this scenario, the length of an annual dry spell is expected to increase by up to 31 days in San Joaquin, Stanislaus, and Merced counties. The number of extreme heat days is expected to increase by 95 and 103 in Merced and Madera counties, respectively, and KBDI values are expected to increase by 125-130 in San Benito, Merced, Stanislaus, and San Joaquin counties.

The top ten counties impacted by climate change using the RCP 4.5 ACHI values currently employ 96,772 hired farmworkers, of which 30,913 are migrant workers. The top ten counties using the RCP 8.5 ACHI values employ 111,833 hired farmworkers, of which 36,513 are migrant workers. Of these counties, Monterey is the largest employer with 26,929 reported farmworkers. San Joaquin county is the largest employer of migrant workers, with 12,097 reported laborers. Although California farmworkers earn an average hourly wage of almost $15 per hour, few farmworkers are employed year-round and even fewer are employed 40 hours per week. In 2015, it was estimated that the average yearly earnings of a farmworker in California was $20,500, which is below the U.S. Department of Housing and Urban Development "Extremely Low-Income Level" salary for a single family household[22]. This would indicate that typical farmworkers in California agriculture are less resilient to climate change and disaster events that could potentially take away their livelihoods. Counties that employ more workers, and particularly more migrant workers, are therefore priorities for mitigation.

Altogether, the top ACHI counties for RCP 4.5 earned $15.2 billion in agricultural product market value in 2017, while the top ACHI counties for RCP 8.5 earned $16.6 billion. Monterey county is a top-earner at $4.1 billion, while Sutter and San Benito counties earned less than $500 million each (Figure 4). Merced, Stanislaus, and San Joaquin are also top-producing counties, earning between $2.2 billion and $2.9 billion. These regions are therefore critical to the economy of California and the national agricultural economy in general.

Discussion and Conclusions

In this paper the causal effect of increased emissions on crop yield was estimated through knowledge of a graphical model and sample data. The results in this case showed that on average, RCP 8.5-level emissions will have a -40% (see Supplementary Information) negative effect on crop yield. It was found through the model that extreme heat, KBDI, and dry day changes due to increasing carbon have a negative causal effect on crop yield, which allowed usage of the weighted average of these variables to examine regions of high predicted change and thus high changes in crop yield over California, in the form of our agriculture climate hazard index (ACHI).

ACHI, when multiplied by cropland exposure and assessed for farmworker and market value vulnerability, gives us an understanding of climate risk for agriculture. Counties with high ACHI values in RCP scenarios, high market values of products sold, and high employment of farm workers in particular should be especially considered for targeted mitigation. From our analysis, these counties include Monterey, Stanislaus, Merced, and San Joaquin counties.
From an impact analysis and mitigation perspective it is important to note changes in regulation that can serve to either directly or indirectly affect crop yield. For example, the Sustainable Groundwater Management Act (SGMA), which was enacted to halt overdraft and bring groundwater basins to balanced levels of pumping and recharge, will make it impossible for many of the high-risk regions such as San Joaquin Valley to continue to draw groundwater for irrigation. This may cause problems for long-term irrigation strategies and also serve to further exacerbate model-estimated negative impacts.

It is important to note that our model did not consider all possible variables or climate states that may have negative effects on crop yield. One notable example is flooding, which was omitted due to its difficulty of characterization and estimation. The variables in our study were chosen for their notable effects on crop yield, availability, and lack of controllability from an agricultural management standpoint. Improved spatial and temporal resolution of the data used in the model might also yield better results as more advanced climate phenomenon can be captured at finer resolutions.

Methods

Climate change causal model for hazard index

We used a causal statistical model to identify the effect of climate change on agricultural outputs and to determine the presence of a relationship between climate variables and crop yield. We used data from the CMIP5 model suite due to its bias correction, which is not yet available for CMIP6 results. Our model relates the atmospheric carbon state to crop yield using three climate variables derived from temperature and precipitation (Figure 3).

The state of carbon (R) is implicit in the model through the use of historical, RCP 4.5, and RCP 8.5 variable data. The Keetch-Byram Drought Index (KBDI) (K) is a metric of drought and wildfire probability[23]. The drought days or length of dry spells (D) is the average number of consecutive dry days in a year. Finally, the number of extreme heat days per year (E) is the number of days when the maximum temperature exceeds the 98th historical percentile based on observed historical data from 1961-1990 between April and October. All climate variables were downloaded as 30-year averages from the Cal-Adapt LOCA derived products[24]. Crop yield in California is estimated by the total field crop planted compared to harvested area, provided by the USDA. Note that a solid unidirectional arrow in the graph represents a known causal effect (e.g., the RCP will cause a change in temperature through increased radiative forcing), and a bidirectional dotted arrow represents confounding exogenous factors between two variables (e.g., an unmeasured variable related to location such as elevation may affect both KDBI and temperature). The inherent risk of wildfire on agricultural production is straightforward, and previous work has shown that both drought and extreme heat have direct effects on agricultural production[22] via root growth, transpiration, photosynthesis, and water use efficiency[26]. Increases in drought and extreme heat have been shown to reduce crop yields by as much as 50%.

