

Yield limitations and production zones of rainfed grain sorghum in the Southern Great Plains

by

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B.S., Kansas State University, 2008

M.P.A., University of Kansas, 2011

AN ABSTRACT OF A DISSERTATION

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Abstract

The Southern Great Plains is a semi-arid cropping region in which two of the primary concerns for local farmers are yield level and yield stability. In this thesis we investigated three central questions related to rainfed cropping systems in the Southern Great Plains. Our first question was i) Why are grain sorghum yields stagnating in Kansas? The yield gap for grain sorghum was estimated using an extensive dataset of crop performance trials, yield contest data, and county-level survey yield data totaling 2997 site-years. State-level yield was 4.7 Mg ha⁻¹, which represents 77% of the attainable yield and 49% of the water-limited yield potential. Sorghum grain yields in Kansas rainfed systems appear to be stagnating due to a small gap between current and maximum attainable yield and a generalized statewide shift in planting area to environments with greater water deficit. Our second question was ii) What are the major homogeneous crop production agro-zones for the state of Kansas? We delineated the state of Kansas using a hierarchical clustering method which first consisted of classifying macro agro-zones based on climate features, and then each macro area was further divided into micro areas based on soil physical features. We identified three optimal clusters of relatively homogeneous climatic conditions that partitioned the state into northwest, southwest, and east, each with two nested micro-AZs based on soil physical properties. Our final question was iii) Has maize surpassed grain sorghum in its ability to yield under drought conditions? We evaluated county-level non-irrigated yield reports from USDA-RMA relative to USDA-NASS for the period of 2019 to 2023. The use of a county-report with combined irrigated and non-irrigated practices resulted in a four-fold overestimation of maize yield advantage to grain sorghum. According to our new findings, grain sorghum maintains a persistent yield advantage to maize in some water-limited environments.

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Chapter 1 - General Introduction

Grain sorghum [*Sorghum bicolor* (L.) Moench] originated from the Horn of Africa and is cultivated between the latitudes of 40° N and 40° S, with prevalent cultivation in the countries of the United States (US), Nigeria, India, and Brazil (FAO, 2024). Globally, grain sorghum is among the top five most important cereals cultivated for feed, food, and fuel with 40 million hectares grown each year (FAO; 2024; Khalifa and Eltahir, 2023). In the US, sorghum is cultivated in the Southern Great Plains on approximately 2.5 million hectares, and more than 90% of the production area occurs under rainfed conditions (USDA-NASS, 2024). This semi-arid production region is prone to high frequency of environmental water stress, and the most prevalent limitation to crop productivity is water scarcity. Here, we seek to address central questions to grain sorghum production systems to garner useful insights on the potentials and limitations of crop system dynamics under water-limitations.

i) The state of Kansas is the leading production region for grain sorghum in the US with approximately half of the total production area (USDA-NASS, 2024). The trajectory of farmer realized yield gains in the U.S. has steadily increased at a rate of 28 kg ha⁻¹yr⁻¹ (USDA-NASS, 2024) since the introduction of hybrid seed technology in 1957 (Duncan et al., 1991). In the same period, Kansas farmers have realized relatively higher increases at a rate of 39 kg ha⁻¹yr⁻¹ (USDA-NASS, 2024). These yield gains are attributable to hybridization of sorghum (Miller and Kebede, 1984), improved agronomic practices related to planting density and planting date (Assefa & Staggenborg, 2010), and widespread use of crop inputs including nitrogen fertilizers (Mengel, 2018). Although the trend in grain yield has remained positive since 1990 with a rate of 0.01 Mg ha⁻¹ yr⁻¹, these trends are no longer statistically significant across both the U.S. and Kansas, indicating yield stagnation. Yield stagnation is widespread in multiple crops across the

world and threatens food security under scenarios of future global food demand (Ray et al., 2012). Crop yield stagnation is often attributed to a lack of exploitable yield gap, which occurs when current farmer yields near ~70% of yield potential (Cassman et al., 2003; Lobell et al., 2009; van Wart et al., 2013). However, many factors can contribute to stagnation in yields including soil quality (Patrignani et al. 2014) and shifts to planting in areas with higher intensity of water stress (Rakshit et al., 2014). Why are grain sorghum yields stagnating in the US? Is there a closure of the exploitable yield gap with current yields approaching water-limited yield potential? Is yield stagnation in grain sorghum attributable to environmental or management conditions?

