A data-driven framework for quantifying flash drought impacts on winter wheat production

by

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Abstract

Flash droughts are increasingly recognized as a major threat to agricultural productivity due to their rapid onset and intensification of drought conditions. Recent evidences from winter wheat systems indicate that yield responses depend strongly on the timing of drought development, highlighting the importance of crop phenology in mediating drought impacts on yield. While newer studies consider crop phenology, there is lack of evidence comparing flash droughts with other extreme weather events that have impacts on yield. Therefore, a quantitative framework that integrates flash drought, crop phenology, and other weather drivers to explain yield variability lacks development, limiting our ability to infer on winter wheat productivity.

Here, we investigated the effects of flash droughts and other climate factors during different phenological phases of winter wheat yield and abandonment. We first estimated crop phenological dates using generalized additive models (GAMs) with Gaussian process smoothing for nonlinear spatial and temporal variation. Using the NDLAS-3 dataset at 1km spatial and hourly temporal resolution, we derived several weather indices, including crop evapotranspiration, a key indictor of flash drought development. We then quantified the effects of flash droughts and other weather drivers on county-level winter wheat yield and abandonment across the Great Plains from 2002-2020 using both statistical and machine learning methods.

Our phenological date estimation framework performed well in prediction, both in interpolation and extrapolation. Mean water-use efficiency during flash droughts were among the strongest predictors of both yield and abandonment, ranking above most other weather variables in variable importance via permutation. Incorporating flash drought metrics improved overall model performance for both linear and random forest models. In particular, mean water-use efficiency during the earlier stages of the winter wheat growing season accounted

for almost 80% of the explained variation in crop abandonment with early freezing, spatial, and temporal features, outranking late-season frost and extreme heat. These findings suggest that current winter wheat production systems in the Great Plains remain insufficiently adapted to flash drought risk and show to have non-linear effects on yield and abandonment.

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Acknowledgments

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Introduction

1.1 Winter Wheat

The United States is recognized as the "wheat breadbasket of the world" and is continually expanding its acreage of winter wheat while continuously encountering unforeseen and unprecedented challenges from extreme weather events[1]. Despite it being one of the world's most staple crops, these increasingly variable environmental conditions pose significant threats to winter wheat production, raising concerns about the crop's resilience under a changing climate and the potential insufficiencies of current breeding[2]. Crop production may continue to struggle as climate trends do not appear to slow in the near future[3]. Understanding different climate extremes and impacts on production is essential when reaching decisions on how to adapt to effects of climate change[4]. Of these extreme events, flash droughts are some of the most alarming due to some crops' inadequate ability to adapt to the sudden onset of large water deficits and heat extremes, resulting in a rapid reduction in productivity[5].

1.2 Flash Droughts

Flash droughts are increasingly recognized as a major threat to agricultural productivity due to their rapid onset and intensification of drought conditions[6]. While long-term precipitation deficits are a key driver of conventional droughts, flash droughts are more strongly influenced by rapid soil moisture depletion associated with increased evapotranspirative demand[7]. The rapid onset of these conditions is particularly consequential for crops, which can become moisture-stressed quickly and are more sensitive to moisture depletion in shallow soil layers[6]. The extremely short timescale of flash droughts compared to conventional droughts also show to have more detrimental effects on vegetation and carbon sequestration global, signifying a lack of crop resilience to these extreme events[8].

1.3 Physiological Traits

Once soil drying is below a critical soil moisture threshold, it limits the crops soil-plant water supply, causing the stomata to downregulate transpiration[9] at the expense of carbon uptake by photosynthesis[10]. With the stomata being the first line of defense against droughts[11], an insufficient or delayed stomatal closure during drought is expected to increase transpirational water loss and reduce drought survival[12]. Evapotranspiration has previously been shown to increase during droughts and possibly be the cause of flash droughts[13], showing that some crops may experience inadequate stomatal closure during these rapid intensification, therefore increase transpiration.

