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Interannual county-level climate–yield relationships for winter wheat on the Columbia Plateau, USA

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ABSTRACT: Climate–yield relationships for winter wheat were examined across primarily dryland agricultural systems for counties in the Columbia Plateau of the northwestern USA from 1980 to 2014. Interannual linear climate–yield relationships were assessed at subregional scales with climate variables of energy and moisture using temperature, precipitation, heat stress, and water balance metrics for varying wheat phenostages. Interannual variability in moisture availability exhibited significant relationships with wheat yields across the Columbia Plateau, with the strongest relationships during the latter phenostages. Actual evapotranspiration generally exhibited the highest correlation with interannual yield variability, with the strongest relationships occurring in counties with intermediate amounts of precipitation. Crop yields were negatively affected by warmer temperatures during latter phenostages, particularly in climatologically cooler counties where temperature-sensitive phenostages occur later in the calendar year when temperatures are higher. Linear stepwise regression models were developed separately for each county, as well as using a single pooled model that is universal for all counties. County-level models explained an average of 37% of the interannual variability in yield, with more explained variance in counties without widespread irrigation. The pooled model yielded generally similar results, but explained an average of 10% less variance than county-level models across the study region, with substantially less explained variance in counties that exhibited strong relationships with temperature. These findings demonstrate the utility of evaluating climate–yield relationships at subregional scales across agricultural regions that traverse climatic gradients.

KEY WORDS: Phenology · Water balance · Agroclimate

1. INTRODUCTION

Winter wheat *Triticum aestivum* L. is the most widespread cultivated crop in the Pacific Northwest of the USA, occupying 1.32 million ha (2010–2014 average; NASS 2014b). Approximately 75% of winter wheat in this region is grown in the Columbia Plateau, which encompasses much of central and eastern Washington, parts of northeastern Oregon, and northwestern Idaho (Fig. 1). Collectively, winter wheat in the Columbia Plateau generates over US$1 billion annually (NASS 2014b), contributing substantially to the rural economy. However, as nearly all the winter wheat grown in the region is dryland farmed, yields can fluctuate from year to year due to moisture limitations (Schillinger et al. 2008, Fuentes et al. 2003). Interannual variability in winter wheat yield not only impacts local economies but also affects global wheat prices (e.g. Sternberg 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 (Cantelaube et al. 2004, Chen et al. 2004, Lobell & Field 2007, Lin & Huybers 2012) due to advances in agricultural techniques (e.g. cultivars) and management (e.g. fertilizer usage, irriga-

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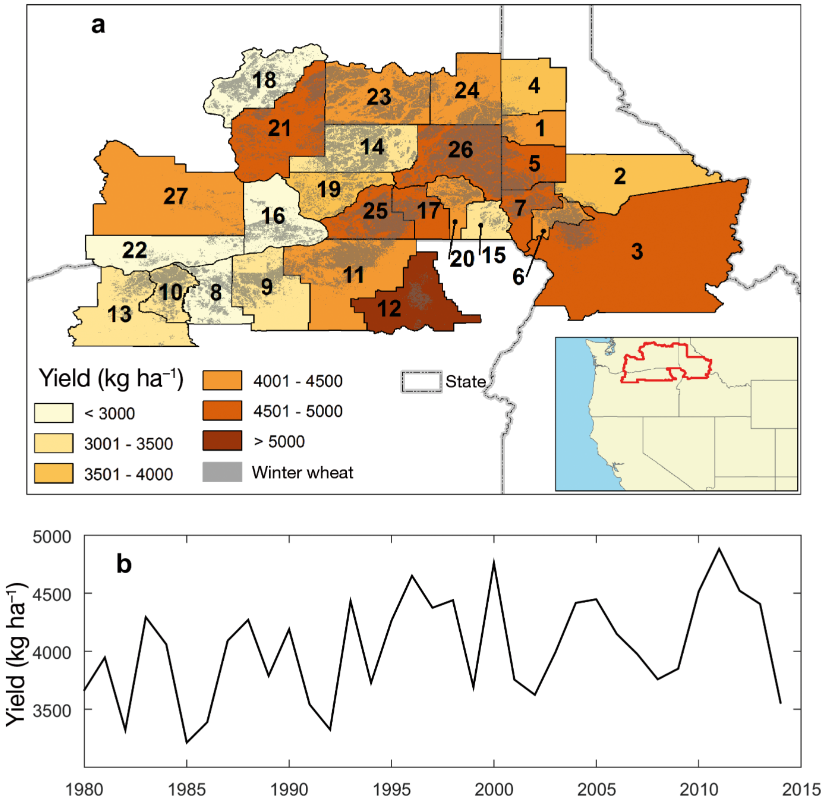