ii) Kansas is a productive agricultural region with nearly 90% of the 212,000 km² land area allocated to crops and rangeland. Kansas leads the U.S. in the production of grain sorghum and winter wheat (*Triticum aestivum* L.) and is third for beef cattle (*Bos taurus*) production (USDA NASS, 2024). The precipitation gradient in Kansas ranges from 1150 mm in the east to 450 mm in the west, and the mean annual air temperature ranges from 11 °C to 14 °C. The predominant soil textures are silt loam or silty clay loam with shallow claypan soils in the southeast and sandy soils in south central Kansas. The dominant crops by planting area are winter wheat, maize (*Zea mays* L.), soybeans (*Glycine max* L.), and grain sorghum with prevalence of summer fallow in the water-limited regions of western Kansas (USDA CDL, 2024). This diverse landscape warrants delineation of agro-zones (AZ). Agro-zones represent homogenous environmental conditions that reflect similar crop production potentials and can be used to inform agricultural management, planning, and policy making. Agro-zones have been proposed for numerous use-cases including the scales of global to field (Boydell and McBratney, 2002; Fischer et al., 2000) level, and specific applications such as site selection for a soybean

breeding program (Gilbert and Martin, 2024) to broad applications including regional government agricultural policy planning in Rwanda (Clay and DeJaegher, 1987). However, most of these AZs rely on climate features (van Wart et al., 2013) with few AZs incorporating soil attributes and often AZs with soil features are highly fragmented (Williams et al., 2008). While the field of AZs is well established, there has yet to be a framework which tests whether the delineated areas of a proposed AZ correspond to areas of corresponding differences in crop potentials. Our objective was to delineate and validate AZs for the state of Kansas. Can we capture soil attributes in the design of AZs while maintaining parsimony in the resulting zones? Can newly available datasets that capture landcover and environmental causes of loss of crop yield be leveraged to validate AZs?

iii) Maize and grain sorghum are similar cereals grown in the warm season and utilized in markets for feed, fuel, and food. These cereals are contrasted by their production environments, with maize typically grown in environments with lower abiotic stress, while grain sorghum concentrates in regions associated with greater abiotic stress, specifically water and heat stress. The environmental placement of these cereals has been justified by the innate adaptation of sorghum to water stress, with traits such as stay-green (Borrell et al., 2014) and deep root architecture (Goche et al., 2020). Maize, on the other hand, has greater photosynthetic capacity with erect leaves and a dense canopy (Li et al., 2021; Loomis and Anthor, 1999; Messina et al., 2022), resulting in greater yield sensitivity to water supply (Grassini et al., 2022), including crop failure under drought conditions and high yield potential in water-rich environments. Maize grown under favorable conditions has spurred substantial investment in crop improvement, in terms of breeding programs and application of biotechnology tools, relative to grain sorghum (Anderson and Sheldon, 2017; Naylor et al., 2004; Troyer, 2009). As such, the rate of genetic

gain in maize has outpaced the gains in grain sorghum (Duvick 2005; Mayor et al., 2022; Pfeiffer et al., 2019; Smith et al., 2014), and in recent decades there has been an expansion of focus in maize improvement to include drought tolerant traits. A recent study challenges the notion of grain sorghum's advantage to maize under drought conditions. Rotundo et al. (2024) concluded that maize has an "undisputed yield advantage" to sorghum in all crop production systems, with the greatest magnitude of yield advantage in the environments with highest frequency of drought stress. However, assessing the magnitude of advantage of maize to sorghum yield may be confounded by the availability of data sets with yield reports that correspond to non-irrigated production. In what environmental conditions do maize and sorghum have relative advantages? What is the water-stress gradients which these crops have relative advantages to each other? Does further evaluation of the conclusion by Rotundo et al. (2024) confirm that maize has outstripped sorghum in yield advantage under drought conditions?

