Weather Variability In Non-growing Season Impacts Agricultural Productivity Prediction

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Abstract

Agricultural productivity is sensitive to temperature and precipitation extremes, which are increasing with climate change. It is well-established that planting and growing season weather affects crop yields, but conditions in other seasons may also be important. We generate a county-level dataset that links yields for six major crops in the US with agriculture-relevant weather variables for four distinct seasons (planting, growing, harvest, and non-growing) over the years 1983 to 2021. The data include binned temperature variables, precipitation, and the Palmer Drought Severity Index (PDSI). We demonstrate that models using weather conditions from all four crop calendar seasons segments outperform those using only growing season or yearlong data at predicting yields, highlighting the importance of considering the impact of non-growing season weather on agricultural productivity.

1 Introduction

In recent years, extreme precipitation and heat have increased in frequency and intensity[1], and this trend is only expected to worsen with climate change [2, 3, 4]. Agriculture is heavily dependent on weather, and it is well-established that extreme events negatively impact productivity [5, 6, 7].

A large literature examines the effect of climate variables on agricultural yields, but these studies have primarily focused on planting and growing season weather. Specifically, many studies estimated the impact of growing degree days [8, 9, 10], a measure of temperature exposure, and precipitation affect crop yields. However, these studies largely overlook the effect of weather variability in other seasons of the crop calendar. This narrow focus may limit our understanding of how weather variability and climate change could impact yield and when intervention and adaptation measures should be taken.

To address this gap, we compile a dataset that measures temperature exposure, precipitation, and drought for six major crops in the United States across four distinct segments of the crop calendar year — planting, growing, harvest, and non-growing season — for the years 1983 to 2021. We aggregate these data to the county-level, weighting by cropped area, so that they can be linked with yield outcomes. These data allow us to examine the impact of weather conditions over multiple seasons, with the aim of developing a more nuanced understanding of how weather variability across the entire year impacts agricultural yields. Using linear regressions and common machine learning models, we demonstrate that using weather across all four seasonal segments as predictors of agricultural yields improves model performance relative to only including mid-season weather or aggregated weather across the year. We hope these estimates will enable better risk assessment and inform mitigation and adaptation strategies.

We make publicly available the source code to reproduce the data used in this analysis from the raw data described below. While not within the scope of this paper, the data could have other applications

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beyond crop yield estimation, such as deepening our understanding of the relationship between weather and pest outbreaks or weather and soil moisture levels.

2 Literature Review

The projected negative impact of climate change on agriculture is a pressing global challenge, especially as a rising global population will necessitate increased food production [11]. Least developed countries tend to be the most reliant on agriculture for incomes and food security, and the projected population surge in these regions further underscores the urgency to address the vulnerabilities of the global agricultural system to climate change. Given the U.S.'s role as a major global food exporter, the resilience and productivity of its agricultural sector is not only crucial for domestic food security but also has significant implications for the global food supply. Establishing the linkages between climate and crop yields can help inform strategies to ensure future food security.

The relationship between climate conditions and agricultural yields has been extensively studied. The integration of crop simulations and future climatic projections produced by general circulation models consistently predict a decline in agricultural yields due to climate change [12]. Prior work finds that temperature fluctuations, altered precipitation patterns, and more frequent of extreme weather events all reduce crop yields [7, 13]. Crops exhibit ideal growth patterns in specific crop-based temperature ranges. Extreme temperatures, either too cold or too hot, can hinder their physiological processes and subsequently reduce yields. In the U.S., statistical analyses indicate that the yields of rainfed maize, soybean, and cotton decrease sharply when temperatures surpass approximately 30°C [14]. Wheat in the U.S. is adversely affected by frost in the fall or by heat in the spring [15].

Studies investigating the effects of weather on crop yields typically employ one of two main methods: biological process-based modeling or regression-based statistical methods [16, 17]. Process-based models [18] simulate the physiological and biological processes governing crop growth, accounting for various factors like atmospheric CO2 concentrations, temperature, precipitation, and soil moisture. These models can offer a deep understanding of how plants grow under different conditions at fine temporal resolutions. However, they require extensive and specific data for calibration and validation, and can be computationally intensive. In contrast, statistics based methods such as Schlenker and Roberts [14] establish the causal relationships between weather and yields using historical obserations. These methods are generally more straightforward, require less computational effort, and can efficiently capture broad trends.