1.4 Flash Drought and Crop Yield Response

Recent evidence from winter wheat systems in the Southern Great Plains indicates that yield responses depend strongly on the timing of drought development: events occurring in late summer and early fall substantially reduce productivity, whereas those occurring later in the crop life cycle may have limited or even positive effects[14]. However, this study characterizes drought timing based on calendar dates rather than crop phenology. As a result, some of the identified drought events occur before the crop is sown, highlighting the importance of accounting for crop phenology when assessing the impacts of flash drought on yield. A more recent study that explicitly incorporated crop phenology found that flash droughts result in greater crop losses than conventional droughts[15]. However, this study did not account for concurrent extreme weather events that may also contribute to crop losses. Despite these findings, a quantitative framework that integrates flash drought characteristics, crop phenology, and other climate drivers to explain yield variability has yet to be developed. Such a framework is needed to disentangle the relative and interacting effects of flash drought and other climate extremes on crop productivity and loss.

Since 2012, numerous approaches have been developed to identify and characterize flash droughts using a variety of climate, hydrological, and land-surface variables and their interactions[16]. One of the most commonly used variables is potential evapotranspiration (PET), which represents the theoretical atmospheric evaporative demand under conditions without limitations in water availability and of a reference crop[17;18]. Indicators based on the ratio of actual evapotranspiration (ET) to PET have gained substantial traction for identifying flash drought conditions[19]. However, many existing indicators are primarily meteorologically or hydrologically based and do not explicitly represent the physiological processes governing plant responses to rapidly developing water stress. Consequently, these indicators may identify rapid-onset drought conditions without necessarily capturing the degree or timing of physiological stress experienced by crops. Attempts to identify agricultural flash droughts using variables such as soil moisture have addressed conditions within the crop root zone[20], but still do not directly account for crop physiological responses or phenological development. This limitation is particularly important for agricultural applications because the same meteorological or hydrological drought conditions may produce substantially different crop responses depending on crop type, phenological stage, and physiological sensitivity to water stress.

Methods

2.1 Climate Data

Daily maximum and minimum air temperatures (K), north and eastward winds (m s^{-1}), and precipitation (kg m^{-2}) were obtained from North American Land Data Assimilation System (NLDAS-3) from 2001 to 2023. NLDAS-3 is a North American gridded product produced by the National Aeronautics and Space Administration (NASA) made available July 2025. NASA has recently improved NLDAS-3 to 1-km spatial resolution compared to NLDAS-2 of on average 12.5-km, along with improvement in land model accuracy. Elevation data was collected from the United States Geological Survey for its use in pressure estimation. The county-level climate data were from the nearest grid points to the county centroid. Input variables for the Penman-Monteith ET equation were implemented using the guidelines from the Food and Agriculture Organization Irrigation and Drainage Paper[21]. All variables but relative humidity (RH%) were calculated using FAO-56, with RH% using a more robust calibration from specific humidity (kg^{-1}) and surface pressure[22].

2.2 Evapotranspiration

A robust method for estimating daily ET is the FAO56 Penman-Monteith (PM) equation, which has proved to be an accurate and extensively applied method across numerous studies[23;24]. Dual crop-adjusted ET coefficients were used to represent climate conditions and winter wheat physiology. Water stress coefficient (Ks) [0-1] weighted ET based on current climate conditions and soil type. ET is a crucial variable for monitoring the stress of crop and land systems. Globally, ET can increase during drought conditions despite limited soil moisture supply[25], representing stomatal conductance fluctuation in crops.

2.3 Gross Primary Productivity

Gross primary productivity (GPP) represents the rate of carbon assimilation by plants through photosynthesis and can provide an indication of plant physiological activity. GPP was obtained from GOSIF[26], and mean GPP was calculated for spatial grid cells containing winter wheat. Winter wheat locations were identified using the Cropland Data Layer from the United States Department of Agriculture's National Agricultural Statistics Service (USDA-NASS). The ratio of GPP to ET provides a measure of water-use efficiency (WUE), which can serve as a proxy for changes in stomatal regulation and plant water-use strategies[27;28]. Because stomatal regulation controls both carbon uptake and water loss, changes in GPP relative to ET may provide information on physiological responses to developing water stress.

