Understanding the food water nexus: Characterizing the impact of climatological anomalies on agrosystems

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UNDERSTANDING THE FOOD WATER NEXUS:
CHARACTERIZING THE IMPACT OF CLIMATOLOGICAL ANOMALIES ON
AGROSYSTEMS.

By

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Understanding the food water nexus: Characterizing the impact of climatological anomalies on agrosystems.

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**Abstract**

Climate variability at global and regional scales is escalating with increased atmospheric carbon and is expected to magnify the intensity and duration of meteorological extremes, especially droughts. From the many environmental stresses that diminish crop production (e.g., soil salinity, frost, soil erosion) drought is one of the most prevalent. This study focuses on the sensitivity of three key crops produced in the northwestern United States to climatological anomalies, while controlling for attribution using anomalies in price. The study differs from similar studies in that we focus on variability in production which captures both yield (tonnes/ha) and cropping area (ha), as opposed to only yield. We use multivariate linear regression to determine the timing and time-scale of precipitation and PET anomalies most correlated with annual crop production anomalies, and develop sensitivity coefficients using Markov chain Monte-Carlo. Counties with similar sensitivity to precipitation, PET, and price were then clustered using k-means analysis. Alfalfa was most sensitive to both precipitation and PET anomalies, with as much as 93% and 81% of the precipitation and PET anomalies translating to the production anomaly. Barley was least sensitive. The timing of precipitation and PET anomalies were generally most important in June-August. The time-scale of precipitation and PET anomaly best correlated to production was variable, but generally greater than similar studies focusing on yield. Sensitivity to precipitation anomalies followed gradients in precipitation, temperature, and soil moisture regimes present across the study area. Our research provides simple models of climate effects on production at the county scale using public data which can be implemented by agricultural producers and decision makers to quantify the impacts of climatological and economic fluctuations on annual crop production.
1 Introduction

Climate variability at global and regional scales is escalating with increased atmospheric carbon (IPCC, 2014) and is expected to magnify the intensity and duration of meteorological extremes, especially droughts (Easterling et al., 2000; Trenberth, 2011). In agricultural regions, climate variability affects soil moisture availability and the reliability of water sources used for irrigation, presenting challenges to agricultural water managers and increasing the risk farmers assume when they allocate resources. Farmer’s perception of risk affect how they make decisions, with potential consequences for regional agricultural production and food security.

Concerns about rural well-being, economic development and food security have led to an increasing number of studies investigating the sensitivity of crop yield and production to climate variability and drought. From the many environmental stresses that diminish crop production (e.g., soil salinity, frost, soil erosion) drought is one of the most prevalent (Shao et al., 2009). Designating a single definition of drought is impractical due to large variations in environmental, ecologic, sociologic, and agricultural responses to the timing, time-scale, and severity of drought conditions (Van Loon, 2015). In terms of agriculture, crops response to the different constituents of drought varies by cultivation and over the phenology of a given crop. Cereal crops, for example, may experience reduced productivity due to unusually high temperatures during the grain filling period, even though precipitation deficits are not present (Guendouz and Maamari, 2012). Alternatively, unusually high temperatures at the beginning of the growing season may increase cereal crop productivity by allowing for earlier sowing dates (Lanning et al., 2010). Therefore, several drought indices have been developed specifically for agriculture.

The most widely used climate index is the Palmer Drought Severity Index (PDSI), based upon precipitation, temperature, available soil water capacity, runoff, and atmospheric water demand (Palmer, 1965). McKee et al. (1993) developed the Standardized Precipitation Index (SPI), which provides a definition of drought severity accumulated over different time-scales using precipitation alone. Hobbins et al. (2016) developed the Evaporative Demand Drought Index (EDDI) which provides a definition of drought severity accumulated over different time-scales based on potential evapotranspiration (PET). Vicente-Serrano et al. (2010) developed the Standardized Precipitation Evapotranspiration Index (SPEI) to describe drought conditions accumulated over different time-scales based on precipitation and temperature. Drought indices with the ability to capture drought conditions accumulated over different time-scales have been shown to perform better for modeling crop production or yields than traditional ‘static’ indices such as the PDSI (Vicente-Serrano et al., 2012).

These indices and metrics to characterize agricultural drought focus on the impact of climate factors
on agricultural yields. However, producers may be able to compensate for yield reductions and maintain crop production by increasing the planted area. Therefore, total crop production (yield * planted area) is an important metric because it captures both the efficacy of agricultural practices through crop yield (i.e., annual crop production per unit area), as well as the response of producers in terms of land allocated to particular crops based on their perception of risk, experience of climate variability, and the impact of other external factors such as agricultural markets and policy incentives (Iizumi and Ramankutty, 2015). Therefore, while crop yield alone is certainly an important component of annual crop production, focusing on yields alone fails to capture farmer response and the compensatory effects that the reallocation of land may have on total food production and may also overemphasize the role of climate variability on food security.

Producers not only react to climate, but are sensitive to other factors such as agricultural markets and may be able to allocate resources to maintain agricultural production even under adverse climate if market conditions are favorable. Therefore, crop price should also be considered in annual crop production models (Lobell et al., 2011). We refer to the prices the farmer receives for their produce as crop price. Crop price can impact both crop yield and crop production in complex ways, and the two are not always directly related (Miao et al., 2016). Higher crop prices could reasonably be associated with decreased crop rotation in preference of the better returning crop, which would temporarily increase production but has been associated with decreased yields over the long term (Hennessy, 2006). Alternatively, higher crop price for a given crop may encourage different crop rotations to improve soil quality, which would be associated with lower productivity but greater yields in the long term (Hennessy, 2006). The expectation of higher crop price may also result in a greater allocation of treatment systems (i.e., fertilizer, higher quality seed, pest treatment, etc.) accompanied by an increase in cropping area, resulting in increases in both yield and production. Therefore, crop prices likely play an important role in inter-annual variability in crop production.