To estimate the effect of carbon emission scenarios and the resulting climate changes on agricultural production, we calculate the average causal effect[27] (ACE) of increased emissions using the Variational Autoencoder[28] deep learning architecture (Supplementary figure 1). The ACE estimates the difference in crop yield given RCP 4.5 or RCP8.5 occurs. We find that in an RCP 8.5 scenario, over years 2070-2099, the carbon state will have a -74% causal effect on yield level, i.e., 74% lower yield at this level compared to historic yield. The ACE from this is -0.4, which is to say that the RCP 8.5 scenario will have an average negative causal effect of -40% (Supplementary figure 3).

After confirming the causal relationship between the model variables and yield level, we created an index to identify agricultural regions that are at risk of decreased crop yield. The agricultural climate hazard index (ACHI) is calculated by normalizing each predicted climate variable over the historical value, then computing an equal-weights average of the three normalized values:

$$ACHI = \frac{E(future)/E(historic) + K(future)/K(historic) + D(future)/D(historic)}{3}$$

"Future" values are the 2070-2099 average values from RCP 8.5 or RCP 4.5, while "historic" values are the 1960-1999 values. We calculated ACHI for 1/16th degree grid cells over California.

Exposure

ACHI values were resampled to 500 km x 500 km grid cells and overlaid with the California Natural Resources Agency 2018 crop mapping shapefile boundary[29] to limit the analysis to existing agricultural land. We calculated the mean ACHI values for each county and normalized the results by multiplying the ACHI value by the percent of cropland in the county. Thus, the counties with a higher percentage of agricultural land have a higher exposure to climate change impacts.

Vulnerability

We used data from the U.S. Census of Agriculture 2017 to infer the number of farmworkers and migrant workers that may be impacted by climate change in high-ACHI counties. The number of farmworkers is the total number of hired agricultural workers in each county. Migrant workers are hired farm workers who are unable to return to their permanent place of residence within the same day[30]. Finally, we collected data on the market value of agricultural products sold per county to understand the potential economic impacts of climate change in these areas. The number of farmworkers, number of migrant workers, and market value of products sold are displayed in Figure 4.

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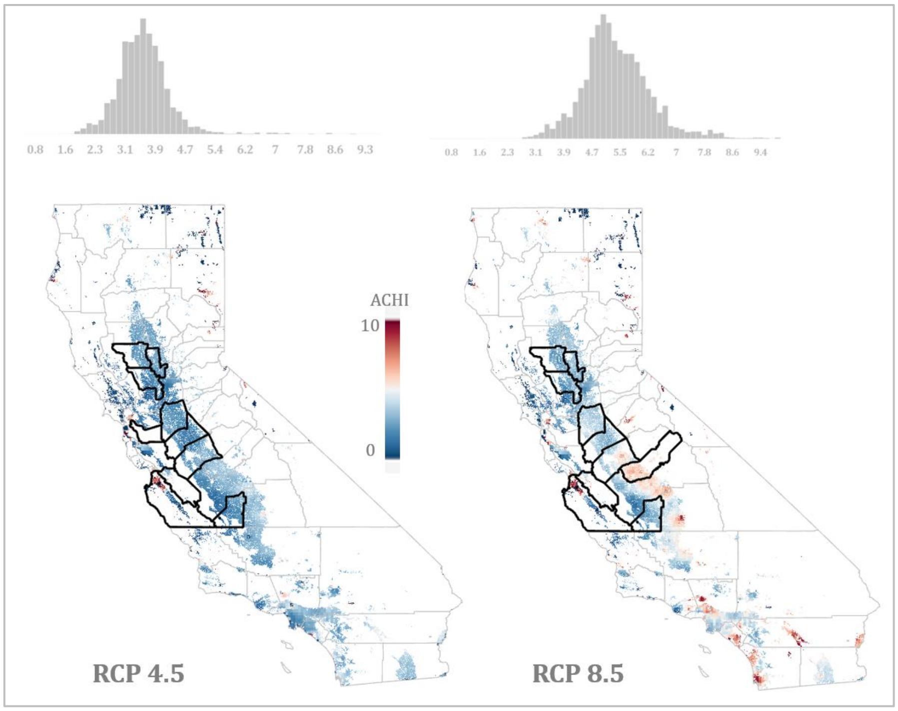


Figure 1 | ACHI results for each RCP scenario. Black outlines indicate counties where ACHI values were high relative to the total percent of cropland in the county. Histograms show ACHI value distributions for all cropland in California.