2.4 Agricultural Flash Drought Indicator

Agricultural flash droughts were identified based on a rapid decline in Ks, the crop water-stress coefficient defined by the FAO-56 framework. The Ks coefficient represents the reduction in crop transpiration resulting from limited soil-water availability and ranges from 0 to 1, with 1 representing no water stress and 0 representing the point in which the crop will begin to experience permanent wilting. As soil-water availability declines, Ks decreases, thereby providing a direct representation of the effect of water availability on crop water use. Using Ks as a flash drought indicator therefore provides a physiologically relevant measure of rapidly intensifying water stress at the crop level, rather than relying solely on meteorological or hydrological conditions.

A decline in Ks of 0.15 within 10 days was identified as the combination most predictive of yield loss in the present analysis. However, this threshold differs from those commonly used by other flash-drought indicators and represents a substantially shorter development period[20]. This distinction highlights the importance of defining flash drought according to the timescale and physiological response relevant to the crop being studied.

2.5 Winter Wheat Study Area

Winter wheat county-level yields were collected for only those with more than 5000 acres of harvested hard winter wheat and at least 15 years of available yield data for climatological standardization. Yield data from 210 counties spanning the U.S. Great Plains (South Dakota (SD), Nebraska (NE), Colorado (CO), Kansas (KS), Oklahoma (OK), and Texas (TX), were used in the study. County-level hard winter wheat yield data were obtained from the USDA-NASS for years between 2001 to 2020. All yield data in this study were directly taken from survey yields from non-irrigated crop sites (Figure 2.1). Winter wheat abandonment was also derived from USDA-NASS data using county-level planted and harvested area.

$$\text{Abandonment}_i = \frac{\text{PA}_i - \text{HA}_i}{\text{PA}_i} \tag{2.1}$$

where $Abandonment_i$ is the proportion of planted area that was not harvested in county i, PA_i is the planted area, and HA_i is the harvested area. This proportion provides an estimate of the unharvested crop area at the county level[1].

2.6 Phenology

The phenological data included planting dates from 199 experimental stations and harvesting dates from 120 experimental stations in the Great Plains. Wheat jointing and heading dates were estimated using the accumulated growing degree days required for winter wheat phenology[29]. The maturity dates were inferred from dates 14 days prior to harvesting dates[30] for all county-years. In each county-year combination, we partitioned the life cycle of winter

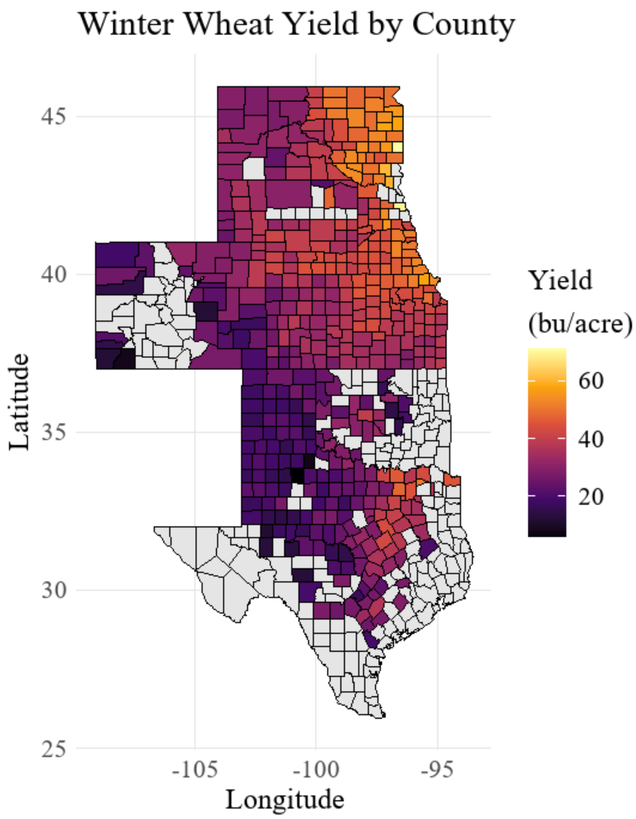


Figure 2.1: USDA-NASS county-level survey crop yield data of non-irrigated winter wheat in the Great Plains from 2001-2020. At least 5000 acres of harvested winter wheat and 15 years of yield data were required.

wheat into three phenological stages: planting to jointing (PJ), jointing to heading (JH), and heading to maturity (HM).