This study investigates annual crop production anomalies in relation to three factors: precipitation anomalies, PET anomalies, and anomalies in the price that producers receive for their crops the year prior to production. We focus on the United States (US) states of Idaho, Montana, North Dakota, South Dakota, and Wyoming. The objectives of this study were 3 fold: 1) Quantify the sensitivity of alfalfa, barley, and winter wheat production to precipitation, PET, and price at the county scale; 2) Compare sensitivities of these factors between crops; 3) Determine and classify spatial patterns of similar sensitivities of annual crop production to precipitation, PET, and price.
2 Methods

2.1 Study Area

The study focused on crop production anomalies in Idaho, Montana, North Dakota, South Dakota, and Wyoming, all located in the inland northwest of the US. The study area covers approximately 1.2 million square kilometers, which is roughly 16% of the contiguous United States. The study region encompasses the portions of the intermountain west and the northern great plains region of the US, and includes significant longitudinal physiographic and climatic gradients associated with proximity to the Pacific Ocean and Gulf of Mexico (Salley et al., 2016). Climate gradients are further enhanced by topography and orographic effects. Idaho, western Montana, and western Wyoming are mountainous areas of the Northern Rockies region, while eastern Montana, South Dakota, North Dakota, and eastern Wyoming are flat prairies of northern Great Plains. Generally, a precipitation gradient exists moving west to east, with some areas in ID receiving an average of 1000 mm/yr of precipitation, and some areas in WY and SD receiving 200 mm/yr. Temperature generally follows a similar gradient, with cooler temperatures in the Rocky Mountains and warmer temperatures in the Northern Great Plains. Precipitation and temperature gradients are reflected in soil moisture regimes, where wetter cooler areas are associated with udic and aquic (wetter) soils in the northwest and eastern portions of the region, and dryer warmer areas are associated with xeric and ustic (drier) soils in the southwest and central portions.

Agriculture is a key industry within the study area, but is traditionally dominated by five or six major crops. We focus on three of these major crops: alfalfa, barley, and winter wheat. States in the study area are important contributors to the national production of the three crops under study. Idaho, Montana, and South Dakota ranked second, third, and fourth in US alfalfa production respectively between 2015 and 2017 (USDA NASS). Idaho, North Dakota, Montana, and Wyoming ranked first, second, third, and fifth in the US for barley production. Montana and Idaho ranked sixth and seventh in the US for winter wheat production between 2015 to 2017 (USDA NASS). Crop producers in Idaho, western Montana, and western Wyoming benefit from widespread irrigation infrastructure, while crop production in eastern Montana, North Dakota, South Dakota, and eastern Wyoming is primarily rain-fed (USDA NASS).

2.2 Data

Here we investigate the response of anomalies in the annual crop production of alfalfa, barley, and winter wheat during the period of 1979 - 2016 to anomalies in precipitation, potential evapotranspiration (PET), and crop price. Precipitation and PET anomalies accumulated over 1-15 months were considered for each
month from March through September. Price anomalies reflected the price received by farmers the year prior to the crop production anomaly.

Crop production and price data were retrieved through the US Department of Agriculture National Agricultural Statistics Service (USDA NASS). Production data was retrieved at the county scale for all available counties with at least 20 years of record across the study period. Prices received were available for each crop at the state scale. Annual irrigated production of each crop was retrieved for available counties using USDA NASS. The amount of irrigation was measured by taking the ratio of total irrigated production of a given crop to the total production of that crop over the study period in each county. Counties with 50% irrigated total crop production was considered as heavily irrigated, and compared to counties with 50% total irrigated crop production.

Precipitation and potential evapotranspiration of alfalfa (PET) data were retrieved from the University of Idaho Gridded Surface Meteorological Dataset (UofI METDATA). UofI METDATA combines the PRISM (Parameter elevation Relationships on Independent Slopes Model) and the NLDAS-2 (NASA Land Data Assimilation System version-2) models to provide a 4 km gridded daily data set for the continental US. UofI METDATA has been validated against a comprehensive network of weather stations across the US (Abatzoglou, 2013).

Prior to the calculation of anomalies, we detrended productivity, prices, and climatologic data over the study period using linear regression. Precipitation anomalies were determined using the Standardized Precipitation Index (SPI) (McKee et al., 1993), which characterizes drought accumulating over different time-scales, relying only on historic precipitation data. The SPI was calculated by taking the difference of precipitation, accumulated over monthly time-scales (we used 1 to 15 months), from the the detrended historic mean of that time-scale, divided by the standard deviation of that time-scale over the period of record (McKee et al., 1993). We follow the methodology of SPI calculations (McKee et al., 1993) to develop the Standardized Crop Production Index (SCPI) and the Standardized Crop Value Index (SCVI) to identify crop production anomalies and prices received anomalies occurring over the period of study at the annual time-scale. Existing studies have shown that 1 year lagged prices received and crop price futures are highly correlated, and can be used interchangeably (Miao et al., 2016). Therefore, we used prices lagged by one year.

Anomalies in potential evapotranspiration were determined using the Evaporative Demand Drought Index (EDDI) (Hobbins et al., 2016). EDDI provides a definition of drought that accumulates over monthly time-scales (we use 1 to 15 months), relying only on historic PET data. Hobbins et al. (2016) describes in-depth EDDI calculations over different time-scales, but is briefly described here as first calculating the empirical probability of ranked PET values summed across the time-scales of interest, and then calculating EDDI
values using inverse normal approximation described by Vicente-Serrano et al. (2010).