Fig. 1. (a) Geographic extent of the 27 counties in the Columbia Plateau of the USA (inset map) and average county winter wheat yields for 1980 to 2014. The extent of agricultural land where winter wheat was grown in at least 1 yr from 2008 to 2014 is shown in grey. The numbering of the counties is referred to in Table S4. (b) Annual county area weighted average winter wheat yields in the Columbia Plateau from 1980 to 2014

tion and crop rotation). However, increases have plateaued in some regions since the 1990s due to a less favorable climate (Lobell & Field 2007) and decreased fertilizer usage (Lin & Huybers 2012). Similar to global wheat yields, winter wheat yields across the Columbia Plateau increased approximately 20% from 1980 to 2000, with little overall change since 2000 (Fig. 1b). Whereas human factors (e.g. cultivar choices or management) contribute to long-term trends in yields, interannual climate variability typically contributes to interannual yield variability (Cantelaube et al. 2004).

Numerous studies have empirically or experimentally examined climate–yield relationships for staple crops such as wheat. Climate variability has been shown to account for roughly one-third of wheat yield variability at global scales (Lobell & Field 2007, Ray et al. 2015). The influence of climate variability on crop yield includes both energy and moisture constraints that can take on different relationships throughout crop development and vary geographically (Porter & Gawith 1999, Schlenker & Roberts 2009, Asseng et al. 2012). Temperature–yield relationships can be nonlinear in nature throughout the growing season (Porter & Semenov 2005). Optimal temperature ranges have been identified for various wheat development stages, with detrimental impacts for both warm and cold excursions from thermal optimums. For example, high temperatures (>30°C) during flowering and grain-filling stages can reduce yields (Porter & Gawith 1999). Warm temperatures can also accelerate the growth cycle thereby limiting photosynthesis and crop biomass (Ferris et al. 1998). Climate–yield relationships for dryland wheat cropping systems typically show linear relationships between moisture availability and yield (e.g. Zhang & Oweis 1999, Schillinger et al. 2008). Water limitation can decrease stomatal conductance and viable leaf area, lead to a decline in photosynthesis, and result in reduced grain number and mass and increased grain protein content (Asseng et al. 2012).

Prior studies have typically examined climate–yield relationships across broad geographic scales (e.g. national and state level) and using climatic summaries tied to fixed calendar dates such as months or seasons (e.g. Ray et al. 2015). However, interannual climate–yield relationships are likely to vary at finer spatial scales due to geographic heterogeneity in underlying climatology and its interplay with thermal and moisture optimums for crop development (e.g. Leng et al. 2016). Additionally, climate metrics (e.g. water balance, solar radiation) that are aligned with plant physiological constraints throughout crop development may have more explanatory power in predicting crop yields than summaries of temperature and precipitation tied to static calendar dates (e.g. Hernández-Barrera & Rodríguez-Puebla 2017). Our study addresses these knowledge gaps in climate–yield relationships for winter wheat across the Columbia Plateau 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 futures on the global market.

2. DATA AND METHODS

2.1. Study region

The agricultural lands of the Columbia Plateau comprise the lower elevations (~170 to 1000 m) 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 receives >75% of its annual precipitation from November to May. Annual average precipitation across the wheat growing lands vary from ~200 mm in the rain-shadowed lee of the Cascade Range in central Washington to >800 mm across the eastern portion of the region where elevation rises on the windward flanks of the Northern Rockies in Idaho. The mean annual temperature generally adheres to elevational relationships with the highest temperatures in the lower elevations of the western Columbia Plateau and lowest temperatures at higher elevations in the eastern Columbia Plateau.

Winter wheat is the major crop in the Columbia Plateau, covering >30% of the 3.35 million ha of cropland across the region. Dryland farming is used in most of the region except in the driest areas in the southwestern extent of the region, where wheat is often irrigated. The county-mean winter wheat yields averaged from 1980 to 2014 vary geographically across the region from 2600 to 5100 kg ha^{-1} (Fig. 1a). Yields increase west to east across the region generally tracking with the gradient of moisture availability. Crop rotations are adopted across the region based primarily on precipitation, with annual cropping in the wetter areas and annual-fallow cropping in the drier areas. Occasional fallowing of cropland is implemented in drier areas to help recharge soil moisture.