We estimated crop phenological dates using generalized additive models (GAMs) with Gaussian process smoothing for nonlinear spatial and temporal variation.

$$\text{PlantingDate}_i = \beta_0 + f_1(\text{Year}_i) + f_2(\text{Latitude}_i, \text{Longitude}_i) + \varepsilon_i, \tag{2.2}$$

$$\text{HarvestingDate}_i = \beta_0 + f_1(\text{Year}_i) + f_2(\text{Latitude}_i, \text{Longitude}_i) + \varepsilon_i, \tag{2.3}$$

where $f_1(\cdot)$ is a smooth function of year, $f_2(\cdot, \cdot)$ is a Gaussian process smooth over longitude and latitude, and $\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$. Smoothing functions had maximum basis dimension parameter (k) optimized via grid search at 18 and 40 for year, latitude and longitude respectfully.

We first trained and validated these models using data from reports and imageries[31] before prediction. Model performance was assessed using the leave-one-site-out cross-validation (LOSO-CV), in which all years from a phenology observation site were withheld simultaneously. We then report summaries of validation metrics MAE and RMSE of model performance on held out sites.

2.7 Crop Model Development

Linear regression and random forest regression were used to examine the impacts of flash droughts and other climate indices on yield and abandonment. Random forest regression was chosen for its ability to test interaction and non-linear relationships. Indices included Hot-Dry-Windy (HDW, hours)[31], freezing days (Frez, days), extreme degree days (EDD, days), and precipitation (Prcp, mm). Frez was calculated based on temperatures below 11°C and 1°C, depending on the stage of the growing season, while EDD represented temperatures above 32°C. We included squared terms for precipitation for all stages to account for non-linear relationship of Prcp to yield and abandonment in the linear models, potentially adding multicollinearity. HDW refers to a hourly compound event with co-occurrence of temperature (T) $\geq$ 32°C, relative humidity (RH) $\leq$ 30%, and wind speed (U) $\geq$ 7m s^{-1} at 2 m height[31]. Mean WUE during agricultural flash droughts were used with duration of 10 days and a drop of 0.15 as stated above. These two indices encapsulate the crop water stress at the hourly and daily time scale, respectively. We evaluated four model configurations: linear regression and random forest models, each trained with and without flash drought events.

2.8 Model Validation & Selection

Leave-one-site-out cross-validation (LOSO-CV)[32], more formally known as leave-one-block-out), was used to validate phenological model performance. This approach evaluates the model's ability to interpolate phenological dates to new spatial locations, matching its intended application. Variable selection Using Random Forest (VSURF) package in R[33] was used for variable selection, eliminating redundant and collinear predictor variables. R^2 and adjusted-R^2 were used to evaluate the linear models, while out-of-bag (OOB) R^2 was used for random forest performance evaluation.

Results

3.1 Phenological Prediction

We used our spatiotemporal framework to estimate planting and harvesting dates at unobserved locations throughout the Great Plains. Using the LOSO-CV approach, our model had an average mean absolute error (MAE) and an average root mean square error (RMSE) of 5.5 (sd = 3.14) and 6.4 (sd = 3.41) days for harvesting, respectively [Figure 3.1a]. Site-level MAE indicate model consistency, with 89% of prediction within 8 days of the observed harvesting date. Model performance was lower for planting than for harvesting. Under LOSO-CV, planting dates were predicted with a mean MAE of 7.4 (sd = 4.5) days and a mean RMSE of 8.4 (sd = 4.7) days across validation sites [Figure 3.1b], compared with 5.5 and 6.4 days for harvesting, respectively. Approximately 65% of planting predictions were within 8 days of the observed date.

