CLIMATE IMPACTS ON COUNTY-LEVEL INTERANNUAL VARIABILITY IN WINTER WHEAT YIELD IN THE COLUMBIA BASIN, USA

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Authorization to Submit Thesis

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Abstract

County level interannual climate-yield relationships for winter wheat were examined across a moisture gradient over primarily rainfed agricultural systems in the Columbia Basin of the United States from 1980-2014. Wheat yields were most strongly correlated with energy and moisture availability during the latter stages of crop development. Estimated actual evapotranspiration calibrated for winter wheat was typically the best predictor of interannual yield variability at the county level, with the strongest relationships for counties with intermediate amounts of mean annual precipitation. Crop yields were negatively impacted by warmer temperatures during the latter stages of crop development, particularly in the climatologically cooler counties as delayed crop phenology results in warmer temperatures during phenostages when crops are most sensitive. A variety of multi-variate statistical models explain an average of 29-37% of interannual county-level yield variance over the Columbia Basin, yet show spatial heterogeneities in climate yield relationships suggesting the importance of subregional climate-crop modeling.

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1. Introduction

Winter wheat (*Triticum aestivum* L.) is the most widespread cultivated crop in the Pacific Northwest of the United States (US), occupying 1.32 million hectares and yielding average 4.27 million metric tons annually from 2010-2014 (USDA). Approximately 75% of winter wheat grown in US Pacific Northwest occurs in the Columbia Basin encompassing much of the central and eastern Washington, and parts of northeastern Oregon and northwestern Idaho. Collectively, winter wheat in the Columbia Basin generates over 1 billion US dollars annually (USDA), contributing substantially to the rural economy. However, as dryland farming accounts for nearly all of winter wheat croplands grown in the region, yields can fluctuate from year to year due to moisture limitations (Schillinger et al.,2008; Fuentes et al., 2003). Interannual variability in winter wheat yields not only impacts local economies, but also affects global wheat prices (e.g., *Sternberg et al., 2012*). Understanding the factors that contribute to interannual variability in wheat production is thus of key importance to local agribusiness, global wheat markets, and global food security.

Global wheat productivity increased substantially from 1960s to 1990s (*Chen et al., 2004; Cantelaube et al., 2004; Lobell and Field, 2007; Lin and Huybers, 2012*) due to advances in agricultural techniques (e.g., cultivars) and management (e.g., fertilizer usage, irrigation and crop rotation). However, yield increases have plateaued in some regions since the 1990s, due to a less favorable climate (*Lobell and Field, 2007*) and decreased fertilizer usage (*Lin and Huybers, 2012*). Similar to global wheat yields, winter wheat yields across the US Columbia Basin showed a 19.5% increase from 1980-2000, with little overall increase since 2000 (Figure 1b). Whereas human factors (e.g., cultivar choices, management) are typically more pronounced in long-term trends of crop yields, interannual climate variability is better coupled with interannual yield variability (*Cantelaube et al. 2004*).

Numerous studies have empirically or experimentally examined climate-yield relationships, typically using monthly or seasonal temperature and precipitation summaries. Climate variability has been shown to account for roughly one third of wheat yield variability at global scales (*Ray et al., 2015; Lobell and Field, 2007*). The influence of climate variability on crop yield includes both energy and moisture constraints that can take on different relationships throughout crop development (*Schlenker and Roberts, 2009; Porter and Gawith, 1999; Asseng, 2012*). Optimal temperature ranges for wheat development have been identified for various crop phenostages, with detrimental impacts for both warm and cold excursions from identified thermal optimums (*Porter and Gawith, 1999*). For example, high temperatures (>30^{o}C) during flowering and grain-filling stages can reduce yields (*Gibson and Paulsen, 1999; Narayanan et al., 2015*). Climate-yield relationships for rainfed wheat cropping systems typically show linear relationships with moisture availability (e.g., *Zhang and Oweis, 1999; Schillinger et al., 2008*). Water limitation can decrease stomatal conductance and viable leaf area, lead to a decline in photosynthesis, and result to reduced grain number and mass and increased grain protein content (*Asseng, 2012; Nicolas et al., 1984*).

Prior studies have typically examined climate-yield relationships across broad geographic scales (e.g., national and state level) and fixed calendar dates (e.g.*, Ray et al., 2015*). However, climate-yield relationships are likely to vary at spatial scales finer than those typically examined due to heterogeneity in baseline moisture and energy within a geographic region and their interplay with known energy and moisture optimums for crop development. Additionally, climate metrics (e.g., water balance) closely aligned with plant physiology during certain phenostages may have more explanatory power for interannual variability in crop yields than summaries of temperature and precipitation tied to static calendar dates. This study addresses these knowledge gaps in climate-yield relationships for winter wheat across the Columbia Basin using county-level crop and climate data. Collectively, the ability to improve our understanding of the climatic factors that influence interannual variability in wheat yields may improve seasonal outlooks for wheat yields and help inform wheat future prices on the global market.

2. Data and methods

2.1 Study region

The agricultural lands of the Columbia Basin comprise the lower elevations (170~1000m) of the Columbia River Basin in the US Pacific Northwest located between the Cascade Range and the Rocky Mountains. Typical of much of the Pacific Northwest, the region experiences a Mediterranean type climate with over 75% of its annual precipitation occurring from November-May. Annual average precipitation varies across the region with around 200 mm in the rain-shadowed lee of the Cascade Rage in central Washington to more than 800 mm across the eastern portion of the basin where elevation rises on the windward flanks of the Northern Rockies in Idaho. The mean annual temperature of the study area generally adheres to elevational relationships with the highest temperatures in the lower elevations of the western Columbia Basin and lowest temperatures at higher elevation in the eastern Columbia Basin.

Winter wheat is the major crop in the Columbia Basin covering over 30% of the 3.35 million hectares of cropland across the region. Dryland farming is primarily used, except in the driest areas in the southwestern extent of the region where irrigation is used. The average annual county yields from 1980-2014 vary geographically across the region from 2600-5100 kg/ha (Figure 1a). Spatial variability in winter wheat yields is evident with yields increasing west to east across the basin generally tracking with the gradient of moisture availability. Crop rotations are adopted across the region based on primarily mean annual precipitation, with annual cropping in the wetter zones and annual-fallow cropping in the drier zones, in an effort to balance sufficient soil moisture for wheat cropping and avoid wheat disease and pests.

2.2 Yield and climate data

County level winter wheat yields from 1980-2014 for 27 counties from Washington, Oregon and Idaho in the Columbia Basin were acquired from the National Agricultural Statistics Service (NASS), US Department of Agriculture (*2014*). Although there were several missing records in this dataset, each county had at least 28 years of valid data from 1980-2014.

Two approaches were considered to minimize conflating climate drivers with long-term increases in yield (Figure 2). First, the 1980-2014 linear trend in yield was separately estimated for each county using a linear least squares regression following previous studies (*Lobell et al., 2011; Olesen et al., 2000; Ray et al., 2015*). We refer to the resultant time series as detrended yields. Alternatively, long-term changes in the wheat yields may not be adequately represented using a linear or higher-order polynomial trend, but instead may occur as abrupt shifts in yield due to the adoption of technological advancements, particularly at smaller geographic scales. To account for this possibility, we also considered first differences (i.e., changes from the previous year) of wheat yields and climate data as used in previous studies (*Lobell and Field, 2007; Rao et al, 2015*). We compare both detrended yield records and first difference records in subsequent analyses.