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Chapter 2 - Yield Gap Analysis for Rainfed Grain Sorghum in Kansas

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Abstract

In the United States, grain sorghum [*Sorghum bicolor* (L.) Moench] production is concentrated in the US Great Plains region, with the state of Kansas accounting for ~50% of the planted area. In Kansas, state-level grain yields steadily increased at a rate of 0.07 Mg ha⁻¹ year⁻¹ from 1957 to 1990. However, since 1990, sorghum yield trends across the United States and Kansas have been exhibiting signs of yield stagnation. The objectives of this study were to (1) quantify the magnitude of the yield gap and (2) identify possible reasons for yield stagnation of rainfed sorghum in Kansas. Current yield (Y_c) was estimated as the average yield of the most recently reported 10 years. Maximum attainable yield (Y_a) and water-limited potential yield (Y_w) were estimated with a frontier yield function using an extensive dataset of crop performance trials, yield contest data, and county-level survey yield data totaling 2997 site-years. State-level Y_c was 4.7 Mg ha⁻¹, which represents 77% of Y_a and 49% of Y_w . At a regional level, there is a trend of increasing yield gap in central and western Kansas sorghum-producing regions. Sorghum yield in Kansas appears to be stagnant due to a small exploitable yield gap relative to Y_a rather than Y_w , a statewide shift in planting area to environments more vulnerable to water deficits, and cultivation in soils with moderate to severe limitations.

Introduction

Grain sorghum [*Sorghum bicolor* (L.) Moench] is a cereal originating from the semi-arid regions of sub-Saharan Africa and is the fifth most important cereal worldwide for food, feed, fiber, and fuel with a total of 40 million planted hectares (FAO, 2023; Khalifa et al., 2023). In the United States, grain sorghum production occurs on ~2.5 million ha concentrated in the Great Plains region, with the state of Kansas accounting for ~50% of the planted area. From 1957 to 1990, farmer grain yields steadily increased at a rate of 0.05 Mg ha⁻¹ year⁻¹ across the United States (Figure 2.1A) and 0.07 Mg ha⁻¹ year⁻¹ across Kansas (Figure 2.1B), which was mostly attributable to sorghum hybridization (Miller & Kebede, 1984; Pfeiffer et al., 2019) and the widespread use of nitrogen fertilizers (Mengel et al., 2018). Although the trend in grain yield has remained positive both across the United States and Kansas since 1990 with a rate of 0.01 Mg ha⁻¹ year⁻¹, these trends are no longer statistically significant, thus indicating signs of yield stagnation.

Yield stagnation is a widespread and pressing problem that has been observed in other regions of the world and multiple crops (Neumann et al., 2010), with current yield trends in the top four crops below the expected 2.4% per year required to meet future global food demands by 2050 (Ray et al., 2012). For instance, stagnating sorghum yield trends like those observed in the United States have been observed in China, Nigeria (Rakshit et al., 2014), and Argentina (Parra et al., 2020). Similarly, stagnating yields have been observed in winter wheat (*Triticum aestivum* L.) in Australia (Hochman et al., 2017) and the United States (Patrignani et al., 2014), in rice (*Oryza sativa* L.) in Southeast Asia (Yuan et al., 2022), in cotton (*Gossypium hirsutum* L.) in West Africa (Constable & Bange, 2015), and in maize (*Zea mays* L.) and soybeans (*Glycine max* L.) in the United States (Dhillon et al., 2022; Egli & Hatfield, 2014, 2015; Grassini

et al., 2011). Crop yield stagnation is often attributed to a lack of exploitable yield gap, which occurs when current farmer yields near ~70% of yield potential (Cassman et al., 2003; Lobell et al., 2009; van Wart et al., 2013). Other factors contributing to yield stagnation include soil conditions and shifts of planting area to land with reduction in land capability or areas with greater water constraints (Rakshit et al., 2014). For instance, Patrignani et al. (2014) used state-level and county-level winter wheat grain yields to identify that soil quality may be the main cause of yield stagnation of winter wheat in Oklahoma. Similarly, Egli and Hatfield (2014) found that soil conditions like water holding capacity may be responsible for yield gaps in Midwestern maize production regions.