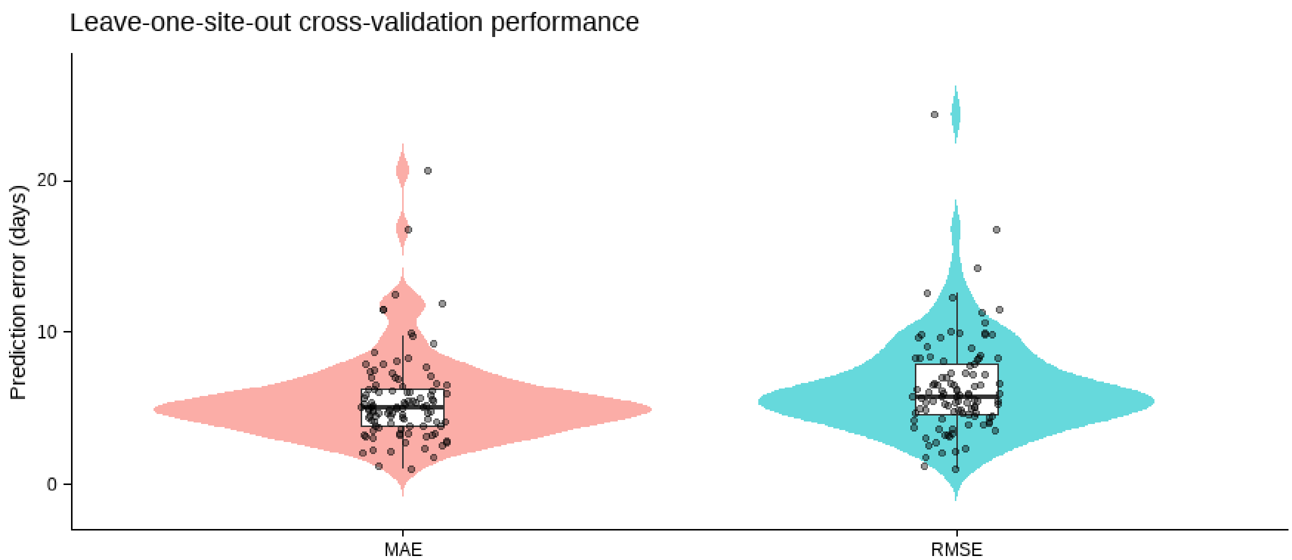
3.2 Abandonment

The USDA observational data from 2002-2019 revealed that mean abandonment of winter wheat was highest in 2011 and 2018, reaching almost 43% and 44% across the Great Plains respectively. In these years, we see the highest occurrences of agricultural flash droughts as well. When including WUE in with the other indices, we seen an increase in model performance, seeing an increase in both R^2 and adjusted-R^2 by 0.081 and 0.073, respectively. When using random forest, we see an increase of model performance to an OOB R^2 of 0.809