Daily meteorological data at ~4km spatial resolution was acquired from Abatzoglou (*2013*) for daily maximum and minimum temperature, specific humidity, precipitation, solar radiation, and wind speed from 1979-2014. We averaged grid cell values across the geographic extent of winter wheat cropland area derived from the aggregation of NASS from 2007-2014 (Figure 1a) for each of the 27 counties to create a county-level dataset. While most prior research examined relationships between climate and yield using static calendar dates, we adopt an approach that uses phenological dates tied to the development of winter wheat for each county and year. Phenological stages of winter wheat were defined using a growing degree day based (GDD) model for winter wheat (*Ritchie, 1991*). The model divides the wheat growing season into seven phenostages based on cumulative GDD with a base threshold of 0^{o}C, consisting germination, emergence, tillering, booting, flowering, and grain-filling and maturity (Table 1).

Dryland wheat production in the Columbia Basin is dependent on soil moisture captured in winter precipitation in combination with spring precipitation. While most prior climate-yield studies have relied on first-order climate variables of temperature and precipitation (e.g., *Ray et al., 2015*), we hypothesized that water balance metrics should be better aligned with crop water use and thus may better relate to interannual variability in yields. We applied a modified Thornthwaite water balance model (*Willmott et al., 1985*) that considers temperature, precipitation and reference evapotranspiration using the Penman-Montieth method (*Allen et al., 1998*). Since reference evapotranspiration assumes a static reference grass surface, we used a seasonally varying single crop coefficient for winter wheat that varied from 0.7, 1.15 and 0.3 for the initial, mid-season and the end of late season, respectively, with linear transitions during the development phase and late season based on GDD (Table 2, *Saadi et al. 2015*). We used county-level available water content data aggregated from winter wheat growing regions from the USDA-NRCS STATSGO database and the water balance model to calculate actual evapotranspiration (AET) and the water deficit (DEF, the difference between the potential evapotranspiration and AET) for each county.

Heat stress can have negative impacts on crop growth (*Liu et al., 2014; Prasad and Djanaguiraman, 2014; Talukder et al., 2014*; *Porter and Gawith, 1999*). We calculated cumulative heat degree days (HDD) from flowering to physical maturity using a base threshold of 30^{o}C for daily maximum temperature as a proxy for heat stress (*Porter and Gawith, 1999; Liu et al., 2014*).

2.3 Climate-yield relationships and models

Pearson's correlation coefficients were calculated between each climate metric and wheat yield for each county from 1980-2014. We calculated correlations for each phenology stage and all combinations of consecutive phenological stages. Correlations were run separately for both detrended yields as well as first difference time series. We sought to identify phenological windows during which climate-yield relationships across the region were maximized. This was accomplished by identifying the maximum county-average squared correlation for temperature, precipitation, AET and DEF. Correlation coefficients and linear regressions were calculated between wheat yield and climate for each county using the optimum phenological window to assess spatial variability across the study region.

Forward stepwise linear regression models were used to estimate climate impact on wheat yield variability (e.g., Tao et al., 2012) separately for each county using the optimized phenological windows from the four climate variables and HDD.

Two modeling schemes were developed, one using linear detrended yields (Y), the second using first difference yields (ΔY). The linear detrended yield model used five climate predictors and their square terms: (i) mean temperature from flowering to maturity (T_{fm}), (ii) cumulative precipitation from booting to maturity (P_{bm}), (iii) AET from grain filling to maturity (AET_{gm}), (iv) DEF over the entire growing season, and (v) HDD from flowering to maturity (HDD). The first-difference model used five first-difference climate predictors and their square terms: (i) first difference of mean temperature from grain filling to maturity (ΔT_{gm}), (ii) first difference of cumulative precipitation from booting to maturity (ΔP_{bm}), (iii) first difference of AET from grain filling to maturity (ΔAET_{gm}), (iv) first difference of DEF over the entire growing season (ΔDEF), and (v) the first difference of HDD from flowering to maturity (ΔHDD). Stepwise linear regression fits variables in order of importance, and is often used to develop models where there are a number of independent variables that may explain variance of the dependent. Independent variables were allowed to enter the model when the p-value for an F-test was <0.05, and removed from the model when p was > 0.10.

As an alternative to constructing separate models from each county, we considered the first difference panel linear model using county-level wheat yields and five predictors (T_{fm}, P_{bm}, AET_{gm}, DEF, HDD) not including their square-terms. The first difference panel model can be viewed as differencing each term in the fixed effect model. Fixed effect panel regression model was used to depict global and provincial climate-yield relationships in recent years (*Lobell, et.al., 2011; Tao, et.al., 2014*). This approach can incorporate time series information with cross-section (geographic units) information to general a universal climate-yield response. Each section has a unique model intercept to reflect cross-section differences which are implied as different yield levels. First differencing approach removes the time-invariant term from the model, which removes the cross-section difference in the model equation. Unlike the stepwise regression approach, the panel model generates a single equation that is used across the entire study area.

3. Results

3.1 Univariate climate correlations

The strength of the interannual relationship between climate and winter wheat yield exhibited more widespread and significant correlations with moisture related metrics than temperature (Figure 2). The strongest correlations for both temperature and moisture metrics covered time periods that include the latter stages of crop development. The county mean squared Pearson's correlation coefficient (r^2) between detrended yield and temperature showed an optimum (r^2 = 0.11) during the period from flowering to maturity (T_{fm}). Similarly, the strongest county mean r^2 between detrended yield and both precipitation (r^2 = 0.18) and AET (r^2 = 0.25) occurred during the latter stages of crop development from booting to maturity, and flowering to maturity, respectively. Significant, but weak correlations (r^2 <0.1) were evident between yield and early season precipitation from germination to tillering. Finally, the strongest correlations between detrended yield and DEF were for phenological periods that included grain filling stage, such as from grain filling to maturity (r^2 = 0.22).

A similar pattern was found using first-differences, although with slightly higher r^2 values for each of the optimums (Figure 2). For example, the county mean r^2 between the first difference of yield and ∆AET from grain filling to maturity was 0.29, and the county mean r^2 between the first difference of yield and ∆P from booting to maturity was 0.22. Minor differences in the timing of the optimum correlations were seen for temperature and AET, with the peak r^2 occurring from grain filling to maturity stages (ΔT_{gm}, ΔAET_{gm}), rather than flowering to maturity stages as found in the detrended yield relationship.

The spatial variability in county-level univariate correlations between wheat yields and optimums for the temperature, precipitation, AET, and DEF, as well as HDD from flowering to maturity are shown in Figure 3. Temperature (T_{fm}, ΔT_{gm}) exhibited negative correlations with yields across the study area. However, most of the significant correlations were found in counties across the northeastern portion of the basin where temperatures are climatologically cooler. The strength of the interannual temperature-yield relationship showed significant positive correlations with mean county annual temperatures (Figure 4a, b), where cooler counties have stronger negative r-values between temperature (T_{fm}, ΔT_{gm}) and wheat yields. Correlations between HDD and yield were mainly weak and non-significant across the Columbia Basin. However, there is a longitudinal dipole whereby a few counties in the warmer southwestern portion of the basin had significant negative correlations, while a few counties in the cooler eastern portion of the basin had significant positive correlations.

Spatially coherent relationships were realized between yield and moisture related variables across much of the study area. Significant positive correlations between yield and both precipitation (P_{bm}, ΔP_{bm}) and AET (AET_{gm}, ΔAET_{gm}) were found over much of the region, with the strongest correlations found in the central and southern portion of the basin. Widespread significant negative correlations were found between the cumulative water deficit (DEF, ΔDEF) and wheat yields, with the strongest correlations for counties in the central basin. Non-significant correlations with precipitation, AET, and DEF were found for counties along the western and eastern flanks of the basin. While the spatial pattern in correlation coefficients to moisture variables did not exhibit significant linear correlation with the county level mean annual precipitation (Figure 4 c-f), the strongest correlations typically were present in counties that intermediate precipitation zones, defined by annual mean precipitation between 300-550mm.