2.2. Yield and climate data

County-level winter wheat yields from 1980 to 2014 for 27 counties from Washington, Oregon, and Idaho in the Columbia Plateau were acquired from the National Agricultural Statistics Service (NASS 2014b). Although there were several missing records in this dataset, each county had at least 28 yr of valid data from 1980 to 2014. Long-term changes in wheat yields may be represented using a linear or higher-order polynomial trend, but may also occur as abrupt shifts due to the adoption of technological advancements, particularly at smaller geographic scales. We used first-differences (i.e. changes from the previous year) of wheat yields (ΔY) and climate data as in previous studies (Lobell & Field 2007, Rao et al. 2015) because this approach attempts to minimize the influence of slowly changing non-climatic factors on yields without *a priori* assuming a functional form of this influence through time.

Daily maximum and minimum temperature, specific humidity, precipitation, solar radiation, and wind speed at ~4 km spatial resolution from 1979 to 2014 were acquired from surface meteorological dataset of Abatzoglou (2013). Abatzoglou (2013) demonstrated good agreement between gridded meteorological estimates and those from *in situ* observations across the study area. We defined the geographic extent of winter wheat within each county by aggregating location data from a composite of 30 m resolution Cropland Data Layer (CDL; NASS 2014a) from 2008 to 2014 (Fig. 1a) to the 4 km spatial resolution grid of the climate data. This spatial layer was used to mask out 4 km pixels within counties where <10% of CDL was classified as winter wheat. Climate data from remaining pixels that had at least 10% of land classified as winter wheat within each of the 27 counties were aggregated to produce a county-level climate collocated with the geographic extent of the crop.

While most prior research examined climate–yield relationships using static calendar dates, we adopted an approach that used phenological dates tied to the development of winter wheat for each county and year. We defined a universal planting date for all counties as 1 Oct, which is approximate for the average planting sowing date across the broader region. However, we acknowledge that sowing dates likely vary geographically and interannually. Phenostages of winter wheat were defined using a growing degree day (GDD) based model for winter wheat (Ritchie 1991). This model divides the growing season into 7 main phenostages based on cumulative GDD with a base temperature of 0°C, consisting of germination, emergence, tillering, booting, flowering, and grain filling and maturity stages (see Table S1 in the supplement at www.int-res.com/articles/suppl/c074p071_supp.pdf). For reference, we report the average timing of each phenostage and county for the 1980–2014 period in Table S2.

Dryland wheat production in the Columbia Plateau is dependent on soil moisture captured in winter precipitation in combination with spring precipitation. While most prior climate–yield studies have relied on 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 yield variability. 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). Because reference evapotranspiration assumes a static reference grass surface, we used a seasonally varying crop coefficient for winter wheat based on GDD to estimate crop potential evapotranspiration (Table S3; Saadi et al. 2015). We used county-level available soil water capacity data for the top 1500 mm of the soil column aggregated from winter wheat growing regions from the State Soil Geographic (STATSGO) database at a 1 km spatial resolution and the water balance model to calculate actual evapotranspiration (AET) and the water deficit (DEF, the difference between the crop potential evapotranspiration and AET).

The climate data that were ultimately considered were mean temperature, precipitation, AET, and DEF for each phenostage, and all combinations of consecutive phenological stages. We also consider a measure of heat stress as the cumulative heating degree days (HDD) from flowering to maturity using a base threshold of 30°C for daily maximum temperature (Porter & Gawith 1999, Liu et al. 2014). All climate−yield relationships were assessed using first-difference values.

2.3. Climate−yield relationships and models

We first explored linear climate−yield relationships by calculating Pearson's correlation coefficients (r) between yield and climate metrics for each phenological stage and all combinations of consecutive phenological stages for 1980 to 2014. This analysis sought to identify phenological windows during which regional climate−yield relationships were maximized, defined by the period for which the maximum county-mean variance was explained (R^2). This optimization was conducted separately for temperature, precipitation, AET, and DEF. Spatial variability in county-level climate−yield relationships was explored using both r and coefficients from bivariate linear regression for each optimized phenological window. Although optima could be identified separately for each county, we wanted to constrain our modeling effort to a single phenological window for each variable to assess climate impacts for the whole region and spatial variability across the study region.

We developed forward stepwise linear regression models separately for each county using the optimized phenological windows from the 4 climate variables and HDD. Results were largely similar using backward stepwise regression. We chose to use stepwise regression models over multiple linear regression to avoid overfitting and to develop more parsimonious models. The stepwise regression model considered 5 climate predictors and their square terms. Stepwise regression fits variables in order of importance, and is often used to develop models where there are several independent variables that may explain the variance of the dependent variable. Independent variables were included in the model when the p-value for the *F*-test of the change in the sum of squared error was <0.05, and were removed from the model when the p-value was >0.10.