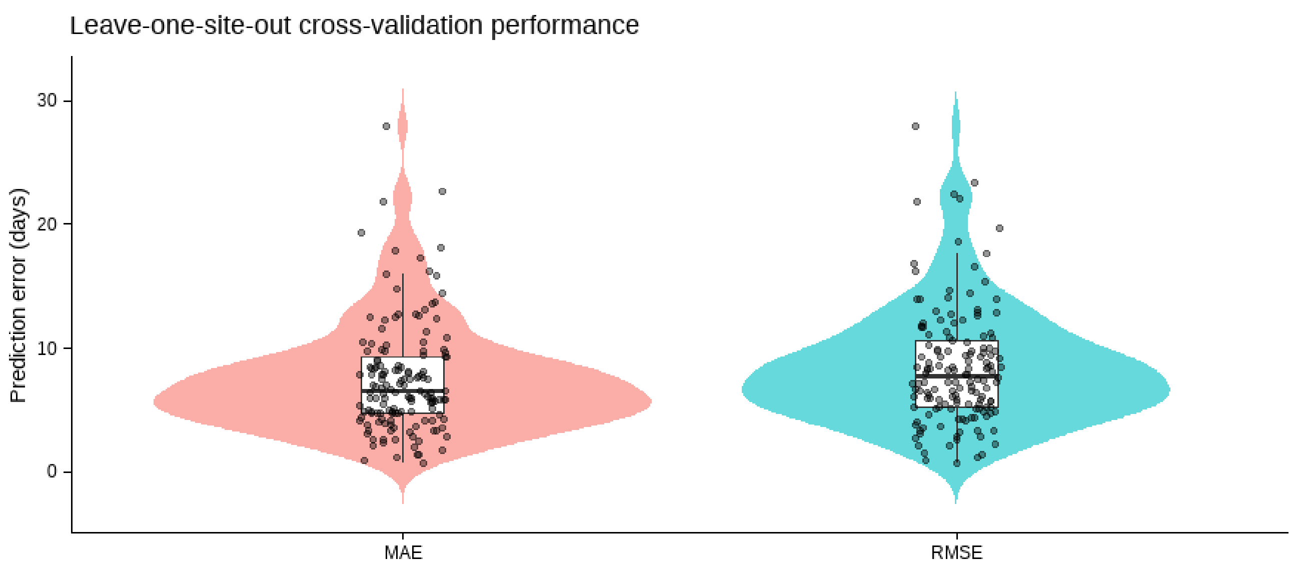
from the adjusted R^2 of 0.770 from the linear model. The random forest model without WUE performed well with 76.59% variance explained. In the full random forest, WUE during flash droughts that occur during the PJ phase are the third most important variable via permutation [Figure 3.2], just behind latitude, and early-season freezing. When conducting variable selection on the full random forest model, we find that location, year, WUE-PJ, and early-season freezing explained 79.84% of abandonment variation alone.

3.3 Yield

When including WUE in the linear model framework for yield, we seen an increase in model performance with an increase in R^2 and adjusted-R^2 by 0.088 and 0.083 respectively, improving to 77.10% and 72.45% variance explained. When using random forest, we see an increase of model performance to an R^2 of 0.825. Here, WUE-PJ is again the third most important variable via permutation, just behind spatial features latitude and longitude [Figure 3.3]. The partial dependence of predicted yield on mean WUE in the full random forest model shows a non-linear relationship with corresponding non-linear 2.5th-97.5th percentile ranges [Figure 3.4]. When conducting variable selection on the full random forest model, a portions of the kept variables included WUE in PJ and JH phases, explaining 80.01% of yield variation.



(a) Harvesting



(b) Planting

Figure 3.1: Violin plots showing the distribution of prediction errors from leave-one-site-out cross-validation (LOSO-CV) for phenological date prediction. **(a)** Harvesting dates and **(b)** planting dates. Each violin represents the distribution of prediction errors across validation sites, with wider regions indicating greater density of observations.