Univariate regression coefficients for temperature, precipitation, AET and DEF to winter wheat yields are shown in Figure 5. Coefficients for T_{fm} and ΔT_{gm} were negative across nearly the entire basin with county-average values of -144.0 kg ha^{-1} $^{o}C^{-1}$ and -143.4 kg ha^{-1} $^{o}C^{-1}$, respectively. The strongest negative coefficients were present across counties in the northern and eastern portion of the basin, exhibited a strong negative correlation with the pattern of county-level annual mean temperature (Figure 6 a,b). This suggests that wheat yields in cooler counties are more sensitive to interannual variability in temperature during the latter stages of crop development than in warmer counties. Coefficients for P_{bm} and ΔP_{bm} were positive across the basin with county-average values of +6.6 kg ha^{-1} mm^{-1} and +7.0 kg ha^{-1} mm^{-1}, respectively. The highest coefficients were present across counties in the central northern portion of the basin. Regression coefficients for P_{bm} exhibited significant negative correlation with mean annual precipitation, which suggests wheat yields in drier counties are more sensitive to precipitation during the latter stages of crop development than in wetter counties (Figure 6c). Coefficients for AET and ΔAET were positive all over the basin with county-average values of +13.4 kg ha^{-1} mm^{-1} and +14.5 kg ha^{-1} mm^{-1}, respectively. The strongest coefficients for AET were apparent across counties in southeastern Washington state. A similar, but inverted pattern was seen for DEF and ΔDEF with county-average values of -6.7 kg ha^{-1} mm^{-1} and -7.9 kg ha^{-1} mm^{-1}, respectively. Significant negative correlations were evident between regression coefficients for ΔDEF and county-level mean annual precipitation, which suggests yields in wetter counties are more sensitive to water deficit changes during the growing season than in drier counties.

3.2 Climate yields models

Stepwise linear regression models explained an average of 30.0% of county-level interannual variability in detrended wheat yields (Figure 7a). Only Yakima County, Washington had no model, whereas climate explained 69.0% of the yield variance in Garfield County, Washington (Table 3). The most frequently selected variable for county level stepwise regression of detrended yields was AET_{gm}. DEF was selected as a predictor in the central and southern portion of the basin, whereas T_{fm} was the only variable to explain yield variability in the northernmost three counties in Idaho.

Stepwise linear regression models explained an average of 36.9% of county level interannual variability in first-difference wheat yields (Figure 7b). Yakima County, Washington and Union County, Oregon had no model, and climate explained 77.4% of the yield variance in Garfield County, Washington. The three most frequently selected predictors for the first-difference stepwise model were ΔAET_{gm}, ΔP_{bm} and ΔDEF. However, due to the collinearity among moisture variables, typically only a single moisture variable was used in each county. One of these three moisture variables was used in all but one county for which a first-difference model was built.

The first difference panel model explained 28.6% of the temporal variance in county level yield records (Figure 7c). The form of the equation (Table 4) suggests negative relationship with ΔT_{fm} and ΔHDD of -18.6 kg ha^{-1} C^{-1} and -1.42 kg ha^{-1} DD^{-1}, respectively. Similarly, the model showed positive relationships with moisture availability with regressions of +1.66 kg ha^{-1} mm^{-1}, +7.66 kg ha^{-1} mm^{-1}, and -2.45 kg ha^{-1} mm^{-1}, for ΔP_{bm}, ΔAET_{gm}, and ΔDEF, respectively. By comparison, univariate first difference panel models using only ΔAET_{gm}, and only ΔP_{bm} had coefficients of +14.5 kg ha^{-1} mm^{-1} and +6.42 kg ha^{-1} mm^{-1}, respectively.

The geographic pattern of explained variance was similar for all three modeling approaches with a larger portion of explained variance for counties in the central portion of the basin than for counties on the periphery. However, the spatial variability in r^2 did not exhibit any apparent relationship to underlying spatial variability in climate unlike for the univariate correlations (e.g., Figures 4 and 6). Part of the spatial variability is likely a function of the underlying non-climatic factors such as irrigation across parts of the study area. For example, the first-difference model explained an average of 25% of the variance in interannual wheat yields in counties where at least 10 percent of harvested land was irrigated, whereas first-difference models explained an average of nearly 40% of the variance in all remaining counties.

4. Discussion and Conclusion

Our modeling results suggest that climate explains between an average of 29-37% of the county-level interannual variability in winter wheat yield across the Columbia Basin from 1980-2014. These results are similar to proportion of explained variance in global wheat yields by climate factors (Ray et al., 2015). Interannual variability in winter wheat yields were found to be more sensitive to moisture and energy variability during the latter stages of the crop development, especially during flowering and grain filling, than during the earlier growing season. These results are consistent with previous studies that have shown wheat yields are more sensitive to temperature during its reproductive phase (from flowering to maturity) than during its vegetative phase (*Porter and Gawith, 1999; Asseng et al., 2012*). Collectively, we suggest that moisture is the primary climatic constraint of winter wheat yields in the Columbia Basin, and that water balance metrics provide more explanatory power than precipitation alone.

Our correlative analysis and models show an inverse relationship between wheat yield and temperature from flowering to maturity, consistent with previous studies that found elevated temperatures during this period reduce grain numbers and grain weight (*Al-Khatib and Paulsen, 1990; Ferris et al.,1998; Narayanan et al., 2015*). Liu et al. (*2016*) suggested a 4.1-6.4% decline in global wheat yield per 1^{o}C warming. Our results support this hypothesis for the study region, although we only address temperature impacts directly through temperature-yield relationships – ignoring the indirect influences through AET and DEF. Univariate regression between wheat yields and temperature variability suggest an average 3.7% decline in wheat yield per 1°C warming across the Columbia Basin.

Paradoxically, the strongest negative relationships between temperature and yield were generally found in the climatologically cooler counties over the eastern portion of the domain. However, our use of phenological calendars allows wheat to reach this phenostage later in the year when day lengths are longer and temperatures are higher. The T_{fm} was over 1.2°C warmer for the climatologically coolest tercile of counties than the rest of the domain. Thus, the delayed phenology in these cooler counties allows them to be more susceptible to temperature variability during a climatologically warmer time of the year. Similarly, we hypothesize that relatively weak relationships between HDD and yields across the Columbia Basin are a consequence of the seasonal mismatch between the phenology of winter wheat and extreme temperatures across the region with wheat reaching maturity in warmer counties before the onset of very warm temperatures.

The univariate regression coefficients for AET suggest slightly lower moisture impacts on wheat yields than shown in previous field studies within the region by Schillinger et al., (*2008*). The county average coefficients for AET_{gm} (ΔAET_{gm}) in detrended (first-difference) univariate regression models were 13.4 kg ha^{-1} mm^{-1} (14.5 kg ha^{-1} mm^{-1}). By contrast, Schillinger et al., (*2008*) showed a regression coefficient of 19.2 kg ha^{-1} mm^{-1} to total available moisture. While there are differences between total available moisture (overwinter soil moisture gain plus April-June precipitation) as defined by Schillinger et al., (*2008*) and AET_{gm}, which represents plant water use from grain filling to maturity, the results are comparable and our results extend these relationships to the larger geographic area.

Stepwise regression models across the 27 counties in the Columbia Basin showed a discrete pattern of climate-yield relationships explaining up 77% of the interannual variability in wheat yield. Unlike previous analyses that have examined climate-yield relationships at broader political units (e.g., *Ray et al., 2015*), we show a large amount of regional heterogeneity across the study area with different climate variability contributing to model skill across the region. For example, we show that the northeastern portion of the basin was more sensitive to temperature variability, whereas the central and southern portion of the basin were sensitive to moisture variability. Although our results did not identify an optimal set of predictor variables, regression models for counties that failed to incorporate a moisture proxy had poor explanatory power (mean of less 19% of the yield variability explained).