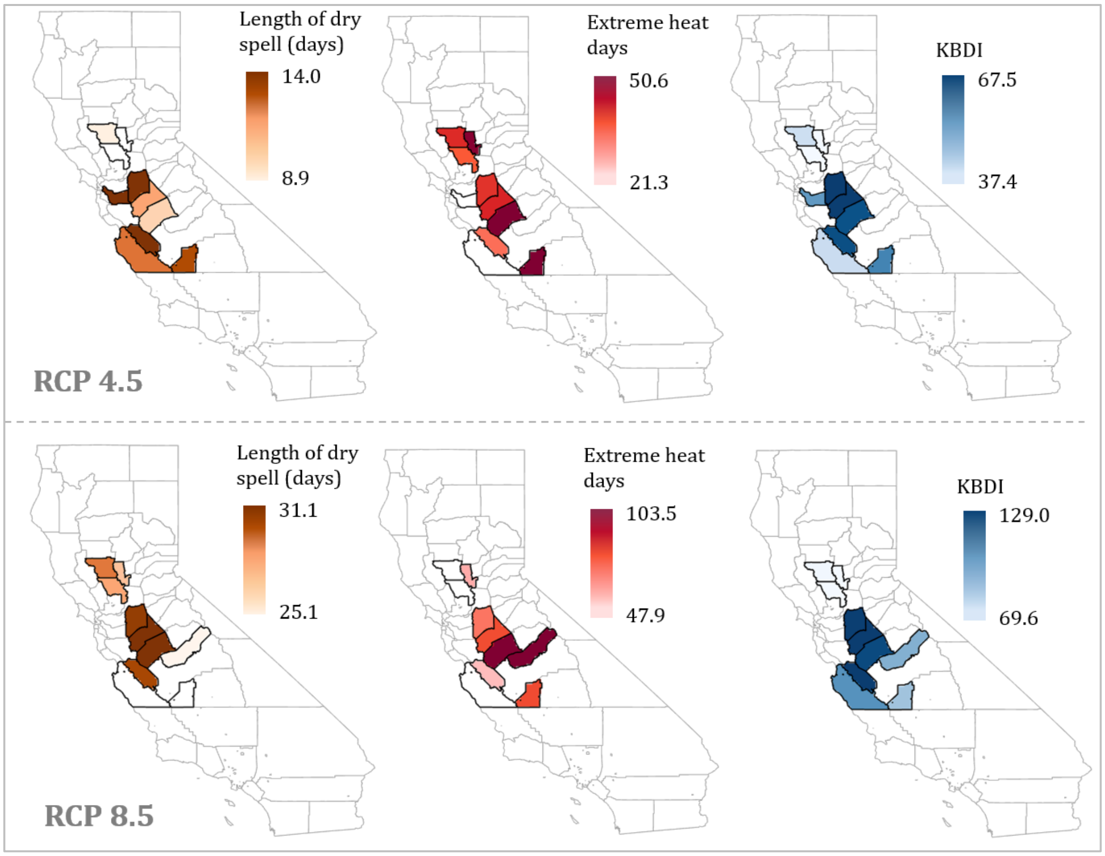


Figure 2 | Change in climate variables in each RCP. Black outlines indicate the top ten counties listed in Table 1 for each RCP. Color gradients show the increases in the length of annual dry spells, number of extreme heat days, and KBDI index values, between historical values and each RCP predicted values.

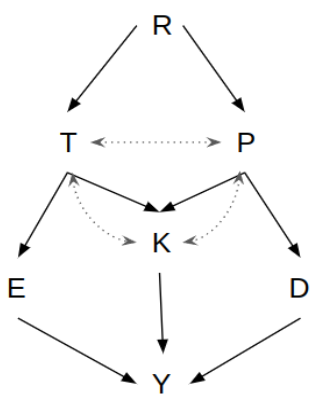


Figure 3 | Climate Change Hazard Model Causal Graph. R is the carbon state, T is Temperature, P is Precipitation, K is KBDI, E is Extreme heat days per year, D is Dry days per year, Y is Crop Yield %. Solid arrows represent causal relationships, while dotted arrows indicate exogenous confounding variables.