2.3 Models

Alfalfa yield has been shown to have a significant linear relationship with available water supply (Retta and Hanks, 1980). Changes in wheat yield in response to changes in temperature were described using linear regression by Lobell and Asner (2003) and Klink et al. (2014). Vicente-Serrano et al. (2006) predicted the ratio of sown to harvested barley and wheat using multiple linear regression based on Normalized Difference Vegetation Index and SPI. We recognized that crop production may have a non-linear relationship with climatological factors (Porter and Semenov, 2005; Schlenker and Roberts, 2009), many counties showed a linear relationship between annual crop production anomalies and climatological anomalies. Therefore, our study operates on the assumption that anomalies in annual crop production respond linearly to combined fluctuations in climatological and price anomalies. Climate fluctuations are analyzed as anomalies in precipitation (atmospheric water supply) and potential evapotranspiration (atmospheric water demand). While climatological indices that combine precipitation and PET (i.e., SPEI) exist, our objective is to analyze the impacts of precipitation anomalies and PET anomalies on annual crop production anomalies separately. To avoid problematic issues with combining correlated independent variables into one model, and to reduce the dimensionality (e.g., degrees of freedom), we developed two separate linear models, one based on precipitation anomalies and price anomalies and the other based on PET anomalies and price anomalies, to describe annual crop production anomalies:

\[ \text{Prod}_A = \alpha P_A + \beta_p P R_A + \gamma_p \]  
\( (1) \)

where \( \text{Prod}_A \) is the annual production anomaly, \( \alpha \) is the precipitation factor, \( P_A \) is the precipitation anomaly, \( \beta_p \) is the price factor produced by Equation 1, \( P R_A \) is the price anomaly, and \( \gamma_p \) is the fixed factor produced by Equation 1, and:

\[ \text{Prod}_A = \delta \text{PET}_A + \beta_e P R_A + \gamma_e \]  
\( (2) \)

where \( \delta \) is the PET factor, \( \text{PET}_A \) is the PET anomaly, and \( \gamma_e \) is the fixed factor produced by 2. Precipitation and PET factors will be referred to simultaneously as climatological factors. The variables were standardized so the coefficients (e.g., factors) could be directly compared, and so that coefficients could be interpreted as the proportion of independent anomaly that translated to crop production anomaly.

To decrease the potential of production data errors and outliers to bias the inference of the model factors,
we used a robust linear regression approach in which we assume that errors are t-distributed. Furthermore, to increase the robustness of the model calibration, we employ a hierarchical regression method that reflects that controls on annual crop production likely operate at different spatial scales (e.g., state wide vs. county wide irrigation infrastructure, state vs. county regulations, intra-state climate variation). Hierarchical regression also accommodated the fact that available data also was only available at a certain spatial scale, for example price data at the state scale and production and climatological data at the county scale.

We ran maximum likelihood simulations to identify the timing and time-scale of precipitation anomalies and PET anomalies which produced models with the lowest root mean square error (RMSE). We then expand our models to include a full distribution of possible factors using Markov chain Monte Carlo (MCMC) hierarchical robust linear regression (Figure 1) based on the timing and time-scale of climatological anomalies that produced the lowest RMSE. We established a significance level of 95% to identify counties with significant factors determined by the MCMC model.

2.4 Clustering Analysis

Clustering analysis was used to aggregate counties where annual crop production anomalies exhibited similar sensitivity to precipitation anomalies, PET anomalies, or price anomalies, presumably revealing spatial patterns due to climatological or economic similarities. For example, the clustering of counties most sensitive to climatological variability and least sensitive to crop price variability, or vice versa.

Cluster analysis is a technique used to group analogous objects (i.e., crop production in a given county) based on similar characteristics (i.e., sensitivity of crop production to precipitation, PET, and price at the county scale). Common implementations of cluster analysis include hierarchical clustering, fuzzy partition clustering, and k-means clustering. We used k-means cluster analysis to group counties with similar crop production sensitivities to precipitation, PET, and price for each crop under study. K-means cluster analysis was conducted using the mean precipitation, PET, and price factors taken from the distribution of MCMC simulations. To maximize available data, all mean factors for each county were used in the clustering analysis, regardless of the significance of these factors in respect to zero.

3 Results

The independent factors \((\alpha, \beta, \delta, \gamma)\) determined by Equations 1 and 2 determined at the optimal month and time-scale represent the proportion of independent anomaly that translated to the crop production anomaly. Examples of errors produced for months during the growing season over time-scales 1-15 are provided in Figure 2, and provided for all counties and crops for Equations 1 and 2 in Appendix A and B.
respectively. The relationship between crop production anomalies and independent anomalies were either
direct or inverse, which was particularly observed for PET anomalies and price anomalies, but also observed
for precipitation anomalies in some counties. Above average PET, for example, was associated with above
normal crop production in some counties, yet was associated with below normal crop production in others.
Similarly, below average price that producers received the year prior was associated with above average crop
production in some counties, but not in others. The spatial distribution of precipitation factors and PET
factors are presented in Figure 5, with counties having non-significant factors also shown. Price factors
determined using both Equations 1 and 2 were similar both spatially and in magnitude, and are presented
for barley and winter wheat in Figure 6 for comparison. However, only price factors determined by Equation
1 are presented in the results for simplicity. Fixed factors were largely non-significant across counties for
each study crop, and were situated around zero, indicating that fixed factors were not important in driving
annual crop production anomalies and so are not further discussed.

3.0.1 Alfalfa

Irrigated annual alfalfa production occurred in counties across Idaho, Montana, and Wyoming. The variance
in annual alfalfa production anomalies explained by Equations 1 and 2 in respect to sensitivity to climato-
logical anomalies is shown in Figure 3a. The mean precipitation factor for counties with greater than 50%
total irrigated annual alfalfa production was 41% and the mean PET factor was -33%, compared to a mean
precipitation factor of 60% and a mean PET factor of -51% in counties with less than 50% total irrigated
alfalfa production. The mean $R^2$ value was near 0.26 for both models in counties with greater than 50%
total irrigated alfalfa production, compared to 0.46 and 0.31 for Equation 1 and Equation 2 respectively for
counties with less than 50% irrigation. There were, however, counties with relatively high irrigated total
alfalfa production which displayed relatively high sensitivity to drought conditions, with precipitation factors
as high as 83% corresponding with a $R^2$ values as high as 0.63.