Overall, more variance was explained with the first difference stepwise model (R^2 = 0.369) than the detrended stepwise model (R^2 = 0.300) and the first difference panel model (R^2 = 0.285). The panel model is an alternative approach and attractive due to the larger number of degrees of freedom and consistency in coefficients across the study area. However, our results show that climate-yield relationships vary geographically across the Columbia Basin, particularly with temperature exerting a stronger influence on wheat yield variability in climatologically cooler counties (Figure 4, Figure 6).

Several caveats in our study may constrain the performance of our yield models. First, the actual planting date of winter wheat is not spatially or temporally constant. Due to the lack of planting date records, we arbitrarily defined planting as Oct 1st, the middle of the general planting window for the region. This assumption can impact the timing of subsequent phenology stages and climate-yield relationships. Second, we didn't consider crop rotation in water balance calculations but assumed a continuous winter wheat cropping system. The influence of antecedent climate variability prior to the current growing season on wheat yields may thus contribute to variability in soil moisture. The third limitation of our study is that we didn't distinguish the irrigated and non-irrigated fields due to a lack of continuous yield records. Irrigation can mitigate climate impacts, particularly related to water limitation, on crop growth thereby leading to weak climate-yield correlations (*Troy et al., 2015*). We hypothesize that poorly performing yield models for counties in the arid western portion of the basin is a function of a higher fraction of harvested wheat being irrigated and thus less sensitive to climate variability.

Our yield models explain approximately one-third of county level winter wheat yield variability over the past three decades. Additional unexplained variance may be related to direct and indirect climate impacts beyond those that we considered, for example the occurrence of stripe rust (e.g., *Sharma-Poudyal and Chen, 2011*) and precipitation events prior to harvest. Non-climatic drivers of variability in wheat yield are also probable and may even alter observed climate relationships. For example, spatiotemporal changes in wheat cultivars could alter the climate sensitivity of yields (*Cattivelli et al., 2008*) and produces non-stationarity in climate-yield relationships. Nonetheless, our yield models may have value in forecasting winter wheat yields during the growing season by incorporating both observed climate and seasonal climate forecasts. Such forecasts may have value for estimating regional wheat yields and for wheat futures markets.

5. Tables and Figures

Table 1. Winter wheat phenological stages and corresponding growing degree days (GDD, base 0^{o}C)

Phenological stages	Germination	Emergence	Tillering	Booting	Flowering	Grain filling	Maturity
Cumulative GDD	70	400	685	875	1075	1575	1825

Table 2. The growing degree days (GDD) and crop coefficients of winter wheat growth stages in FAO-56 model.

Stages	Initial	Crop development	Mid-season	Late season
GDD (^{o}C·day)	0-400	400-1250	1250-1900	1900-2150
Crop Coefficient	0.7	0.7-1.15	1.15	1.15-0.3

Table 3. Summary table of stepwise linear regression models for detrended and first difference models. The units of yields (Y, ΔY) are kg/ha; °C for mean temperature (T_{fm}, ΔT_{gm}); °C·day for heat degree days (HDD, ΔHDD); mm for precipitation (P_{bm}, ΔP_{bm}), actual evapotranspiration (AET_{fm}, ΔAET_{gm}), and water deficit (DEF, ΔDEF). Model fit is reported as the coefficient of determination (R^2) and adjusted R^2. The second column lists the state abbreviation, ID: Idaho, OR: Oregon, WA: Washington. The far right column shows the proportion of total harvested area for winter wheat that was irrigated based on 2012 USDA Census records.

			Detrended yield stepwise model			**First difference yield stepwise model**			**Panel Model**	
No.	**State**	**County**	**Equation**	**R^2**	**Adj R^2**	**Equation**	**R^2**	**Adj R^2**	**R^2**	**Irr. rate**
1	ID	BENEWAH	$Y= -7.04e3 + 142\ AET_{gm} - 0.432\ AET_{gm}^{2}$	0.27	0.22	$\Delta Y= -164 +18.6\ \Delta AET_{gm}+ 0.258\ \Delta AET_{gm}^2$	0.46	0.43	0.33	0.000
2	ID	CLEARWATER	Y= 3.57e3 + 12 HDD	0.18	0.15	$\Delta Y= -119 + 14.4\ \Delta AET_{gm} + 54.2\ \Delta T_{gm}^2$	0.37	0.32	0.23	0.000
3	ID	IDAHO	Y= 4.16e3 + 11.5 HDD	0.15	0.12	$\Delta Y= 34.9 + 14.5\ \Delta AET_{gm}$	0.26	0.24	0.23	0.000
4	ID	KOOTENAI	Y= 3.69e3 + 17.2 HDD	0.19	0.16	$\Delta Y= -199 - 408\ \Delta T_{gm} + 0.0754\ \Delta P_{bm}^2$	0.40	0.35	0.15	0.000
5	ID	LATAH	$Y= 5.64e{+}03 - 0.0136\ DEF^2$	0.17	0.15	ΔY= 18.9 - 7.64 ΔDEF	0.29	0.26	0.26	0.000
6	ID	LEWIS	$Y= -2.10e4 + 295\ AET_{gm} - 0.868\ AET_{gm}^2 + 0.0234\ DEF^2$	0.56	0.52	$\Delta Y= 30.8 + 19.9\ \Delta AET_{gm}$	0.53	0.52	0.46	0.000
7	ID	NEZ PERCE	$Y= 3.19e3 + 11.1\ AET_{gm}$	0.12	0.09	ΔY= 51.0 - 14.3 ΔDEF	0.35	0.33	0.27	0.000
8	OR	GILLIAM	$Y= 3.88e3 - 0.0135\ DEF^2$	0.49	0.48	$\Delta Y= -3.76+15.9\ \Delta AET_{gm}$	0.42	0.40	0.45	0.000
9	OR	MORROW	Y= 5.24e3 - 7.54 DEF	0.26	0.23	ΔY= -30.8 - 5.81 ΔDEF - 3.89 ΔHDD	0.33	0.29	0.28	0.034
10	OR	SHERMAN	$Y= 1.63e3 + 15.8\ AET_{gm}$	0.52	0.50	$\Delta Y= 140 + 12.6\ \Delta AET_{gm} -0.0293\ \Delta DEF^2$	0.47	0.44	0.39	0.000
11	OR	UMATILLA	Y= 7.08e3 - 13.1 DEF	0.37	0.35	ΔY= -32.0 - 11.1 ΔDEF	0.37	0.35	0.34	0.093