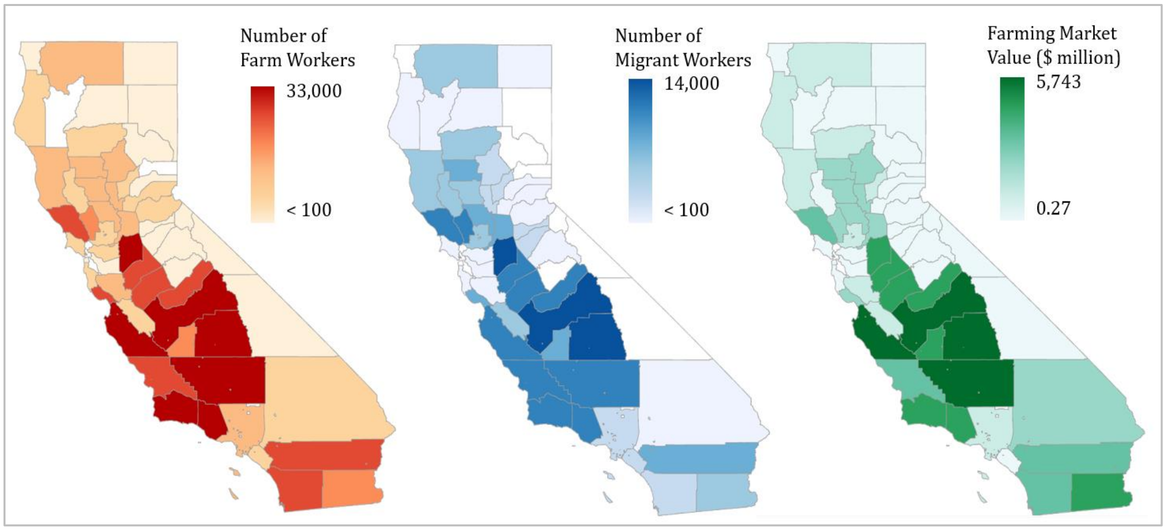


Figure 4 | Farming statistics for each county. The number of farm workers, number of migrant farm workers, and market value of agriculture (in millions of dollars) from the year 2017. Source: US Census of Agriculture 2017.

RCP 4.5			RCP 8.5		
County	Mean ACHI	$ACHI_n$	County	Mean ACHI	$ACHI_n$
Sutter	*3.57*	*3.50*	Sutter	*4.93*	*4.82*
San Joaquin	*3.39*	*2.87*	San Joaquin	*5.36*	*4.54*
Merced	*3.56*	*2.66*	Merced	*5.71*	*4.27*
Monterey	*3.89*	*2.46*	Stanislaus	*5.11*	*3.81*
Stanislaus	*3.18*	*2.37*	Kings	*4.92*	*3.41*
San Benito	*3.96*	*2.31*	San Benito	*5.72*	*3.34*
Kings	*3.31*	*2.29*	Yolo	*4.67*	*3.28*
Yolo	*3.14*	*2.20*	Monterey	*4.92*	*3.11*
Colusa	*3.49*	*2.15*	Madera*	*6.41*	*3.00*
Alameda*	*5.54*	*2.12*	Colusa	*4.69*	*2.90*

Table 1. Counties with the highest ACHI values normalized by percent cropland ($ACHI_n$). Stars indicate counties that appear only in one RCP scenario; all other counties appear in both lists. Mean ACHI is the average ACHI value for all cropland in the county. $ACHI_n$ is the Mean ACHI multiplied by the percent of cropland area per county area.

Supplementary Information

Causal model approach

Since the carbon state (R) is independent of crop yield (Y) given extreme heat (E), KBDI (K), and drought days (D), it is only necessary to condition on these variables. For RCP8.5, the ACE can be estimated as:

$$ACE = P(Y|do(R = RCP8.5)) - P(Y|do(R = hist))$$

Where we can use the back-door theorem[32] to approximate our query as:

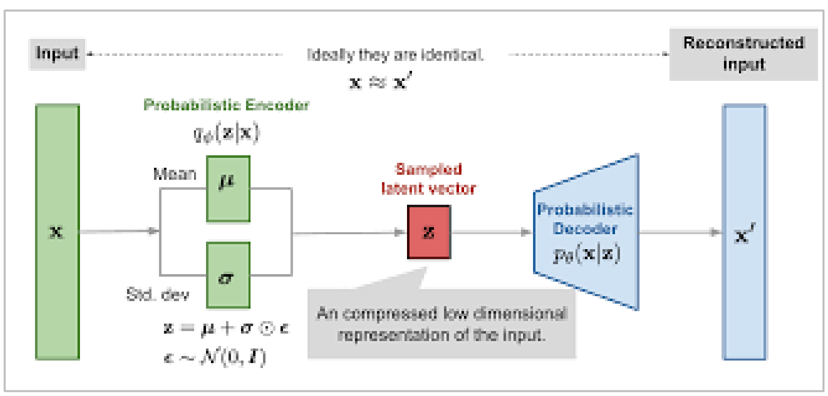
$$P(Y|do(R = r)) \sum_{z} P(Y|R, Z)P(Z)$$