Previous research studies in the United States have identified that environmental factors (e.g., heat stress and water deficit) accounted for most yield variability in low yielding site-years, management factors (e.g., planting date and irrigation) accounted for most yield variability in high-yielding areas (Carcedo & Ciampitti, 2023), and genetics accounted for yield gains by increasing the grains per panicle (Demarco et al., 2023; Miller & Kebede, 1984; Pfeiffer et al., 2019). However, previous studies in this region have not quantified the magnitude and possible causes of grain sorghum yield stagnation. Thus, drawing on existing evidence in the scientific literature, this study investigates sorghum yield stagnation employing the multiple working hypotheses method (Chamberlin, 1890). We hypothesize that (1) grain sorghum yields are stagnating due to a small exploitable yield gap, (2) grain sorghum yields are stagnating due to a shift in production area from wetter to drier regions, and (3) grain sorghum yields are stagnating due to cultivation in poor soils. The main objective of this study was to quantify the magnitude of yield gap for rainfed grain sorghum in Kansas and identify possible factors causing yield stagnation.

Materials and Methods

Study area and datasets

The state of Kansas has an area of 213,000 km² and an annual precipitation gradient that ranges from 1,150 mm in the east to 450 mm in the western portion of the state. The mean annual air temperature across Kansas ranges from 11 °C in the northern part of the state to 14 °C in the south. The predominant soil types in western and central Kansas are deep, well drained, silt loam soils typically represented by the Ulysses series (Fine-silty, mixed, superactive, mesic Torriorthentic Haplustolls), Harney series (Fine, smectitic, mesic Typic Argiustolls), and the Crete series (Fine, smectitic, mesic Pachic Udertic Argiustolls). In eastern Kansas, the soil is typically represented by the Pawnee (Fine, smectitic, mesic Oxyaquic Vertic Argiudolls) and Kenoma (Fine, smectitic, thermic Vertic Argiudolls) soil series. The dominant crops in this region are winter wheat with a total of 3.3 million ha, followed by maize with 2.3 million ha, and soybean with 1.8 million ha (USDA-NASS, 2023).

The yield gap analysis for rainfed grain sorghum in Kansas was conducted at the state and district levels using three sources of yield data (i.e., county surveys, plot trials, and yield contests) and growing season precipitation (Figure 2.2). The first source of yield data consisted of county-level farmer-reported survey yield data for rainfed grain sorghum from 1980 to 2020 that was obtained from the USDA-NASS for all 105 Kansas counties, which totaled 2635 county years (USDA-NASS, 2023) (Figure 2.2). In years where the USDA-NASS report included combined irrigation and rainfed yields, we removed counties where irrigation area exceeded 15% of the annual sorghum production area. The second source of sorghum yield data consisted of a total of 244 site-years (1986–2020) of sorghum grain yield from the Kansas State University Crop Performance Program (Figure 2.2), which conducts small plot (about 6 m in width and 9 m

in length) replicated experiments annually to provide scientists, producers, outreach specialists, and seed industry personnel with unbiased performance of typical crops in Kansas. The third source of sorghum yield data consisted of a total of 118 observed yields from 2013 to 2018 that were obtained from the National Sorghum Producer's (NSP) yield contest, which allows farmer entries for a harvested area of 4 ha of sorghum (Figure 2.2).

Growing season rainfall (GSR) was estimated for each corresponding yield observation. For yield observations obtained from the USDA-NASS report, GSR was estimated as the total precipitation in the period from June 1 to October 1 for each county centroid using daily precipitation data obtained from the Gridded Surface Meteorological dataset (Abatzoglou, 2013) with a spatial resolution of 4 km. For yield observations from the NSP dataset, GSR was estimated with the same gridded precipitation product using the farmer-reported planting and harvest dates. For yield observations obtained from the crop performance trials, GSR was estimated using the nearest station of the Kansas Mesonet environmental monitoring network (Patrignani et al., 2020) using available planting and harvest dates for each trial. Crop performance trials are predominantly conducted at research experiment stations either having or situated near a station of the Kansas Mesonet.