12	OR	UNION	$Y = 2.94e3 + 14.1\ AET_{gm}$	0.17	0.15	NA	NA	NA	0.08	0.315
13	OR	WASCO	$Y = 4.81e3 - 0.0155\ DEF^2$	0.36	0.34	$\Delta Y = -12.6 + 15.3\ \Delta AET_{gm}$	0.36	0.34	0.38	0.065
14	WA	ADAMS	$Y = -249 + 72.0\ AET_{gm} - 0.313\ AET_{gm}^2$	0.56	0.53	$\Delta Y = -25.1 + 11.3\ \Delta AET_{gm}$	0.28	0.26	0.28	0.107
15	WA	ASOTIN	$Y = 1.85e3 + 16.0\ AET_{gm}$	0.41	0.39	$\Delta Y = -135 - 210\ \Delta T_{gm} - 11.5\ \Delta DEF + 0.057\ \Delta P_{bm}^2$	0.67	0.64	0.51	0.000
16	WA	BENTON	$Y = 2.26e3 + 0.100\ AET_{gm}^2$	0.12	0.10	$\Delta Y = 179 + 12.8\ \Delta AET_{gm} - 3.86\ \Delta HDD$	0.28	0.23	0.20	0.000
17	WA	COLUMBIA	$Y = 6.17e3 - 0.0303\ DEF^2$	0.30	0.28	$\Delta Y = -174 - 19.7\ \Delta DEF + 0.0593\ \Delta HDD^2$	0.55	0.52	0.39	0.000
18	WA	DOUGLAS	$Y = 3.67e3 - 0.00498\ DEF^2$	0.19	0.16	$\Delta Y = -19.5 + 9.03\ \Delta AET_{gm}$	0.22	0.20	0.20	0.000
19	WA	FRANKLIN	$Y = 6.07e3 - 5.96\ DEF - 0.013\ HDD^2$	0.39	0.35	$\Delta Y = -40.7 + 143\ \Delta T_{gm} - 7.43\ \Delta DEF - 3.92\ \Delta HDD$	0.52	0.48	0.29	0.212
20	WA	GARFIELD	$Y = 4.72e3 + 4.43\ P_{bm} - 0.0296\ DEF^2$	0.69	0.67	$\Delta Y = -124 + 3.64\ \Delta P_{bm} - 14.2\ \Delta DEF + 0.094\ \Delta HDD^2$	0.77	0.75	0.64	0.000
21	WA	GRANT	$Y = 3.68e3 + 13.5\ AET_{gm}$	0.26	0.23	$\Delta Y = -53.5 - 5.12\ \Delta DEF$	0.23	0.20	0.25	0.000
22	WA	KLICKITAT	$Y = 2.21e3 + 5.79\ P_{bm}$	0.19	0.16	$\Delta Y = -24.9 - 3.37\ \Delta HDD$	0.22	0.20	0.20	0.065
23	WA	LINCOLN	$Y = 2.73e3 + 14.3\ AET_{gm}$	0.35	0.33	$\Delta Y = 30.5 + 14.7\ \Delta P_{bm}$	0.37	0.35	0.37	0.057
24	WA	SPOKANE	$Y = 2.78e3 + 11.7\ AET_{gm}$	0.19	0.16	$\Delta Y = 6.06 + 9.51\ \Delta P_{bm}$	0.44	0.42	0.41	0.011
25	WA	WALLA WALLA	$Y = 2.53e3 + 19.3\ AET_{gm}$	0.36	0.34	$\Delta Y = 27.2 + 23.1\ \Delta AET_{gm}$	0.46	0.44	0.51	0.108
26	WA	WHITMAN	$Y = 3.94e3 + 0.0513\ AET_{gm}^2$	0.29	0.27	$\Delta Y = 23.1 + 15.7\ \Delta AET_{gm}$	0.33	0.31	0.39	0.000
27	WA	YAKIMA	NA	NA	NA	NA	NA	NA	0.001	0.786

Table 4. The summary table of the first difference panel regression model. The units of temperature (ΔT_{fm}) is degree Celsius; mm for precipitation (ΔP_{bm}), actual evapotranspiration (ΔAET_{gm}), and water deficit (ΔDEF); ºC·day for heat degree days (ΔHDD).

Variable	**Coefficient**	**Pr(>|t|)**
Intercept	22.33	0.32
ΔT_{fm}	-18.61	0.26
ΔPbm	1.66	<0.01
ΔAETgm	7.66	<0.01
ΔDEF	-2.45	<0.001
ΔHDD	-1.42	<0.01
R-Square	0.286	
Adj. R-Square	0.284	

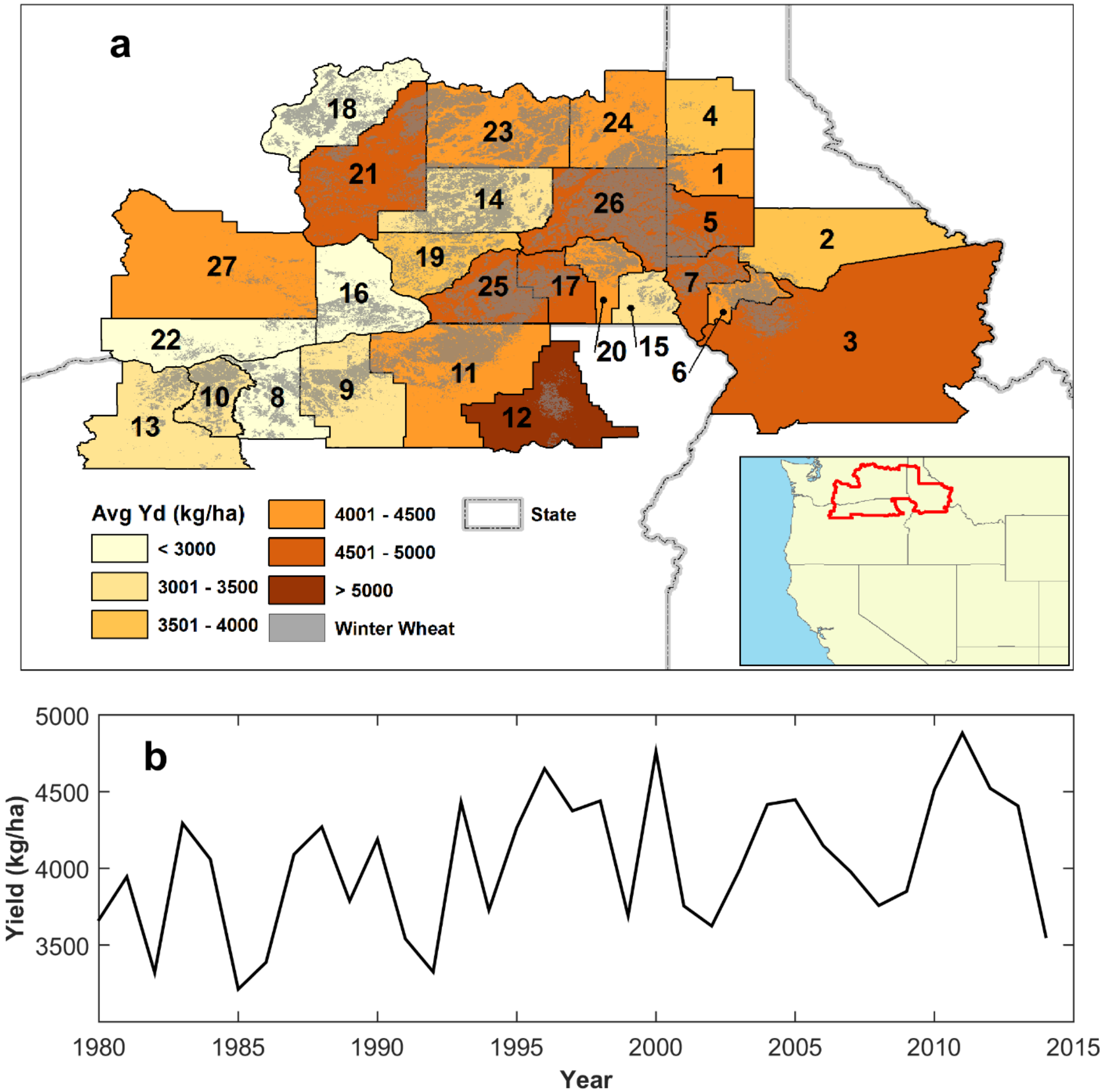

Figure 1: a) Geographic extent of the 27 counties in the Columbia Basin of the United States (inset map) and average county winter wheat yields for 1980-2014. The extent of agricultural land where winter wheat was grown in at least one year from 2008-2014 is shown in grey. The numbering of the counties is referred to in Table 3. **b)** Annual county area weighted average winter wheat yields in the Columbia Basin from 1980-2014.