Where Z represents the set of variables Z= {E, K, D} as it d-separates R from Y in our graph (that is to say, in our model, agricultural yield is independent of the RCP given the KBDI, dry day, and extreme heat duration). To estimate this query, we build upon the Variational Autoencoder[28] deep learning architecture.

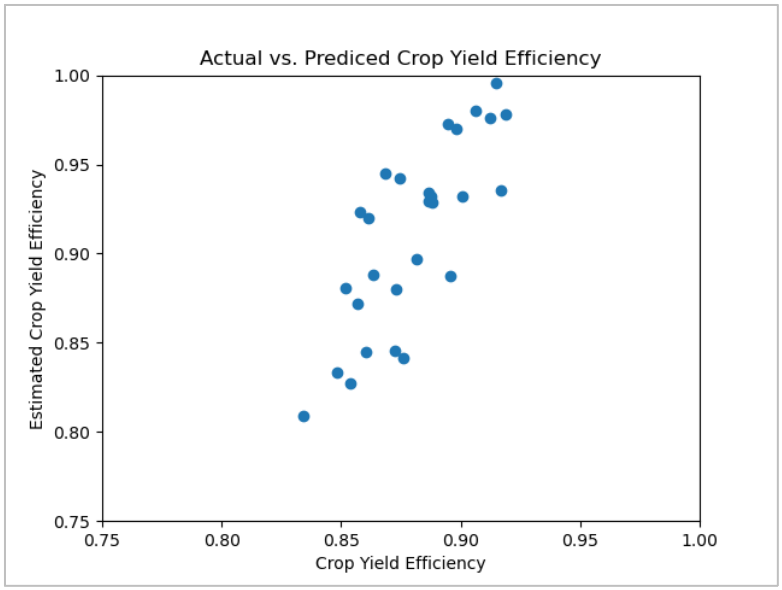
We use the distribution q of the probabilistic encoder to estimate P (Y|R, Z) by modifying the loss function to train the latent space to represent our agricultural area-yield efficiency metric. The loss function of our model then becomes:

$$L = -E_{z \sim q(Y|Z)}[log(p(Z|Y))] + KL(q(Y|Z)||p(Y)) + (Y - Z)^2$$

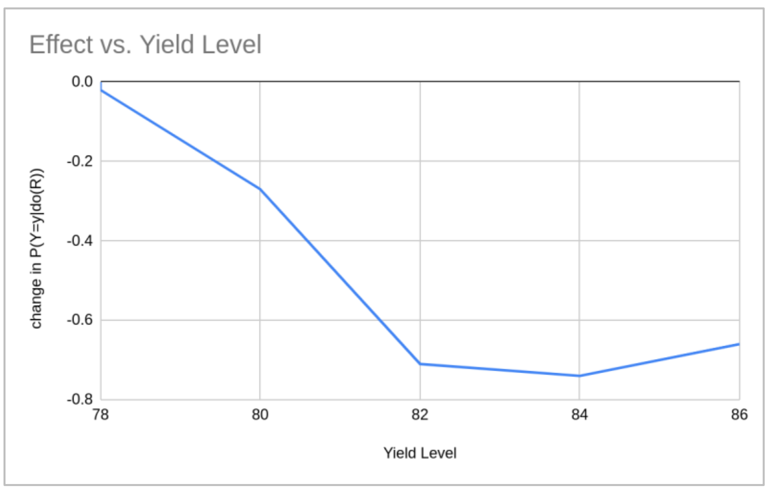
Where the first two terms represent the standard VAE loss and the third term represents the squared error between the agricultural yield Y and the estimated agricultural yield Y.



S1. Example of VAE Architecture.



S2. Historical field crop yield and associated latent risk metric post model training.



S3. Causal Effect (P(Y|do(RCP8.5))-P(Y|do(Hist)) for different yield levels. Higher negative causal effects at higher yield levels indicates that the change in climate to RCP8.5 will have a larger diminishing effect on higher crop yield levels. The average value of this plot (~-0.4 or -40%) represents the average causal effect of the change in carbon emissions on crop yield level.