Soil quality was represented by the land capability class of sorghum croplands. Land capability is a classification by the USDA Natural Resources Conservation Service (NRCS) that groups soils based on suitability to produce crops and pastures, with classes ranging from I (best) to VIII (worst). Classes I–IV indicate suitability for cultivating crops, whereas classes V–VIII are typically unsuitable for crops and often designated for wildlife habitat or recreation (Levin et al., 2017). The values for the land capability class of sorghum cropland fields were obtained from the gridded Soil Survey Geographic database (gSSURGO) created by the USDA-NRCS.

County-level land capability class for farmland with and without grain sorghum was determined as the mean land capability for cropland fields with and without a sorghum occurrence within a county. Sorghum cropland areas were identified using the gridded USDA Cropland Data Layer (CDL) for any sorghum occurrence in the period of 2008–2022. The CDL contains land cover information at a 30-m spatial resolution, which is determined using multiple sources of information such as satellite imagery, land units, and farmer reports collected by the USDA Farm Service Agency. The trendline of sorghum planting was calculated as a moving count of sorghum crops for each pixel in a 3-year window with a linear fit for number of sorghum crops in each successive 3-year cropping period. The typical sorghum crop rotation for each county was quantified as the most frequent (i.e., mode) rotation in five, three-year crop sequences from 2016 to 2022 using the CDL dataset.

To quantify the dominant thermal regime across the state of Kansas we used cumulative growing degree units (GDU, $T_{\text{base}} = 10\text{ }^{\circ}\text{C}$) from June to October. The GDU was computed as described by Roozeboom and Prasad (2019) using daily values of maximum and minimum air temperatures in the period of 2020–2022 obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) gridded product at 4-km spatial resolution. To quantify the dominant water regime across the state of Kansas, we used the atmospheric water deficit (AWD), which is defined as the annual reference evapotranspiration minus the annual precipitation for each county (Purcell et al., 2003; Torres et al., 2013). The AWD was computed using long-term (i.e., 1991–2020) annual reference evapotranspiration and mean annual precipitation from the TerraClimate dataset (Abatzoglou et al., 2018). We used the annual totals instead of the growing season totals because rainfall during fallow periods contributes to the soil water recharge. To analyze shifts in the sorghum planted area in terms of AWD, the mean AWD was calculated

based on grain sorghum planting area. Planting area was obtained from USDA-NASS Statistics which provides county-level survey reports for planted area of sorghum (USDA-NASS, 2023).

Yield gap estimation

The yield gap analysis for grain sorghum in Kansas was conducted for each of the nine crop districts using county-level farmer-reported grain yields and GSR. Working at the district level allowed us to pool data for multiple counties to better capture yield trends as a function of GSR. Current yield (Y_c) was defined as the median grain yield from 2011 to 2020 for each crop reporting district based on the county-level yield data from the USDA-NASS survey (Figure 2.3A). The typical GSR for each district was calculated as the median GSR for each corresponding county observed between the typical planting and harvest dates from 2011 to 2020. Maximum attainable yield (Y_a) was defined as the yield corresponding to the GSR based on a frontier yield function fitted to all available USDA-NASS survey yield data within each district. Similarly, water-limited yield potential (Y_w) was estimated for the corresponding GSR using a frontier yield function fitted to all available yield sources, including county-level USDA-NASS, plot-level sorghum performance trials, and available yield contest data for each district. Transpiration efficiency (TE) is the amount of grain yield per unit of transpired water and was estimated as the slope of the linear portion of the frontier yield function fitted to all available yield data (e.g., French & Schultz, 1984; Figure 2.3B), where yields were mostly limited by the growing season water supply. This approach assumes that the change in soil water storage between the beginning and end of the growing season is zero. The minimum water losses (MWL) during the growing season, which in this region primarily represent losses due to soil evaporation and, to a lesser extent, runoff and drainage, were estimated as the x-intercept of the

frontier yield function (Sadras, 2020). The calculations of TE and MWL were conducted only at the regional level by grouping crop reporting districts with similar precipitation and atmospheric demands. The western region included the northwest (NW), westcentral (WC), and southwest (SW) districts; the central region included the northcentral (NC), central (C), and southcentral (SC) districts; and the eastern region included the northeast (NE), eastcentral (EC), and southeast (SE) districts.