194 counties had sufficient alfalfa production over the study period to be considered in this study, with
annual alfalfa production anomalies in 138 of these counties having significant sensitivity to precipitation
anomalies. Precipitation factors for alfalfa were significant across much of Montana, North Dakota, South
Dakota, and north-eastern Wyoming, but were non-significant for much of Idaho and western Wyoming.
The timing and time-scale of both precipitation and PET anomalies with the highest correlation with annual
alfalfa production is shown in Figure 4a. Most counties with significant sensitivity to precipitation anomalies
had the greatest correlation with precipitation anomalies occurring in June ($n = 39$) and July ($n = 43$) over
time-scales 10 - 13 months ($n = 28$). All significant precipitation factors indicated a direct relationship
between alfalfa production anomalies and precipitation anomalies. Sensitivity of annual alfalfa production
anomalies to precipitation anomalies generally increased moving east across the study area, until reaching maximum sensitivity around counties located in eastern Montana, eastern Wyoming, western North Dakota, and western South Dakota, and then decreased moving further east into eastern North Dakota and eastern South Dakota. Annual alfalfa production anomalies in west central North Dakota was the most sensitive to precipitation anomalies, with a max precipitation factor of 93% ($R^2 : 0.75$), and was representative of surrounding counties in western North Dakota, eastern Montana, eastern Wyoming, and western South Dakota. Alfalfa production near eastern border of North Dakota was shown to be the least sensitive to precipitation anomalies, with a minimum precipitation factor of 13% ($R^2 : 0.23$), and was also representative of counties located around the eastern border of South Dakota. The area wide mean precipitation factor for counties having significant precipitation factors was 53%, the highest among the three crops under study. $R^2$ values using Equation 1 ranged from 0.0 and 0.83, with a mean $R^2$ of 0.38 in counties with significant precipitation factors.

Annual alfalfa production anomalies were significantly sensitive to PET anomalies in 149 counties, and the spatial distribution of significant PET factors was similar to that of precipitation factors. The timing of PET anomalies having the greatest correlation with annual alfalfa production anomalies was more spatially variable than with precipitation, however the most common month was June ($n = 33$) over time-scales of 1 to 5 months ($n = 22$). Alfalfa production in north western South Dakota was most sensitive to PET anomalies, with a maximum PET factor of -81% ($R^2 : 0.67$). Annual alfalfa production anomalies near the western Idaho border were least sensitive to PET anomalies with a minimum PET factor of -23% ($R^2 : 0.23$). The area wide mean PET factor for counties having significant PET factors was -48%, which was significantly lower than the mean of significant precipitation factors. Therefore, precipitation anomalies were more important than PET anomalies in driving alfalfa production anomalies, although PET anomalies were still important. Alfalfa production anomalies were also significantly more sensitive to precipitation anomalies and PET anomalies than barley or winter wheat. $R^2$ values using Equation 2 ranged from between 0.0 and 0.72, with a mean $R^2$ of 0.29 in counties with significant PET factors.

Price factors for alfalfa were mostly non-significant across the study area, except for in a relatively few scattered counties. Annual alfalfa production anomalies showed a inverse relationship with price anomalies in some counties, but a direct relationship in others. 15 of 25 counties which had significant price factors had an inverse relationship, or about 60%. The inverse relationship was strongest in near the southwest border of Idaho where the price factor was -65% ($R^2 : 0.22$), and weakest in south-central Idaho where the price factor was -18% ($R^2 : 0.37$). The mean price factor for counties with an inverse relationship with price was -35%. 10 of the 25 counties with significant price factors had alfalfa production anomalies with a direct relationship with price, or about 40%. This relationship was greatest in south-central Montana with a price factor of 36%
(R^2 : 0.58), and weakest at the south-eastern Idaho border with a price factor of 2% (R^2 : 0.63). The mean 
price factor in counties with a direct relationship between alfalfa production anomalies and price anomalies 
was 27%. Price anomalies was least important to annual alfalfa production anomalies than precipitation 
anomalies and PET anomalies, and alfalfa was less sensitive to price anomalies than barley or winter wheat.

3.0.2 Barley

Total barley production was primarily irrigated in Idaho, western Montana, and Wyoming, and was primarily 
rain fed in eastern Montana, North Dakota, and South Dakota. Irrigation had minimal effect on annual barley 
production anomalies compared to rainfed annual production anomalies. The variance in annual barley 
production anomalies explained by Equations 1 and 2 in respect to sensitivity to climatological anomalies is 
shown in Figure 3b. The mean precipitation factor for counties with greater than 50% irrigated annual barley 
production, a direct relationship with precipitation and a indirect relationship with PET saw essentially no 
change in precipitation factors or PET factors. Counties with annual barley production anomalies with a 
inverse relationship with precipitation anomalies and a direct relationship with PET anomalies were only 
observed in one county with greater than 50% irrigation.

190 counties had adequate barley production over the study period to be considered in this study, with 
annual barley production anomalies in 120 of these counties having significant sensitivity to precipitation 
anomalies. The timing and time-scale of both precipitation and PET anomalies with the highest correlation 
with annual winter wheat production is shown in Figure 4b. Precipitation factors were found to be significant 
across much of Montana and southern Idaho, and non-significant across northern Idaho. The significance 
of precipitation factors in North Dakota, South Dakota, and Wyoming were mixed. Most counties with 
significant sensitivity to precipitation anomalies had the greatest correlation with precipitation anomalies 
occurring in July (n = 52), however time-scales across counties were very mixed between 1 and 12 months. 
Annual barley production anomalies in counties with significant precipitation factors showed a direct relation-
ship with precipitation anomalies in 115 counties with significant precipitation factors, or about 96% of 
counties with significant precipitation factors. The direct relationship was strongest in the north-west corner 
of South Dakota with a maximum precipitation factor of 63% (R^2 : 0.42), and the direct relationship was 
weakest near the eastern border of North Dakota with a minimum precipitation factor of 12% (R^2 : 0.04). 
The mean precipitation factor of counties shown to have had a direct relationship between precipitation 
anomalies and barley production anomalies was 34%. R^2 values using Equation 1 ranged from between 
0.0 and 0.48 in counties with significant precipitation factors and a direct relationship between annual barley 
production anomalies and precipitation anomalies, with a mean R^2 of 0.17. Annual barley production 
anomalies showed an inverse relationship with precipitation anomalies in 5 counties, or about 4% of coun-