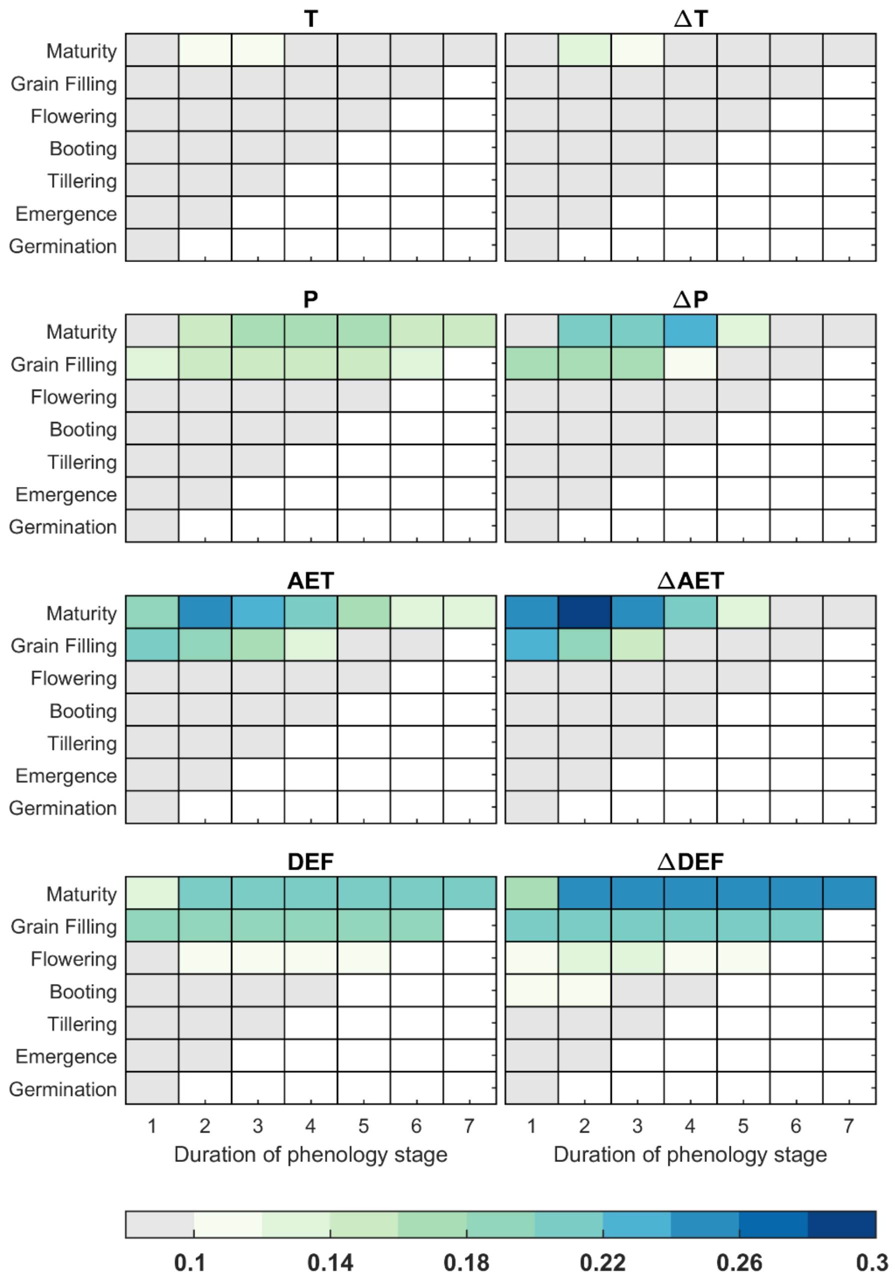

Figure 2: Matrices of county-mean r^2 value between (left) detrended winter wheat yields and climate variables, and (right) first difference winter wheat yields and first difference climate variables for (top-to-bottom) mean temperature (T), accumulated precipitation (P), climatic water deficit (DEF), and actual evapotranspiration (AET). The y-axes denote the ending phenology stage, and x-axes denote the number of consecutive phenology stages. Note, values in bottom-right of each matrix are shown in white and were not evaluated.

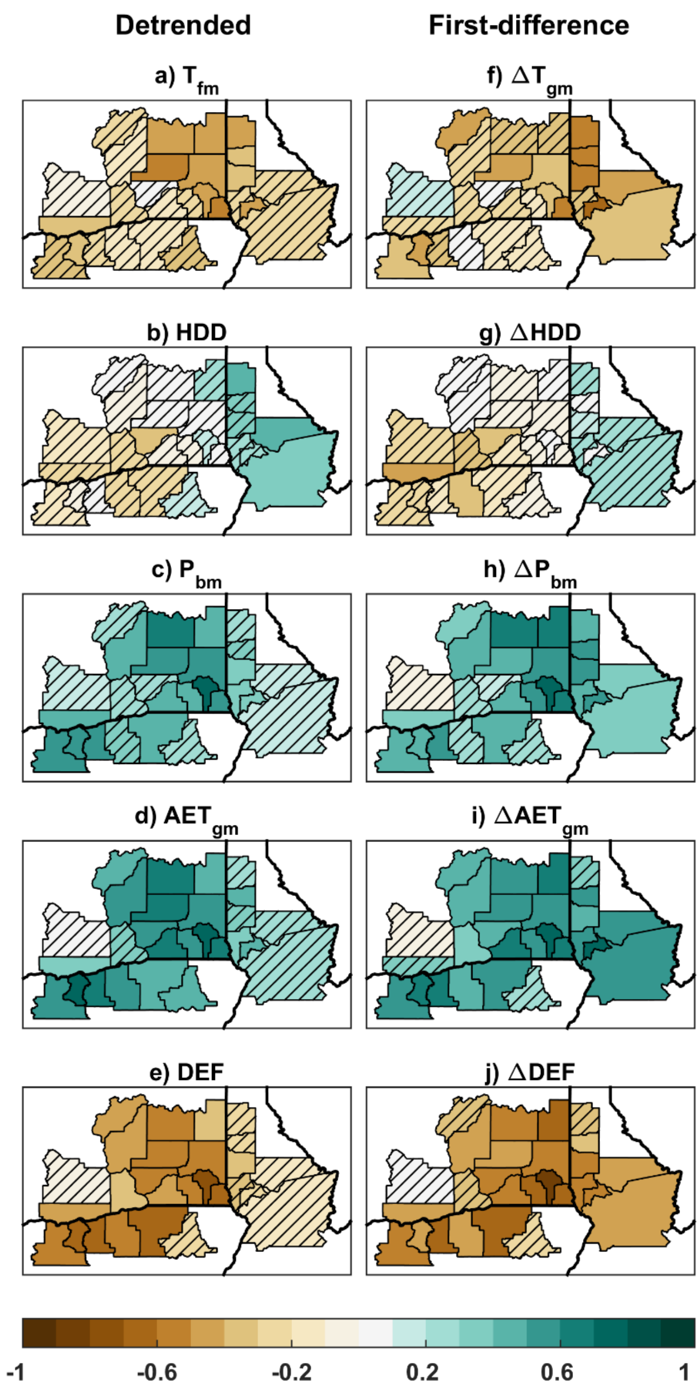

Figure 3: Pearsons correlation coefficients (r) between (left) detrended yields and climate variables, and (right) first difference yields and first difference climate variables for (top-to-bottom) mean temperature (T), accumulated precipitation (P), climatic water deficit (DEF), actual evapotranspiration (AET), and heat degree days (HDD). Counties that exhibited non-significant relationships are denoted by hatched area.