The frontier yield functions for Y_a and Y_w (Figure 2.3) were calculated by: (i) applying the Doane's histogram method to divide bins of all observed GSR observations with corresponding grain yields, (ii) identifying the 99th percentile of observed grain yield for each GSR bin range, and (iii) fitting the Cobb-Douglas (Equation 1) frontier function to the 99th percentile yields:

$$Y_a = \beta_0 + \beta_1 \ln GSR + \beta_2 (\ln GSR)^2, \quad GSR > 0 \quad (1)$$

where β_0 , β_1 , and β_2 are fitting parameters. The only difference between the frontier function for Y_a and Y_w is that the model for Y_w had a yield ceiling determined by optimal GSR whereas Y_a was determined from farmer attained yields. The yield gap relative to maximum attainable yield (YG_a) was computed as the difference between Y_a and Y_c , while the yield gap relative to water-limited potential yield (YG_w) was computed as the difference between Y_w and Y_c .

Results and Discussion

Characterization of sorghum environments

Grain sorghum production spanned areas with typical GSR ranging from 250 mm in the western portion of the state to 550 mm in the eastern portion of the state (Figure 2.4A). Growing season reference ET ranged from 800 mm in the western portion of the state and 600 mm in the eastern portion of the state. The AWD intensified to the west, with annual values ranging from

0 mm year⁻¹ in eastern counties to 1,100 mm year⁻¹ in western counties (Figure 2.4B). The growing season GDUs ranged from 1,500 GDU (°C-day) in the far northwest part of Kansas to 2,000 GDU (°C-day) in the southeast part of the state (Figure 2.4C). The mean land capability class for sorghum croplands was 2.5, which represents soils with moderate (class II) to severe (class III) limitations to crop production.

State level yield gaps

Since 1990, state-level grain sorghum yields in Kansas averaged 4.7 Mg ha⁻¹, with yields ranging from 2.44 Mg ha⁻¹ in 2012 with a GSR of 181 mm to 5.71 Mg ha⁻¹ in 2016 with a GSR of 345 mm. Low grain yields during this period have been mostly caused by severe statewide drought conditions that reduced grain yield by ~50–60% relative to yields in growing seasons with typical supply of water. In this period, yields have remained nearly constant with a non-statistically significant yield trend of only 0.01 Mg ha⁻¹ year⁻¹ (Figure 2.1B). In the same period, state-level grain sorghum yields in the United States have ranged from as low as 0.32 Mg ha⁻¹ in the drought-stressed growing season of 2011 in New Mexico to as high as 6.5 Mg ha⁻¹ in 1994 in Nebraska (USDA-NASS, 2023). In the global context, average sorghum yields observed in the top ten production countries in the period of 2013–2022 ranged from a low of 0.49 Mg ha⁻¹ in Niger to a high of 4.28 Mg ha⁻¹ and 4.78 Mg ha⁻¹ in the United States and China, respectively (FAO, 2023). The highest recorded sorghum yield in Kansas under rainfed conditions was 16.4 Mg ha⁻¹, which was observed in the 2021 NSP yield contest in Kiowa County, Kansas. For comparison, the highest yield observed under irrigated conditions was 16.5 Mg ha⁻¹ in 2023 in Stanton County, Kansas, which provides some evidence that our dataset for rainfed conditions covers a wide range of grain yields in this region.

Based on the frontier yield functions, maximum attainable yield was 6.1 Mg ha^{-1} and water-limited potential yield was 9.6 Mg ha^{-1} . As a result, state level Y_{G_a} was 1.4 Mg ha^{-1} and the Y_{G_w} was 4.9 Mg ha^{-1} (Table 2.1), with Y_c representing 77% of Y_a and 49% of Y_w . Thus, we reject the hypothesis that sorghum yields in Kansas are stagnating due to a narrow yield gap relative to Y_w , which is often evidenced when $Y_c \geq 70\%$ of Y_w (Lobell et al., 2009; van Ittersum et al., 2013). However, because farmers in this region likely seek to minimize risk and maximize profit, rather than maximizing yield, we recognize that some level of yield stagnation could be attributed to Y_c resulting in 77% of Y_a , a narrower gap than when comparing Y_c to Y_w . Under a risk minimizing approach farmers will manage for lower yield goals that are more likely to be realized under water stress conditions, reducing financial exposure associated with costs such as fertilizer inputs. Relative to this study, larger yield gaps have been reported for grain sorghum in other parts of the world. For instance, van Oort et al. (2017) found that sorghum Y_c was 18% of Y_w for African producing countries and a study by Murty et al. (2007) found that Y_c represents 29–49% of Y_w in India. For other crops in this region, Patrignani et al. (2014) reported that Y_c represents $\sim 30\%$ of Y_w for winter wheat in Oklahoma and Grassini et al. (2011, 2015) reported that Y_c represents $\sim 80\%$ of potential yield in irrigated soybean and irrigated maize in Nebraska.