9
ties with significant precipitation factors. All counties which showed an inverse relationship between annual barley production anomalies and precipitation anomalies occurred in August over a time-scale of one month, and were located around central and north-central North Dakota. The inverse relationship was strongest in north-central North Dakota with a maximum precipitation factor of -25% ($R^2 : 0.14$), and weakest near the center of North Dakota with a minimum precipitation factor of -21% ($R^2 : 0.01$). $R^2$ values using Equation 1 ranged between 0.0 and 0.24 for models of annual barley production anomalies in counties with significant precipitation factors and an indirect relationship with precipitation anomalies, with a mean $R^2$ of 0.15.

Annual barley production anomalies were significantly sensitive to PET anomalies in 149 counties. PET factors for barley were significant in most counties in North Dakota, while the remaining states were a mix of counties with significant and non-significant PET factors. Most counties with significant sensitivity to PET anomalies had the greatest correlation with PET anomalies occurring in September ($n = 36$) and July ($n = 24$) over time-scales of 3 months ($n = 19$) and 1 - 2 months ($n = 21$) respectively. Barley production anomalies showed a direct relationship with PET anomalies in 10 of the 81 counties with significant PET factors, and were mostly located around eastern Montana with PET factors ranging from 16% to 22% and a mean of 19%. $R^2$ values using Equation 2 ranged between 0.0 and 0.16 for models of annual barley production anomalies in counties with significant PET factors and a direct relationship with PET, with a mean $R^2$ of 0.03. The remaining 71 counties with significant PET factors had an inverse relationship, or around 88% of counties with significant PET factors. The greatest inverse relationship between barley production anomalies and PET anomalies was located near the center of North Dakota with a maximum PET factor of -45% ($R^2 : 0.23$), and was weakest in northern Idaho with a PET factor of -15% ($R^2 : 0.01$). The mean significant PET factor of counties which had an inverse relationship between barley production anomalies and PET anomalies was -32%. $R^2$ values using Equation 2 ranged between 0.0 and 0.55 for models of annual barley production anomalies in counties with significant PET factors and an indirect relationship with PET, with a mean $R^2$ of 0.18.

Barley production was more sensitive to price than alfalfa production, but less sensitive to price than winter wheat production. Price factors of barley production were significant in many counties in Montana, but were mixed across counties in Idaho, North Dakota, South Dakota, and Wyoming. Annual barley production anomalies showed a direct relationship with price in 114 of 126 counties with significant price factors, or about 90%. The direct relationship between barley production anomalies and price anomalies was greatest near the south eastern border of Idaho with a price factor of 53% ($r^2 : 0.16$), and least in north-eastern Montana with a price factor of 0.16% ($R^2 : 0.07$). The mean price factor for counties with a direct relationship between barley production anomalies and price anomalies was 27%. Barley production anomalies showed an inverse relationship with price anomalies in 12 of 126 counties, or about 10%. The
inverse relationship between barley production anomalies and price anomalies was greatest was near south-
eastern North Dakota with a price factor of -54% ($R^2 : 0.28$), and was the least in north-central South
Dakota with a price factor of -10% ($R^2 : 0.26$). The mean price factor for counties which had an inverse
relationship between barley production anomalies and price anomalies was -39%.

3.0.3 Winter Wheat

Irrigated total winter wheat production was extensive in western Wyoming, moderate in southern Idaho,
and present but light in Montana and eastern Wyoming. The variance in annual winter wheat production
anomalies explained by Equations 1 and 2 in respect to sensitivity to climatological anomalies is shown in 3c.
Counties with greater than 50% total irrigated winter wheat production had a mean precipitation factor of
31% and a mean PET factor of 30%, compared to a mean precipitation factor of 38% and a PET factor of
29% in counties with less than 50% total irrigated winter wheat production. The mean $R^2$ value in counties
with greater than 50% total irrigated winter wheat production was 0.20 for Equation 1 and 0.13 for Equation
2, compared to 0.26 and 0.18 in counties with less than 50% total irrigated production. Similar to annual
barley production anomalies, no inverse relationship between annual winter wheat production anomalies and
precipitation or direct relationship with PET anomalies was observed in any counties with greater than 50%
total irrigated winter wheat production.

201 counties had adequate winter wheat production over the study period to be considered in this study,
with 138 of these counties having significant sensitivity to precipitation anomalies. Winter wheat production
was generally less sensitive to precipitation than alfalfa production, but more sensitive to precipitation than
barley production. The timing and time-scale of both precipitation and PET anomalies with the highest
correlation with annual winter wheat production is shown in Figure 4c. Most counties with significant
sensitivity to precipitation anomalies had the greatest correlation with precipitation anomalies occurring
in June ($n = 30$) over time-scales of between 5 and 15 months ($n = 24$). Precipitation factors for winter
wheat production were significant across counties in Montana and Wyoming, and in many counties in South
Dakota, while counties in Idaho and North Dakota were a mix of significant and non-significant precipitation
factors. Winter wheat production anomalies showed a direct relationship with precipitation anomalies in
143 of the 144 counties where precipitation factors were significant, or about 99%. The direct relationship
between winter wheat production anomalies and precipitation anomalies was greatest in south-central South
Dakota with a maximum precipitation factor of 65% ($R^2 : 0.41$), and least in the north-west corner of
North Dakota with a minimum precipitation factor of 14% ($R^2 : 0.19$). The mean precipitation factor for
counties which had a significant and direct relationship with winter wheat production was 37%. Only one
county located near the south-west corner of North Dakota had an inverse relationship between precipitation
anomalies and winter wheat production anomalies with a precipitation factor of -17% ($R^2 : 0.18$). $R^2$ values using Equation 1 ranged between 0.0 and 0.73, with a mean $R^2$ of 0.26.