Finally, we compared climate−yield relationships developed at the county level to a pooled model that combined first-differences of yields and climate variables from all 27 counties in the study region into a single equation. The pooled model assumes that climate−yield relationships are identical across the study region. Conversely, climate−yield models developed at the county level can portray spatial variations in these relationships, and hence may be more adept at capturing differences in climate−yield relationships across agricultural regions that span distinct climatic gradients.

3. RESULTS

3.1. Bivariate climate−yield relationships

Interannual relationships between climate and winter wheat yield exhibited higher correlations with moisture-related metrics than temperature (Fig. 2). The strongest climate−yield correlations covered time periods that include the latter stages of crop development. The county mean squared Pearson's correlation coefficient ($\overline{R^2}$) between first-difference yield (ΔY) and first-difference temperature showed an optimum ($\overline{R^2}$ = 0.14) during the period from grain filling to maturity (ΔT_{gm}). The optimum R^2 for first-difference precipitation ($\overline{R^2}$ = 0.22), first-difference AET ($\overline{R^2}$ = 0.29), and first-difference DEF ($\overline{R^2}$ = 0.26) also occurred during the latter stages of crop development from booting to maturity (ΔP_{bm}), grain filling to maturity (ΔAET_{gm}), and booting to maturity (ΔDEF_{bm}), respectively. Although the maximum $\overline{R^2}$ values of ΔDEF occurred between booting to maturity, there were only minor reductions in $\overline{R^2}$ values during other phenological windows that included

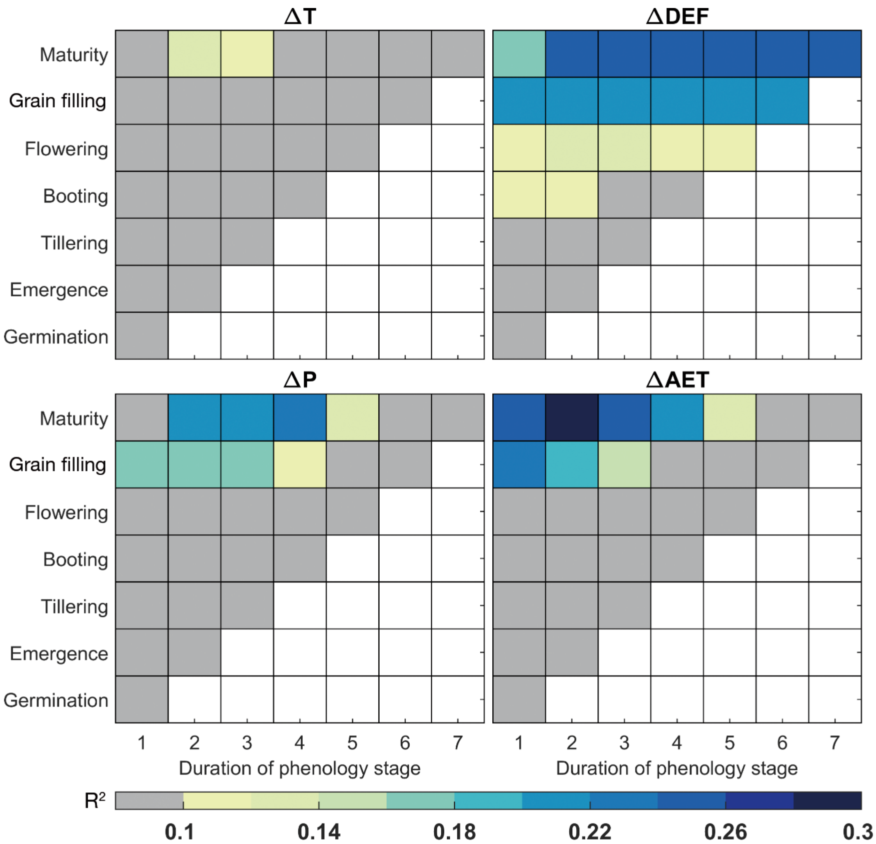

Fig. 2. Matrices of county-mean R^2 value between first-difference winter wheat yields (ΔY) and first-difference climate variables for mean temperature (ΔT), accumulated precipitation (ΔP), actual evapotranspiration (ΔAET), and climatic water deficit (ΔDEF). The *y*-axes denote the ending phenology stage, and *x*-axes denote the number of consecutive phenology stages. White cells: not evaluated

grain filling. Therefore, we adopted growing season (germination-maturity) ΔDEF in subsequent analyses. Heat stress on winter wheat only occurs during the latter stages of development, given the climatology of the region, so we used ΔHDD from flowering to maturity in subsequent analyses ($\overline{R^2}$ = 0.05, not shown).