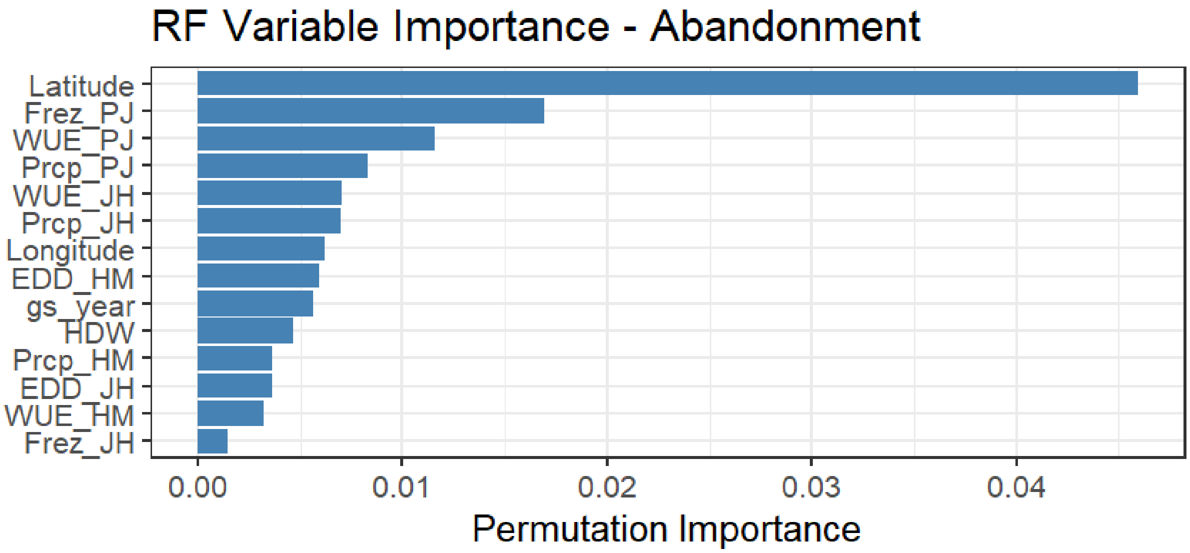


Figure 3.2: Permutation-based variable importance for the random forest model predicting winter wheat abandonment across the Great Plains. Variables are ranked by their contribution to model predictive performance, with larger values indicating greater importance. WUE-PJ denotes the water-use efficiency during the planting to jointing stage and contributes the third most to model predictive performance.

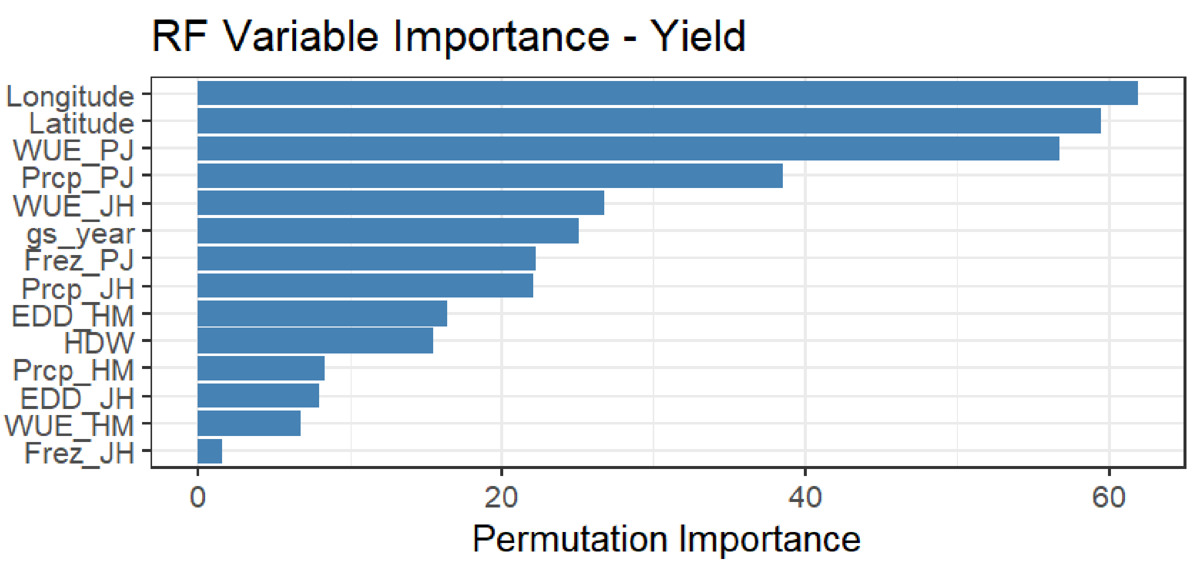


Figure 3.3: Permutation-based variable importance for the random forest model predicting winter wheat yield across the Great Plains. WUE-PJ and WUE-JH denote the water-use efficiency during the planting to jointing and jointing to heading stages. Both WUE-PJ and WUE-JH contribute highly to model predictive performance.