Significant PET factors were found across counties in Wyoming, central Montana, much of North Dakota, western South Dakota, and in counties on the southern border of Idaho. Winter wheat production anomalies showed a direct relationship with PET in 27 of the 99 counties where PET factors were significant, or about 27%. Counties with a direct relationship between winter wheat production anomalies and PET anomalies were largely found in North Dakota, with a few counties also found in eastern Montana. The direct relationship between winter wheat production anomalies and PET anomalies was greatest on the eastern border of Montana with a maximum PET factor of 40% ($R^2 : 0.20$), and least in eastern North Dakota with a minimum PET factor of 11% ($R^2 : 0.12$). Winter wheat production anomalies showed an inverse relationship with PET anomalies in 72 of the 99 counties where PET factors were significant, or about 73%. The inverse relationship between winter wheat production anomalies and PET anomalies was greatest in the south-east corner of Wyoming with a maximum PET factor of 60% ($R^2 : 0.51$), and least in the south-east corner of Idaho with a minimum PET factor of -5% ($R^2 : 0.0$). The mean PET factor for counties with a significant and indirect relationship between precipitation anomalies and annual winter wheat production anomalies was -29%. $R^2$ values using Equation 2 ranged from 0.0 and 0.58, with a mean $R^2$ of 0.25.

Annual winter wheat production was more sensitive to price anomalies than alfalfa and barley. Price factors were significant in many counties across Montana, and most counties in North Dakota, although price factors were non-significant in most of Idaho, South Dakota, and Wyoming. Winter wheat production showed a direct relationship with price anomalies in 158 of 160 counties where price factors were significant, or about 99%. The direct relationship between winter wheat production anomalies and price anomalies was greatest near the western border of South Dakota with a maximum price factor of 100%, and least near the center of South Dakota with a minimum price factor of 9%. The mean price factor for counties which had a significant direct relationship with price was 46%. The two counties with significant factors showing an inverse relationship between price and winter production anomalies were both located in Idaho, with the greatest inverse relationship with a price factor of -0.25, and the least inverse relationship with a price factor of -0.09.

### 3.0.4 Clustering Analysis

The clustering analysis grouped counties with similar sensitivity of annual crop production anomalies to precipitation anomalies, PET anomalies, and price anomalies for each crop. An optimal number of three clusters was determined for all three crops. Counties cluster classifications and the distribution of factors
within each cluster are presented for alfalfa, barley, and winter wheat in Figures 7, 8, and 9 respectively.

Alfalfa production anomalies in cluster one counties had the greatest negative drought response to both precipitation anomalies and PET anomalies. Cluster one counties were also least sensitive to price, where price factors were generally weak and situated around zero. Counties classified by cluster one were mostly found in North Dakota, South Dakota, north-east Wyoming, and a few counties in eastern Montana; counties primarily rain-fed with little irrigation. Cluster two counties generally had the greatest positive response to price anomalies. Cluster two counties were generally less sensitive to precipitation and PET than counties in cluster one, but more sensitive than cluster three. Cluster two mainly described annual alfalfa production in Montana. Alfalfa production anomalies in counties classified in cluster three were generally least sensitive to precipitation anomalies and PET anomalies. Cluster three also described counties where alfalfa production anomalies had a negative response to positive price anomalies, indicating farmers increase alfalfa production after receiving lower prices the year prior. Cluster three mainly described counties in Idaho, Wyoming, counties toward the western boundaries of North Dakota and South Dakota. Alfalfa production in many counties in Idaho and western Wyoming is irrigated.

Barley production anomalies in cluster one counties was largely associated with a negative drought response in terms of both precipitation anomalies and PET anomalies. Price factors in cluster one were mostly positive and similar in magnitude to cluster three counties. Counties classified in cluster one were found in all states within the study area, describing most of Idaho, Wyoming, South Dakota, and western Montana. Cluster two largely described counties where barley production anomalies showed a positive response to negative price anomalies. Cluster two had high variability in terms of sensitivity to precipitation anomalies, where counties had both negative and positive drought response. Barley production anomalies in cluster two counties generally showed a negative drought response in terms of PET. Cluster two counties were largely located in North Dakota. Barley production anomalies in cluster three counties was unique in that most counties had a positive drought response in terms of PET, where increased atmospheric demand was associated with increased barley production. However, cluster three counties had a similar negative drought response to precipitation as cluster one. Annual barley production anomalies generally had a positive response to positive price anomalies. Cluster three counties were largely located in eastern Montana, but were also scattered around Idaho, North Dakota, and South Dakota.

Annual winter wheat production anomalies in counties characterized by cluster one were least impacted by anomalies in precipitation, PET, and price. Counties classified as cluster one were mostly found in Idaho and counties near the eastern borders of North Dakota and South Dakota. Cluster two had the greatest positive price response, and largely consisted of counties where annual winter wheat production had a positive response to higher atmospheric demand, with a few counties where a weak negative drought
response to positive PET anomalies was observed. Generally, annual winter wheat production showed
a negative drought response to negative precipitation anomalies. Cluster two counties comprised much of
North Dakota and eastern Montana, and northwest Montana. Annual alfalfa production anomalies in cluster
three had the greatest negative drought response in terms of precipitation and PET, and had a weak and
mostly positive response to price. These counties comprised annual wheat production in most of North
Dakota, eastern Wyoming, west and central Montana, and parts of southern Idaho.