The spatial variability in county-level bivariate climate–yield correlations is shown in Fig. 3. Temperature (ΔT_{gm}) exhibited negative correlations with yields across the most of study area. Statistically significant correlations ($p < 0.05$) were found primarily in climatologically cooler counties in the northeastern portion of the region. Correlations between HDD and yield were mainly weak and not significant across the Columbia Plateau, except for a few significant negative correlations for a few counties in the warmer southwestern portion of the region. In contrast, more coherent relationships were realized between yield and moisture related variables across the study area, with positive correlations between ΔY and both ΔP_{bm} and ΔAET_{gm}, and negative correlations with ΔDEF. The strongest correlations with moisture-related variables were seen in the central and southern portion of the plateau, for counties with mean annual precipitation between 300 and 550 mm. Nonsignificant correlations with moisture variables were evident in counties along the western flanks of the plateau where irrigation was more prevalent (see Table S4 in the supplement at www.int-res.com/articles/suppl/c074p071_supp.pdf).

Bivariate linear regression coefficients between climate variability and yield exhibited similar spatial patterns as seen for correlations (Fig. 3). Averaged across all counties, the mean coefficient for ΔT_{gm} was –143.4 kg ha^{-1} °C^{-1} (Table 1). However, we show a strong linear correlation (r = 0.85) across the 27 county study area between county-level coefficients for ΔT_{gm} and annual mean temperature (Fig. 4a), suggesting that wheat yields in cooler counties were more sensitive to interannual variability in temperature during the latter stages of crop development than in climatologically warmer counties. County-average coefficients (Table 1) for ΔP_{bm}, ΔAET_{gm}, and ΔDEF were 7.0 kg ha^{-1} mm^{-1}, 14.5 kg ha^{-1} mm^{-1}, and –7.9 kg ha^{-1} mm^{-1}, respectively. A significant negative correlation (r = –0.49) was seen between the coefficient of ΔDEF and annual mean precipitation (Fig. 4b), suggesting larger overall sensitivity to moisture deficits for wheat yields in wetter counties than in drier counties.

Pooled results of first-difference yields and first-difference climate for all 27 counties showed analogous linear climate–yield relationships. Unlike correlations or regressions at the county-level, pooled results only provide single values for the study area, and cannot capture subregional variability in climate–yield relationships. Pearson's correlation coefficients and regression coefficients generally resembled those for county-level means. Bivariate linear regressions to temperature variables (Table 1) were –132.7 kg ha^{-1} °C^{-1} and –1.6 kg ha^{-1} °C^{-1} d^{-1} for ΔT_{gm} and ΔHDD, respectively. Pooled linear regressions coefficients (Table 1) for ΔP_{bm}, ΔAET_{gm}, and ΔDEF were 6.3 kg ha^{-1} mm^{-1}, 14.0 kg ha^{-1} mm^{-1}, and –6.6 kg ha^{-1} mm^{-1}, respectively.