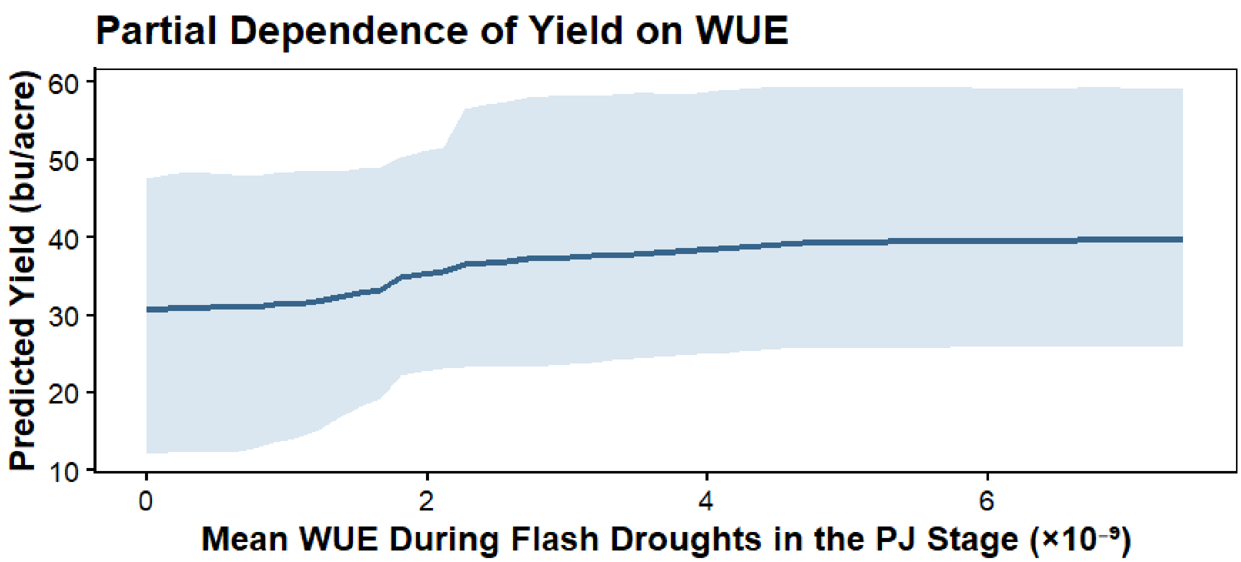


Figure 3.4: Partial dependence of predicted yield on mean water-use efficiency (WUE) during flash droughts. The solid line represents the mean partial dependence estimated from the random forest model. The shaded region represents the 2.5th–97.5th percentile range of predicted yields across observations at each value of WUE, reflecting variation in model predictions associated with differences in the other predictor variables.

Discussion

The predicted harvesting and phenological dates were within range of other phenological prediction frameworks within this study area[34], whose prediction fell within a reasonable range of 3-8 days and included more than just spatial and temporal factors. The lower predictive accuracy for planting likely reflects greater variability in producer management decisions and short-term weather conditions that are not fully captured by the predictor variables. Including genetic, environment, and management information would most likely improve the accuracy of this framework as well as the inclusion of more observation based on remote sensing and satellite imagery[35].

We see a high correlation between total season flash drought days and percentage of crops abandoned, reflecting ideas of flash droughts causing large scale crop loss across the United States[36]. The increase model performance in random forest compared to linear model when including WUE indicates nonlinear relationship between abandonment and weather indices as we see in the HDW framework. It is important to note that if we were to evaluate the partial difference for the full random forest model, we would see a slight non-linear relationships between abandonment and WUE, suggesting linear models may possible capture the relationship and explaining the incremental jump in variance explained from linear and random forest models. Variable selection results indicate chance of multicellularity between weather variables and suggest flash drought metric during PJ accounts for variation in other weather for abandonment.

The greatest performance increase when including flash drought metrics is in yield modeling, increasing explained variance by 9.22% when capturing non-linear effects. We see again that WUE measured during the PJ phase is most important outside of spatial features, going against other literature that suggests the most impact occurs during the crop maturing phases[15;27]. We also see nonlinear relationships between yield and WUE when evaluating partial differential plots, suggesting linear models may not be capturing the full relationships and linear assumptions may not be adequate. The plot also suggests predictions across observations at each WUE value have relatively the same non-linear shape. These results signify the importance of accounting for non-linearity in crop-climate prediction[31], which we demonstrate here using random forest models that can also capture interactions among variables. It is important to note that we did not compare OOB R^2 to non-adjusted R^2 due to high likelihood of multicollinearity when also including squared terms for Prcp. Almost all variance can be attributed to flash drought metrics and precipitation alone.

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