One widely used climate variable in the agronomic literature is growing degree days [8, 9, 10]. Degree days represent the cumulative measure of heat accumulation used to predict plant development stages. Many studies focus predominantly on the effects of growing season weather. While this approach captures the direct effects of temperature and precipitation during the crop's most active growth phase, it does not capture how weather variability throughout the entire year affects agricultural productivity. Papers studying soil chemistry [19, 20] demonstrate how early-season weather patterns can influence factors that subsequently impact crop productivity. These studies underscore the need for a holistic approach to understanding crop-weather interactions, spanning from parts of the year outside the growing season.

3 Methodology

We produce a county-level panel dataset that links high resolution weather data with yield data across the entire U.S. for the years 1983-2021. Weather data include temperature and precipitation measures from the PRISM Climate Group [21] and a drought indicator from the Gridded Surface Meteorological Dataset (gridMET) [22]. Both of these datasets are gridded products with approximately 4km resolution. Yield data come from USDA's National Agricultural Statistics Service [23]. We include six major US crops: soy, corn, sorghum, cotton, spring wheat, and winter wheat. Each crop has three or four different crop seasons with the timeframe defined by the USDA crop calendar [24]. Except for winter wheat, each crop has a non-growing season and three distinct growing seasons: planting season, mid season, and harvest season.

To capture temperature exposure, we construct growing degree days in increments of 1°C from 0°C to 40°C. Temperatures below 0°C are binned together, as are temperatures above 40°C. We construct these measures using daily minimum and maximum temperature from PRISM and the sine method described in Zalom et al. [9] which closely approximates the daily temperature cycle. This method models the temperature exposure over a day using a function:

$$y(t) = A \cdot \cos(2\pi(t - h)) + k \tag{1}$$

A is the amplitude of the cosine wave, defined as half the absolute difference between the daily maximum and minimum temperatures. h is the horizontal shift of the cosine function, set to 0.5. k is the vertical shift of the cosine function, which is the average of the daily maximum and minimum temperatures. This shifts the cosine function to have its minimum values at the start and end of the day. We estimate the temperature for a series of time values t ranging from 0 to 1 in increments of 0.01, representing roughly 15 minute intervals from the start to the end of the day:

$$t_i \in \{0, 0.01, 0.02, \ldots, 1\} \tag{2}$$

We calculate the proportion of the day that the temperature remains within the bounds of the binned intervals [lower_temp, upper_temp] using the equation:

$$\text{portion\_in} = \frac{\text{Number of } t_i \text{ where lower\_temp} \leq y(t_i) \leq \text{upper\_temp}}{\text{Total number of } t_i} \tag{3}$$

We also obtain daily precipitation estimates from PRISM to construct two measures of rainfall for each season: total precipitation and precipitation squared. Data on drought come from gridMET. In particular, we use the Palmer Drought Severity Index (PDSI), which is widely used in the agronomic literature to summarize abnormal dryness and wetness. PDSI is based on a water balance model, which takes into account factors like precipitation, soil moisture, and evapotranspiration. It is a continuous index ranging from +10 to -10, where positive values indicate wet conditions and negative values indicate dry conditions, with values closer to 0 being closer to normal conditions. We calculate the mean and median of daily PDSI for each crop season. Additionally, we separate the PDSI variable into dry and wet variables with the break point at 0 to capture differential effects of wet and dry conditions on crop yields.

All weather variables are constructed at the native resolution of the data (∼4km) and then aggregated to the county by year by crop by season level, a procedure that allows us to recover local non-linear effects of weather on yields [25]. When spatially aggregating weather variables to the county level, we weight by crop-specific area from the USDA's Cropland Data Layer [26]. In particular, we first assign each 4km weather grid cell to a county using its centroid. Then, we calculate the area of the grid cell covered by each crop. Weights are constructed as the cropped area of the grid cell divided by its county's total cropped area. This process yielded a dataset with county-level, crop-specific weather measures for each growing season and year.