Breeding of sorghum hybrids has almost exclusively been conducted in drought-prone environments, which may have limited gains in the Y_w ceiling. This is evidenced by historical evaluation of field studies that observed a narrowing of the gap between dryland and irrigated sorghum yields (Assefa & Staggenborg, 2010). In the United States and Argentina, era studies (Demarco et al., 2023; Gizzi & Gambin, 2016; Pfieffer et al., 2019) evaluating sorghum hybrids released in recent decades by public and private sorghum breeding programs found that sorghum

yield increase was attributed to an increased harvest index. Specifically, these studies found that selection has primarily resulted in an increase of grain number per panicle while grain weight and above-ground biomass have remained stable (Demarco et al., 2023). Further, the phenomenon of improved sink in the absence of improved source mechanisms is also noted by Messina et al. (2021) when maize selection occurred under water limitations.

To investigate possible causes of sorghum yield stagnation in Kansas, we also analyzed regional yield gaps for eastern, central, and western districts as areas of similar precipitation regime and atmospheric demand (Figure 2.3). This analysis revealed that yield gaps are increasing in the western region compared to the eastern region (Figure 2.5). A possible reason may be that investments in grain sorghum genetic gains are relatively small and have concentrated selection to water-limited environments. Over the time series, the western region had a marked increase of exploitable yield gap due to increase of Y_w . However, in the east region, farmer yields stagnated and the YG_w narrowed over time due to decline in Y_w . Gerber et al. (2024) suggests that patterns in yield gap like those observed in eastern Kansas point to a ceiling limitation, which can be alleviated by improved farming technologies, adapting breeding programs, and adopting better agronomic practices. Strategies for breeding programs may include selecting for erect leaves to increase capture of solar radiation or development of early season chilling tolerance to extend the growing season. Agronomy interventions include increasing seeding populations or precision fertilizer management such as split-rate or in furrow application.

Examination of sorghum planted area over time revealed that the planting area of sorghum has slightly shifted from wetter (~360 mm of mean GSR) to drier (~325 mm of mean GSR) regions across the state of Kansas (Figure 2.6). Planting areas in the east have been

declining since the 1980s, with a more rapid decline since the year 2000. On the other hand, the planted area of grain sorghum in the western portion of the state has increased by ~20% in the 21st century relative to the 1990s (Figure 2.1B). This shift in the planting area of rainfed grain sorghum from regions with lower AWD to regions with greater AWD may help explain the increased yield variability observed in recent years due to drought conditions. For instance, the average AWD of sorghum cropland has increased from 596 to 760 mm, which represents a ~30% increase from the 1980s to present (Figure 2.6). Thus, we accept the hypothesis that statewide yield stagnation is in part caused by a shift of the sorghum planting area from regions of lower AWD to regions with greater AWD, which was also reported in previous studies investigating yield trends in major sorghum-producing countries (Rakshit et al., 2014). Our analysis also revealed that while grain sorghum yields in eastern Kansas are declining, grain yields in western and central Kansas have shown signs of yield increased since 2010, suggesting that state-level yield stagnation across the state could be driven partially by declining yields in eastern Kansas that offset yield gains in other parts of the state.