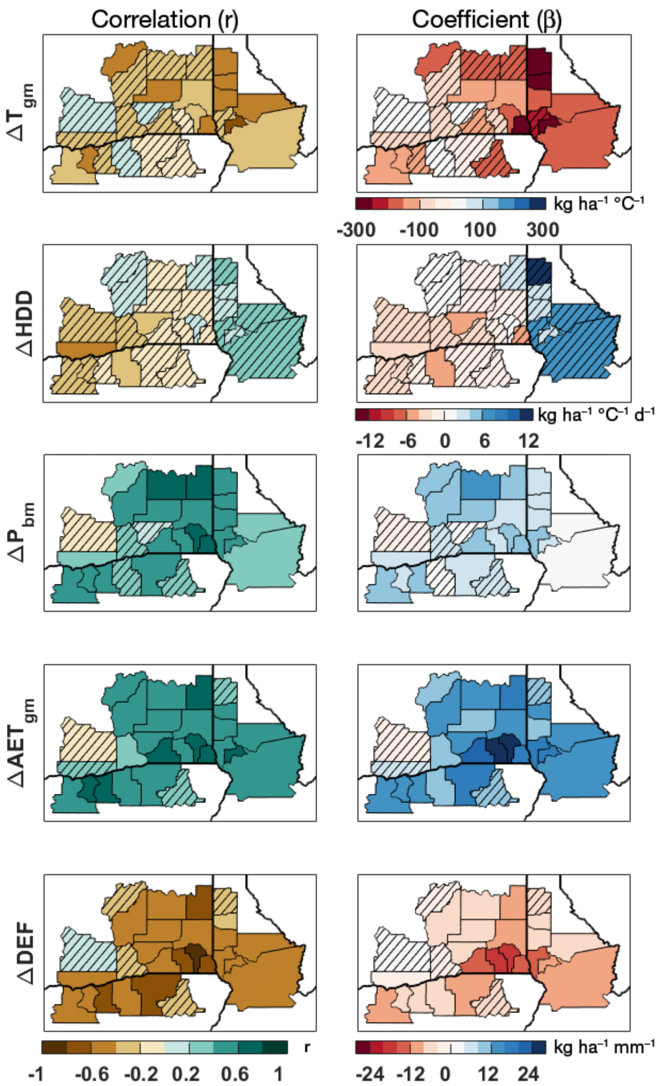

Fig. 3. Pearson's correlation coefficients (r) and coefficients of linear regression (β) between first-difference yields and first-difference climate variables for mean temperature from grain filling to maturity (ΔT_{gm}), heat degree days from flowering to maturity (ΔHDD), accumulated precipitation from booting to maturity (ΔP_{bm}), actual evapotranspiration from grain filling to maturity (ΔAET_{gm}), and climatic water deficit during the entire growing season (ΔDEF). β values for the 3 moisture-related variables share a common color bar. Counties that exhibited non-significant relationships are denoted by hatched area

3.2. Multivariate climate-yield relationships

Stepwise linear regression models for each county explained an average of 37% of county level ΔY (Table S4, Fig. 5a). Yakima County, Washington and Union County, Oregon had no model, whereas climate explained 77.4% of the yield variance in Garfield County, Washington. The 3 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. All but a single county for which a first-difference model was built incorporated a moisture variable. Seven counties selected square terms of climate variables as wheat yield predictors, indicating potential nonlinear climate–yield relationships. Fifteen counties used a single climate predictor, with 8 of these selecting ΔAET_{gm}. Residuals between observed and modeled yields were normally distributed and centered around zero, suggesting that our modeling choices were reasonable.

The geographic pattern of explained variance suggests a larger portion of explained variance for counties in the central portion of the plateau than for counties on the periphery, similar to that seen in bivariate relationships (Fig. 5). However, the spatial variability in modeled R^2 did not exhibit any apparent relationship to underlying spatial variability in climate, unlike for the bivariate relationships. Part of the spatial variability is likely a function of the underlying non-climatic factors such as spatial variability in irrigation usage. For example, the first-difference model explained an average of 25% of the variance in interannual wheat yields in counties where ≥10% of harvested land was irrigated, compared to nearly 40% of the variance in all remaining counties (Table S4).

The stepwise model that used pooled data from all counties explained 27% of the interannual variability in ΔY using ΔP_{bm}, ΔAET_{gm}, ΔDEF, and ΔHDD as predictors (Table S5). The sign of the coefficient for each

Table 1. Pearson's correlation coefficient (r) and linear regressions (β) averaged for the 27 counties (parentheses: no. of counties with statistically significant [$p < 0.05$] correlations) and for pooled variables. Data are mean (±SD, where indicated). *Significant ($p < 0.05$)

	$\bar{r}_{county}$	$\bar{\beta}_{county}$	r_{pooled}	β_{pooled}
ΔT_{gm}	−0.32 ± 0.19 (13)	−143.4 ± 88.2 kg ha^{-1} °C^{-1}	−0.30*	−132.7 kg ha^{-1} °C^{-1}
ΔP_{bm}	0.44 ± 0.17 (22)	+7.0 ± 3.4 kg ha^{-1} mm^{-1}	0.43*	+6.3 kg ha^{-1} mm^{-1}
ΔAET_{gm}	0.51 ± 0.17 (23)	+14.5 ± 5.8 kg ha^{-1} mm^{-1}	0.50*	+14.0 kg ha^{-1} mm^{-1}
ΔDEF	−0.49 ± 0.17 (22)	−7.9 ± 4.5 kg ha^{-1} mm^{-1}	−0.46*	−6.6 kg ha^{-1} mm^{-1}
ΔHDD	−0.06 ± 0.21 (3)	+0.3 ± 4.4 kg ha^{-1} °C^{-1} d^{-1}	−0.10*	−1.6 kg ha^{-1} °C^{-1} d^{-1}