We establish baseline benchmarks of yield predictions using these weather data by applying OLS regression and ensemble methods such as Random Forest, XGBoost, LightGBM, and CatBoost. For the ensemble methods, we use 100 estimators, 12 max depth for Random Forest, and 0.06 learning rate for the gradient boost models determined through hyperparameter tuning. We evaluate model performance using Mean Squared Error, Root Mean Squared Error, Mean Absolute Error, and R-squared. We exclude winter wheat due to the fact that non growing season is absent, and the categorical crop column was one-hot encoded to create dummy variables. The data was split with an 80-20 training-testing ratio by year with the last 20% of years in the series as the test set. This split was designed to evaluate out-of-sample model performance for predicting yields in future years.

4 Results

Table 1 presents a comparison of four scenarios: training only on all growing season, only on the mid season, on all four segments, and on both planting and mid season. We find that the models using weather data across all four seasons of the crop calendar achieve the highest performance by MSE, RMSE and R-squared. For the best performing model (CatBoost), using all four seasons increases performance by R-squared = 0.02 relative to using growing seasons only, the standard in this literature. This differentiation likely captures the impact of weather across different segments of plant growth on crop yield as well as effects of non growing season weather on factors such as soil chemistry and pest abundance. The results demonstrate the importance of considering non-growing season weather

Table 1: Benchmark performance comparison evaluated across all crops by scenarios

Model	All four season segments MSE	RMSE	MAE	R-squared	Mid season MSE	RMSE	MAE	R-squared
OLS	11418.38	106.86	49.29	0.813	11566.40	107.55	47.58	0.810
Random Forest	6318.58	79.49	36.43	0.896	6473.66	80.46	36.60	0.894
XGBoost	5175.47	71.94	33.96	0.915	5698.22	75.49	34.97	0.907
LightGBM	5322.05	72.95	34.99	0.913	6014.28	77.55	35.92	0.901
CatBoost	5111.62	71.50	33.81	0.916	5407.12	73.53	33.74	0.911
	Planting & mid season				**All growing season**			
Model	MSE	RMSE	MAE	R-squared	MSE	RMSE	MAE	R-squared
OLS	11516.50	107.31	48.06	0.811	12146.70	110.21	48.68	0.810
Random Forest	6282.53	79.26	36.07	0.897	9407.24	96.99	45.00	0.846
XGBoost	5248.92	72.45	33.97	0.914	7786.25	88.24	41.38	0.872
LightGBM	5548.24	74.49	35.26	0.909	7037.41	83.89	40.14	0.885
CatBoost	5190.71	72.05	33.77	0.915	6416.72	80.10	39.57	0.895

data in yield prediction, which has previously been neglected in the agricultural statistics modeling literature.

We examine which weather variables in which seasons have the greatest importance using a leave-one-out approach. We combine weather variables into five categories: cold temperatures ($< 10°$C), moderate temperatures (10 to 30°C) hot temperatures ($> 30°$C), precipitation measures, and PDSI measures by segments of the crop calendar year. Table 2 shows the difference in the MSE between the baseline scenario with all variables from all four segments and the leave-one-out scenario where one set of variables (corresponding to the table cell) are omitted. Negative values indicate that the omitted category adds predictive power, while positive ones suggest over-specification. Our results demonstrate that precipitation and PDSI variables as well as moderate temperature exposure in the non growing season are important predictors of yields.

Table 2: Leave-one-out test MSE difference by season-variable group

Variable Group	Cold	Moderate	Hot	Precipitation	PDSI
Non-growing season	42.60	-1.83	40.04	-25.04	-30.48
Harvest season	28.92	55.04	26.25	-27.83	-184.38
Mid season	46.04	-299.26	-133.06	-167.57	-39.69
Planting season	-51.34	44.75	-65.77	-52.41	-30.48

This study presents a more comprehensive approach and data for understanding the impact of weather variability across different crop calendar seasons on agricultural productivity. The baseline benchmark illustrates the importance and improved performance of considering non-growing season weather data in yield prediction, which has previously been neglected in the literature. The benchmark results support better understanding of crop-weather interactions and highlights the value of examining weather across the year in seasonal segments.

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