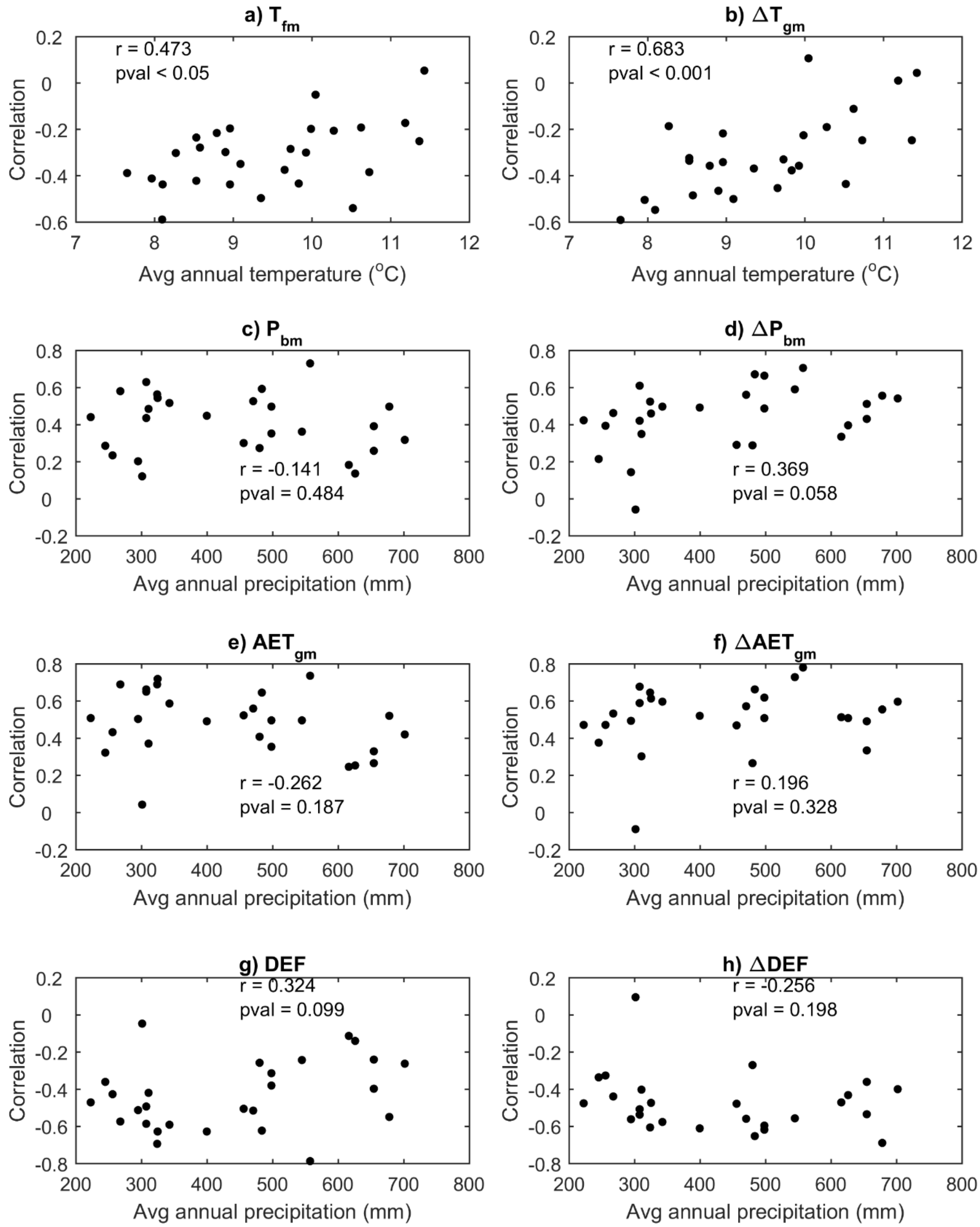

Figure 4: Scatterplot of county-level 1981-2010 climate normals and climate-yield correlations for (left) detrended winter wheat yields and (right) first difference yields and climate. The linear correlation coefficient and p-value is reported for each relationship.

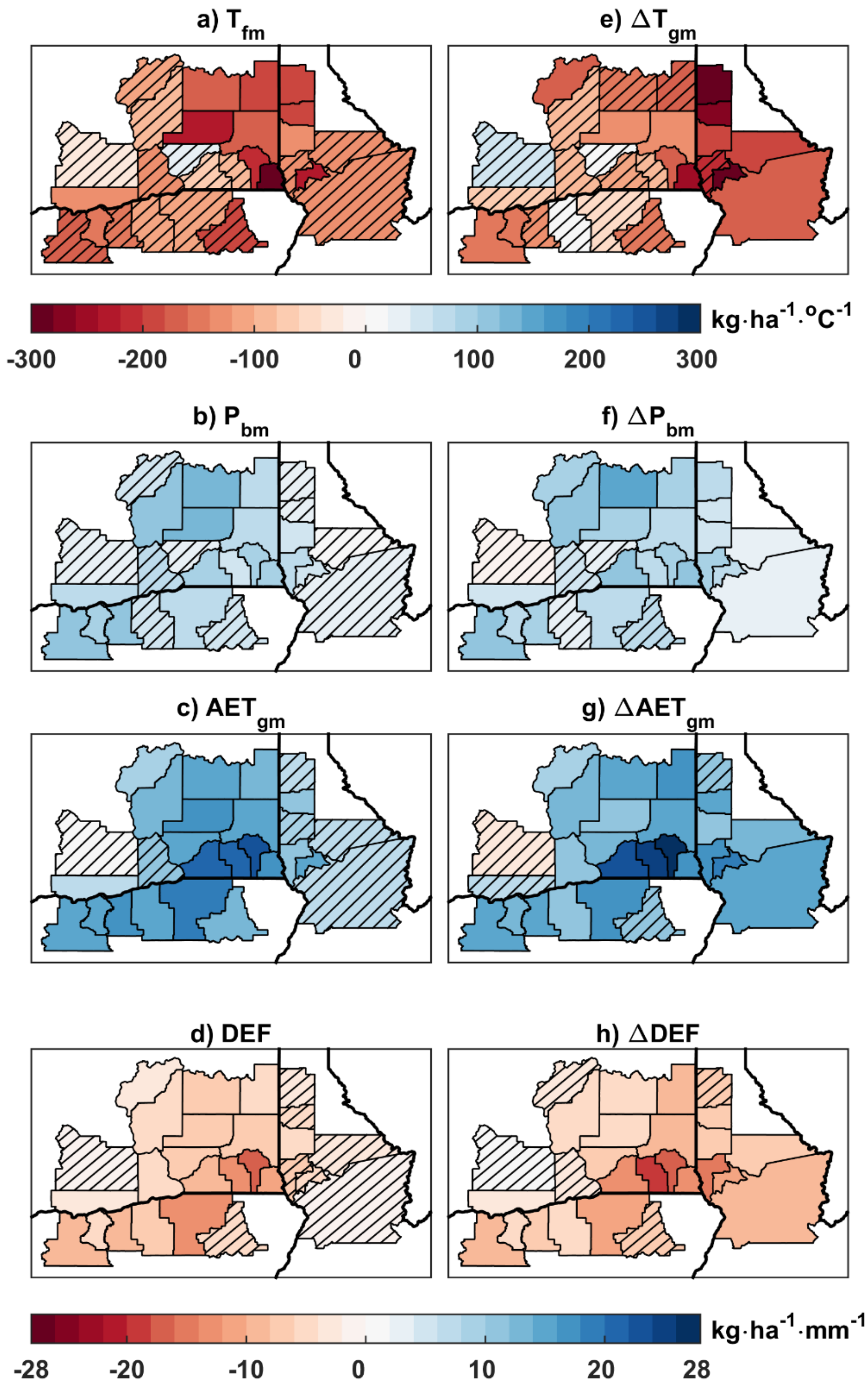

Figure 5: Coefficients of linear univariate regression for (left) detrended yield models and (right) first difference yield models for variables for (top-to-bottom) mean temperature (T), accumulated precipitation (P), actual evapotranspiration (AET), and climatic water deficit (DEF). Counties that exhibit statistically non-significant relationships are denoted by hatched area.