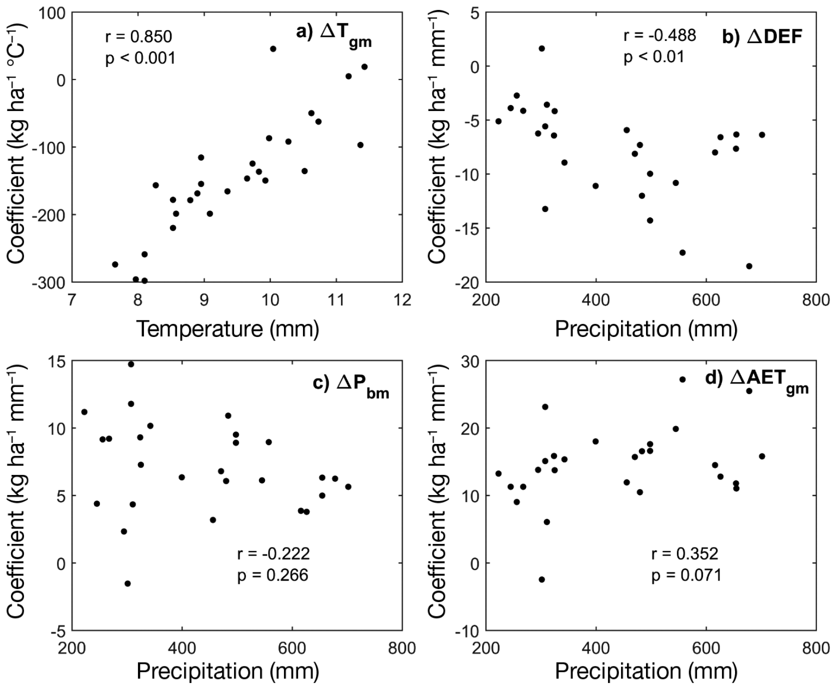

Fig. 4. Scatterplot of county-level 1981 to 2010 climate normals and climate-yield coefficients for first-difference yields and climate for (a) mean temperature from grain filling to maturity (ΔT_{gm}) and mean annual temperature, (b) climatic water deficit during entire growing season (ΔDEF) and mean annual precipitation, (c) accumulated precipitation from booting to maturity (ΔP_{bm}) and mean annual precipitation, and (d) actual evapotranspiration from grain filling to maturity (ΔAET_{gm}) and mean annual precipitation. The correlation coefficient and p-value is reported for each relationship

term in the pooled model was consistent with results bivariate county-level regression analyses. However, absent in the pooled model is the direct incorporation of temperature during the latter stages of crop development, which exhibited substantial subregional variability in bivariate analysis. The spatial pattern of explanatory power from the pooled model was similar to that of the county-level model (Fig. 5b). However, the pooled model explained 10% overall variability in crop yields with reduced explanatory power for counties in the eastern portions of the region that exhibited significant relationships with temperature.

4. DISCUSSION AND CONCLUSION

Stepwise linear regression models indicate that climate explains 27 to 37% of the county-level interannual variability in winter wheat yield over the Columbia Plateau from 1980 to 2014. These results are similar to the proportion of explained variance in global wheat yields by climate factors (Ray et al. 2015). Interannual variability in winter wheat yields was 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 & Gawith 1999, Asseng et al. 2012). Collectively, we suggest that moisture is the primary climatic constraint of winter wheat yields in the Columbia Plateau, and that water balance metrics provide more explanatory power than precipitation alone.

Our results demonstrate a negative relationship between wheat yield and temperature during the

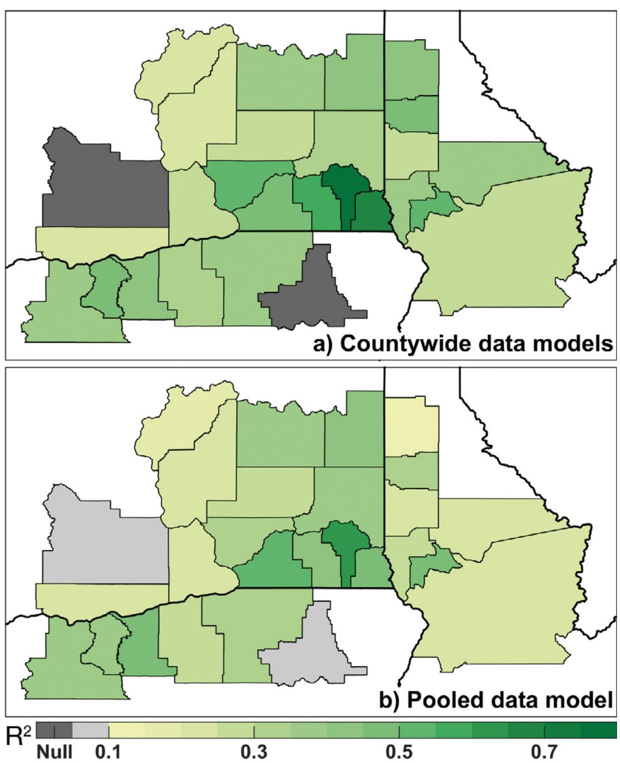

Fig. 5. The spatial distribution of coefficient of determination (R^2) from (a) county-level stepwise regression models and (b) pooled stepwise regression model. Dark grey: counties for which no climatic predictor entered in the stepwise regression model was developed