4 Discussion

A comprehensive understanding of the main drivers behind crop production variability is key to ensuring that
resources are appropriately allocated to maximize the efficacy of future agricultural practices Lipper et al.
(2014). This study focused on the sensitivity of annual crop production anomalies to climatological anomalies
and price anomalies for three key crops produced in the northwestern United States. Our research differs
from existing studies which focused specifically on yield, in that we focused on productivity to incorporate
into our analysis both variability in yield and variability in farmer response through cropping area allocation.
We found large spatial and temporal variability in sensitivities of annual crop production to precipitation,
PET and price anomalies, indicating that small scale analysis (e.g., county scale) is optimal for understanding
or predicting variability in annual crop production. Our research provided two simple models at the county
scale using public data which can be implemented by agricultural producers and decision makers to quantify
the impacts of climatological and economic fluctuations on annual crop production. Furthermore, we provide
classifications of counties which describe the appropriateness of the models.

Multiscalar climatological indices have been used to identify the timing and time-scale of drought condi-
tions that most impact crop productivity in several recent studies with relatively clear results. Zipper et al.
(2016) showed how maize and soy yield anomalies in the US were most correlated with drought conditions
occurring during July and August over time-scales of 1-3 months, or about 1 to 2 months prior to harvest.
Vicente-Serrano et al. (2006) used a one and three month SPI in February, 4 months prior to harvest, to
explain greater than 80% of temporal variability in wheat and barley production (defined as the proportion
between sown and harvested crop) in north-east Spain. However, Peña-Gallardo et al. (2018) showed more
spatial variability in the timing of SPEI for county scale barley and winter wheat yields in the US, with
many counties being most sensitive over time-scales longer than three months. The highest correlation in this
study often occurred at longer time-scales (> 7 months), much longer than the shorter time-scales identified
in Zipper et al. (2016) and Vicente-Serrano et al. (2006). This is likely due to our focus on production which
is a function of both yield and cropping area, thus incorporates farmer decision making into the analysis.
Higher correlations at longer time-scales indicated that farmers likely considered current climate conditions, seasonal forecasts, or used traditional knowledge to estimate the possibility of drought conditions during the season when deciding cropping area, months before crops are sown. This relationship between farmer decision making early in the season and drought conditions occurring later in the season over long time-scales is supported by Haigh et al. (2015), who found that over 80% of producers in the US Corn Belt decided on cropping area between mid-fall and late-winter, and that over 50% of the same producers used current, monthly or seasonal drought forecasts to aid in their decisions. However, this largely speculation, as studies focusing on annual crop production in respect to the timing and time-scale of climatological anomalies is limited.

Sensitivity of annual crop production to precipitation and PET anomalies generally coincided with gradients in precipitation, temperature, and soil moisture regimes moving across the study area. This is generally in agreement with Lobell et al. (2011), who showed that crop yields in warmer regions were generally more sensitive to climatological variability than cooler regions. Existing studies provide insight into how these sensitivities may affect future variability in annual crop production. Ficklin and Novick (2017) showed that vapor pressure deficit has decreased in eastern Montana and North Dakota from 1979-2013. This trend could not only impact annual crop production in terms of atmospheric water supply and demand, but may also have implications to changes in soil moisture regime. Salley et al. (2016) found that the soil transition from ustic (drier) to udic (wetter) soils is closely related to the isohyet running roughly north to south through western North Dakota and central South Dakota where precipitation equals PET. While precipitation trends within the study area over the same period are, to the best of our knowledge, not currently available in the literature, decreased VPD alone may be associated with the isohyet migrating west. This trend could have positive implications for alfalfa production in the region (e.g., counties described by cluster one), where alfalfa was most sensitive to atmospheric water demand. However, winter wheat production described by cluster two, and barley production described by cluster three showed a slightly positive production response to increased atmospheric water demand. It is therefore a reasonable expectation that production of winter wheat and barley production may decline with decrease in VPD. Furthermore, winter wheat production in cluster two and barley production in cluster three had greater sensitivity to price, likely made possible by lesser sensitivity to climatological anomalies. Decreases in VPD in the region may be cause for farmers to reassess future production strategies to put more emphasis on climatological variability. Ficklin and Novick (2017) also showed that VPD is increasing in many counties where crop production was least sensitive to PET and precipitation. These regions are buffered from climatological anomalies by irrigation and wetter soils. However increased VPD may stress irrigation supply and diminish soil moisture, thus increasing sensitivity to climatological anomalies and reducing production. Further work concerning historic sensitivity
to climatological anomalies in conjunction with historic trends in atmospheric water supply and demand, and if these relationships are changing, would provide useful insights into how the equilibrium between crop production and climate variability will shift moving into the future.

The positive crop production response to drought observed in this study for barley and winter wheat was also observed by Lobell and Asner (2003) and Zipper et al. (2016) for corn and soybean yields, where increased crop yields occurred during periods of below average precipitation or above average atmospheric water demand. Zipper et al. (2016) attributed negative drought sensitivity to shallow groundwater and poorly drained soils, or the presence of irrigation. We found in our study area that positive production response to drought occurred in rainfed areas where minimal irrigation was present, largely in eastern Montana and North Dakota. Our study indicated that negative drought sensitivity was primarily associated with a direct relationship between production and PET, and was less associated with an inverse relationship between annual production anomalies and precipitation anomalies. While irrigation can work to mitigate stress caused by above normal temperatures associated with above average PET by removing energy from the plant surface through latent heat (Asseng et al., 2011), irrigation would need to be continuously available to the plant surface over the entire course of the PET anomaly for the temperature mitigation affect to be fully realized, something not always possible due to water limitations often associated with periods of drought. Thus, the positive crop production response to drought observed for barley and winter wheat production is most likely due to areas with poorly drained soils where increased atmospheric water demand worked to dry soils to moistures more suitable for plant growth.