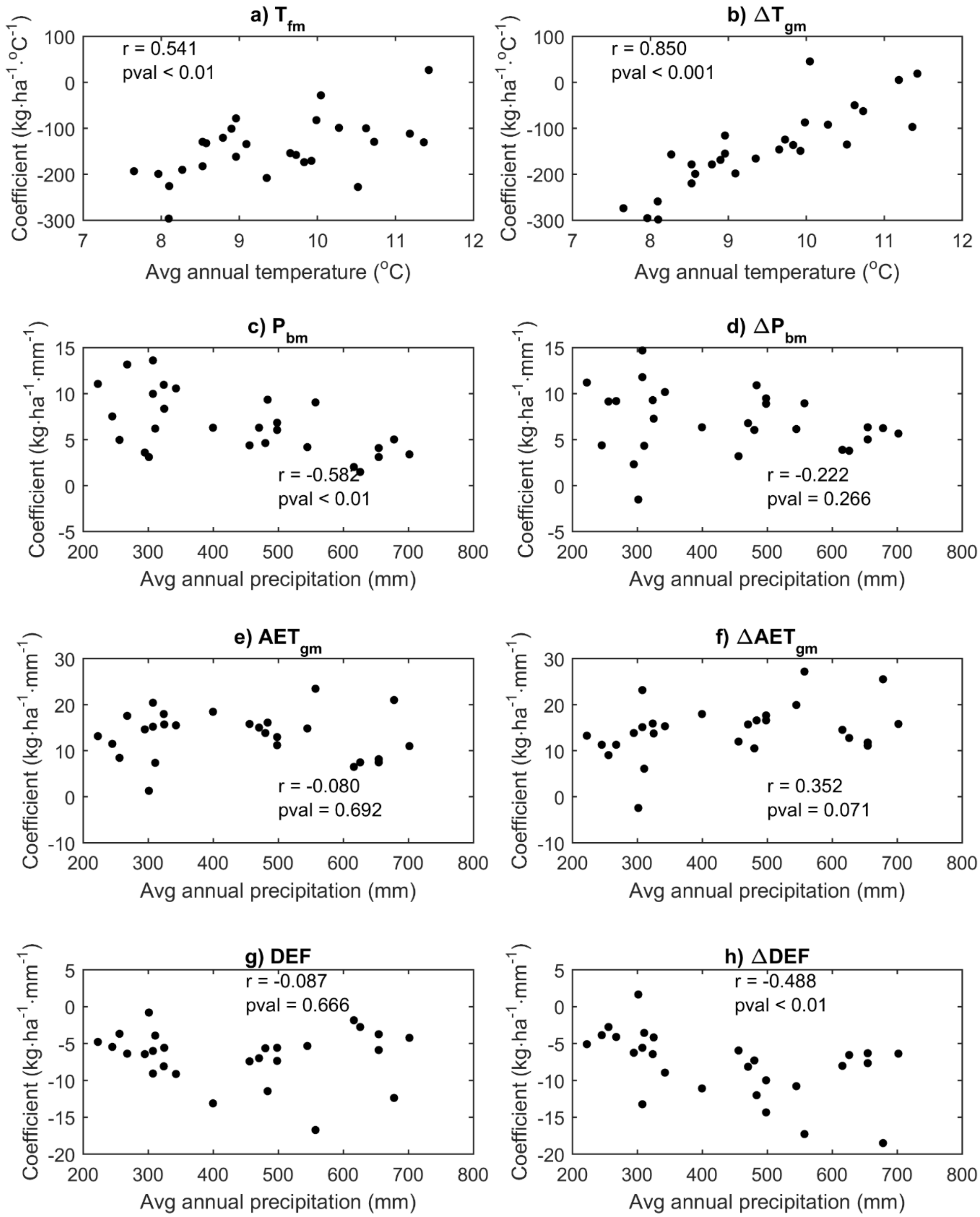

Figure 6: Scatterplot of county-level 1981-2010 climate normals and climate-yield coefficients for (left) detrended winter wheat yields and (b) first difference yields and climate. The linear correlation coefficient and p-value is reported for each relationship.

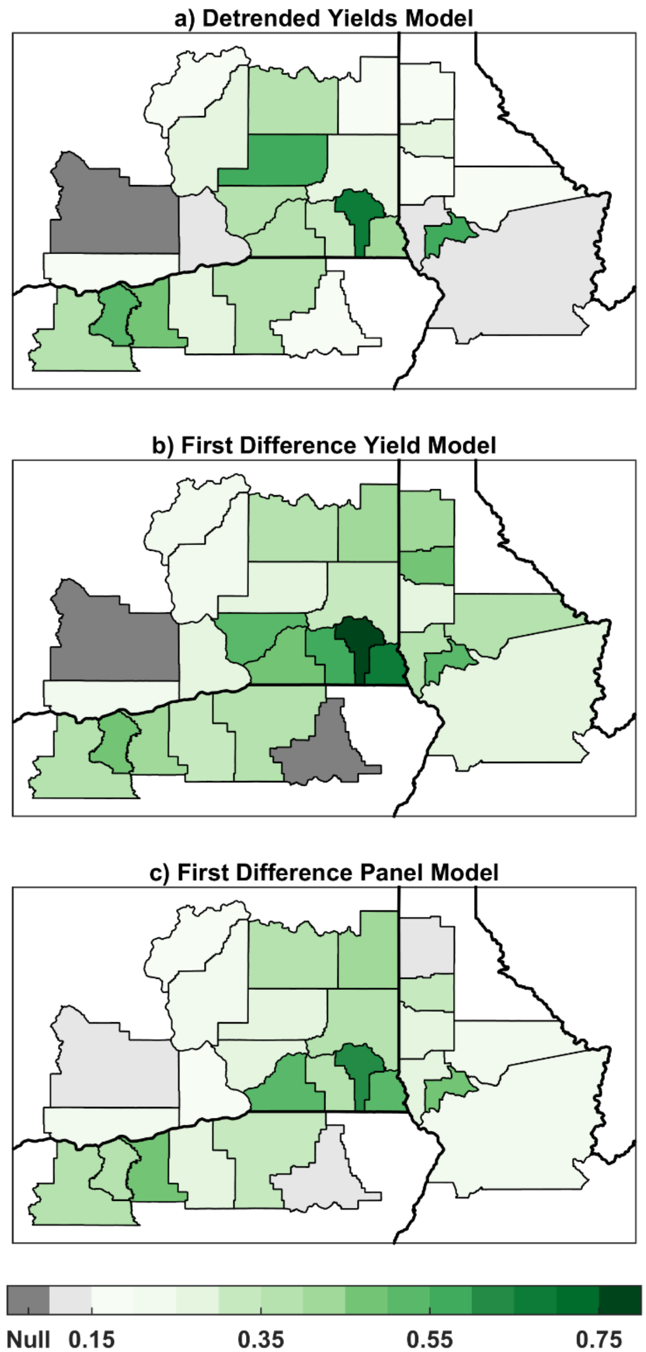

Figure 7: The spatial distribution of r squared correlation coefficients (R^2) from (a) detrended wheat yield stepwise regression model, (b) first difference wheat yield stepwise regression model, and (c) first difference panel regression model. Counties for which no model was developed are denoted by dark grey.

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