later phenostages of wheat development from flowering to maturity, consistent with previous studies that found that elevated temperatures during this period reduce grain numbers and grain weight (Ferris et al. 1998, Narayanan et al. 2015). Liu et al. (2016) and Asseng et al. (2015) suggested a 4.1 to 6.4% decline in global wheat yield per 1°C warming. Our results support this hypothesis for the study region, although we only address temperature impacts directly through temperature–yield relationships over 1 period of crop development — ignoring the indirect influences of warming through AET and DEF and how warming influences phenology. Bivariate regression between wheat yields and temperature variability suggest an average 3.6% decline in wheat yield per 1°C warming during grain filling to maturity phenostages across the Columbia Plateau.

Paradoxically, the strongest negative relationships between temperature and yield were generally found in the climatologically cooler counties of the study domain. However, our use of phenological calendars allows wheat to reach the grain filling-maturity phenostages later in the calendar year when day lengths are longer and temperatures are higher. Mean air temperature from grain filling to maturity was, on average, 1.2°C warmer for the climatologically coolest tercile of counties (for mean annual temperature) than the rest of the domain. We hypothesize that the delayed phenology in these cooler counties, where the average onset date of grain filling is 25 d later than in other warmer counties (Table S2), allows them to be susceptible to temperature variability during a climatologically warmer time of the year when temperatures may deviate from thermal optimums for wheat growth. Similarly, we hypothesize that relatively weak relationships between HDD and yields across the Columbia Plateau are a consequence of the seasonal mismatch between the phenology of winter wheat and extreme temperatures across the region, with wheat typically reaching maturity in warmer counties before the onset of temperatures exceeding 30°C.

The bivariate 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). Estimated bivariate coefficients for AET_{gm}, which integrates water use by wheat during the latter stages of development, were 14.5 kg ha^{-1} mm^{-1} and 14.0 kg ha^{-1} mm^{-1} for county-mean and pooled regression models (Table 1), respectively. In 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 soil moisture reserved and precipitation occurring from grain filling to maturity, the results are comparable, and extend the field-study relationships defined by Schillinger et al. (2008) to the broader geographic area.

Several caveats in our study may constrain the performance of our yield models. First, the actual planting date of winter wheat varies across the study region. Due to the lack of planting date records, we arbitrarily defined planting as 1 Oct, the middle of the general planting window for the region. This assumption may impact the timing of subsequent phenology stages and climate–yield relationships. Secondly, we did not distinguish irrigated and non-irrigated cropland due to a lack of continuous yield records. Irrigation can mitigate climate impacts on crop development, particularly related to water limitation, thereby leading to weakened climate–yield correlations (Troy et al. 2015). We hypothesize that poorly performing yield models for counties in the arid western portion of the plateau are a function of a higher fraction of harvested wheat being irrigated, and thus less sensitivity to moisture variability. Additional unexplained variances 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 & Chen 2011) and precipitation events prior to harvest may be detrimental to yield. Non-climatic drivers of variability in wheat yield are also probable, and may even interact with observed climate relationships. For example, spatio-temporal changes in wheat cultivars could alter the climate sensitivity of yields (Cattivelli et al. 2008) and produce non-stationarity in climate–yield relationships.

Stepwise regression models across the 27 counties in the Columbia Plateau showed that climate explained up to 77% of the interannual variability in wheat yield. Unlike previous analyses that have examined climate–yield relationships at broader political or spatial units (e.g. Ray et al. 2015), we show sub-regional variability in climate–yield relationships across the study area. Pooled models may fail to capture these subregional differences because they assume a fixed relationship across geographic space. This finding highlights potential limitations of climate–yield models that use pooled data or that aggregate climate and yield data to broader geographic units in regions that traverse climatic gradients. Our yield models may have applied value in forecasting winter wheat yields during the growing season by incorporating both observed climate and seasonal climate forecasts, such as those from downscaled seasonal forecasts that have demonstrated skill across the study area (Barbero et al. 2017). Collectively, improved understanding of the subregional variability of climate impacts on agriculture can help improve seasonal forecasts of yield. Simple empirical climate–yield models may also provide insight on potential subregional agricultural impacts in a changing climate to complement results from processed-based crop models (e.g. Stockle et al. 2017).

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