While the analysis in this study provided reasonable results in quantifying the sensitivity of annual crop production anomalies to anomalies in precipitation, PET, and price in primarily rainfed counties, it is important to note several limitations of the linear relationship proposed in our study. Overwhelming pluvial conditions would likely break the direct relationship between annual crop production anomalies and precipitation anomalies observed in most counties. These occurrences are rare in the semi-arid climate within our particular study area, however may be observed in wetter regions. Furthermore, isolated events such as hail storms or tornadoes may not produce adequate precipitation to result in an anomaly, but can result in serious crop damage and drastic decrease in annual crop productivity. Insect or disease outbreaks in croplands associated with drought may be present during some years and not others (Rosenzweig et al., 2001). While these phenomena are beyond the scope of this study, they are important considerations to understanding interannual variability in crop production and are generally poorly understood (Iizumi and Ramankutty, 2015).
4.1 Conclusion

This study quantified the sensitivity of annual crop production anomalies to climatological and price anomalies of three crops produced in the northwest US at time-scales most correlated with variability in annual crop production. Spatial variability of sensitivity to these driving factors were classified into three clusters for each crop. Annual alfalfa production was shown to be most sensitive to precipitation anomalies, particularly in rain-fed counties, and barley was least sensitive. Irrigation most reduced the sensitivity of alfalfa to climatological anomalies, while the effect of irrigation on barley production was less clear. Clustering analysis generally grouped counties spatially coincident with gradients in precipitation, temperature, and soil moisture regimes moving across the study area. Further study into changing sensitivity to climatological variability and changes in atmospheric water demand and supply may provide insight into how variability in annual crop production may change moving into the future. Our research provided simple models at the county scale using public data which can be implemented by agricultural producers and decision makers to quantify the impacts of climatological and economic fluctuations on annual crop production. Furthermore, we provide classifications of counties which describe the appropriateness of the models.
Figure 1: Kruschke style diagram of the Markov chain Monte Carlo hierarchical robust linear regression model showing the probability distributions used in Equation 1. The same model structure was used for Equation 2, except the EDDI index was used as the independent climatological variable.
Figure 2: Heatmap examples showing root mean square error (RMSE) for months during the growing season using 1 (left) and 2 (right) for alfalfa (a), barley (b), and winter wheat (c).
Figure 3: Plots showing the relationship between variance explained and climatological factors determined by 1 (left) and 2 (right) for alfalfa (a), barley (b), and winter wheat (c). Cooler colors indicate greater total irrigated production for the study period.
Figure 4: Plots showing the (randomly jittered) month and time scale having the highest correlation with annual crop production anomalies for each county, scaled by precipitation factors (left) and PET factors (right) for alfalfa (a), barley (b), and winter wheat (c). Warmer colors indicate a greater negative drought response, and cooler colors indicate a greater positive drought response.
Figure 5: Spatial distribution of precipitation factors (left column) and PET factors (right column) for alfalfa (a) and (b), barley (c) and (d), and winter wheat (e) and (f). Warmer colors indicate a negative response in crop production anomalies to negative precipitation anomalies or positive PET anomalies (i.e., negative drought response), and cooler colors indicate a positive response in crop production anomalies to negative precipitation anomalies or positive PET anomalies (i.e., positive drought response). Diagonal lines across counties indicate non-significant factors.
Figure 6: Spatial distribution of price factors derived from Equation 1 (left column) and Equation 2 (right column) for barley (a) and (b) and winter wheat (c) and (d). Purples indicate a negative response of crop production anomalies to positive price anomalies and greens indicate a positive response of crop production anomalies to positive price anomalies. Diagonal lines across counties indicate non-significant factors. Price factors for alfalfa were non-significant in most counties and so is not included.

Figure 7: (a) is a map showing county classifications for alfalfa production based on clustering. (b) are violin plots showing the distribution of precipitation factors (left), PET factors, (middle), and price factors (right) for clusters 1 (blue), 2 (green) and 3 (orange).
Figure 8: Same as Figure 7 but for barley.

Figure 9: Same as Figure 7 but for winter wheat.
References


K. Klink, J. J. Wiersma, C. J. Crawford, and D. D. Stuthman. Impacts of temperature and precipitation variability in the Northern Plains of the United States and Canada on the productivity of spring


Appendix A  RMSE from Equation 1 over months 3-9 and time-scales 1-15

Root mean square error (RMSE) produced by Equation 1 from March-September over time-scales 1-15 for all counties and crops under study. Darker colors indicate lower RMSE.
Winter Wheat in Fall River County, SD
Winter Wheat in Faulk County, SD
Winter Wheat in Grant County, SD
Winter Wheat in Gregory County, SD
Winter Wheat in Hamlin County, SD
Winter Wheat in Jackson County, SD
Winter Wheat in Jackson County, SD
Winter Wheat in Jefferson County, SD
Winter Wheat in Jones County, SD
Winter Wheat in Kingman County, SD
Winter Wheat in Lawrence County, SD
Winter Wheat in Lyman County, SD
Winter Wheat in Marshall County, SD
Winter Wheat in McPherson County, SD
Winter Wheat in McPherson County, SD
Winter Wheat in Meade County, SD
Winter Wheat in Meade County, SD
Winter Wheat in Mellette County, SD
Winter Wheat in Oglala Lakota County, SD
Winter Wheat in Perkins County, SD
Appendix B  RMSE from Equation 2 over months 3-9 and time-scales 1-15

Root mean square error (RMSE) produced by Equation 2 from March-September over time-scales 1-15 for all counties and crops under study. Darker colors indicate lower RMSE.
Barley in Oneida County, ID (EDDI)

Barley in Owyhee County, ID (EDDI)

Barley in Payette County, ID (EDDI)

Barley in Twin Falls County, ID (EDDI)

Barley in Flathead County, MT

Barley in Cascade County, MT

Barley in Oneida County, ID

Barley in Blaine County, MT

Barley in Washington County, ID

Barley in Beaverhead County, MT (EDDI)

Barley in Big Horn County, MT

Barley in Bannock County, MT

Barley in Beaver County, MT

Barley in Bonner County, MT

Barley in Carbon County, MT

Barley in Benewah County, ID (EDDI)

Barley in Beaverhead County, MT

Barley in Big Horn County, MT

Barley in Bannock County, MT

Barley in Bonner County, MT

Barley in Carbon County, MT

Barley in Benewah County, ID (EDDI)