To understand why grain sorghum planted area has been shifting from eastern to western Kansas counties, we inspected the role of grain sorghum within typical crop rotations (Figure 2.7). In eastern counties, sorghum was mainly part of the sorghum-winter fallow-soybean rotation (dominant in 35 out of 105 Kansas counties) with soybean planted following the winter fallow period after fall sorghum harvest. In western counties, the dominant sorghum rotation was winter wheat-sorghum-summer fallow (dominant in 42 out of 105 Kansas counties) with sorghum planted in the summer following the winter fallow after the previous summer's wheat harvest. Increased frequency of sorghum in crop rotations from 2008 to 2020 was observed most typically with a shift from winter wheat-summer fallow to winter wheat-sorghum-

summer fallow, reducing the duration of the fallow period of the entire rotation from 63% to 58%. Although our crop rotation analysis relied solely on the CDL dataset, a previous study by Lark et al. (2021) reported that the classification accuracy of the CDL for grain sorghum fields is ~83%, providing sufficient accuracy to create a first-order approximation of crop rotation changes at the county level. Our findings agree with several prior studies in this region documenting a reduction of summer fallow periods in crop rotations that include wheat and grain sorghum compared to wheat-only crop rotations (Simon et al., 2022; Stewart et al., 2016). The introduction of grain sorghum in crop rotations of western counties has been driven by a shift of soil management practices from tilling to no-till or minimum tillage (Majrashi et al., 2022; Nilahyane et al., 2023). No-till management has been related to increased soil water storage, which enables farmers to reduce the length of fallow periods and add grain sorghum to the rotation (Hansen et al., 2012). The intensification of the crop rotation with sorghum may serve to increase regional crop productivity and food security while also increasing soil organic carbon (SOC). For instance, a study by Simon et al. (2022) evaluating multiple alternative crop rotations to the traditional winter wheat-summer fallow rotation found that winter wheat-sorghum-summer fallow had the greatest potential for increasing SOC. Furthermore, the introduction of shorter maturity sorghum hybrids that can decrease exposure to periods of water stress (Raymundo et al., 2021; Reddy, 2019) and extend the planting window to periods with favorable soil moisture conditions (Felter et al., 2006; Holman et al., 2016, 2018) is another factor contributing to the adoption of grain sorghum in this region. Other factors, which may encourage the planting of sorghum include higher grain prices or planting sorghum into areas of failed wheat due to drought.

Regional and district level yield gaps

Further inspection at the district level revealed that Y_c ranged from a low of 4.1 Mg ha⁻¹ in both the SW and SC districts to a high of 6.1 Mg ha⁻¹ in the NE district. The highest Y_a of 7.5 Mg ha⁻¹ was observed in the NE district (Table 2.1) with a GSR of 375 mm. The lowest Y_a was 5.7 Mg ha⁻¹ observed in the SW district (Table 2.1) with a GSR of 297 mm. The magnitude of Y_c relative to Y_a ranged from 73% in the southern (i.e., SW, SC, and SE) crop reporting districts to 81% in the three northern (i.e., NW, NC, and NE) districts. For Kansas counties, Kukal and Irmak (2019) quantified a relatively small county-level yield gap between irrigated and rainfed yields where dryland yields ranged from 0.6 to 1.0 of irrigated sorghum yields. The narrowest exploitable yield gap was observed in the NE district, where Y_c was 59% of Y_w . Generally, yield gaps were higher in the west and south-central districts, which are characterized by lower GSR and higher atmospheric water deficit.

As expected, TE was lowest in the western region with a value of 0.08 Mg ha⁻¹ mm⁻¹ and highest in the eastern region with a value of 0.12 Mg ha⁻¹ mm⁻¹. The TE of the central region had an intermediate TE with a value of 0.09 Mg ha⁻¹ mm⁻¹. Tolk and Howell (2009) observed TE for aboveground grain sorghum biomass of 0.04 to 0.06 Mg ha⁻¹ mm⁻¹ in Bushland, Texas, an observation lower than this study which may be related to a greater vapor pressure deficit at Bushland compared to Kansas regions. The magnitude of MWL was 75 mm in the western region, 80 mm in the central region, and 120 mm in the eastern region. The higher MWL in the central and eastern regions are likely attributed to small (<10 mm) and more frequent growing season rainfall events (Patrignani et al., 2014) and canopy interception (Fink et al., 2022; Sadras & Rodriguez, 2007).

Statewide cultivated lands with occurrence of sorghum planting have soils with reduced land capability class compared to cropland without a sorghum occurrence (Figure 2.8). The mean land capability class for sorghum croplands was 2.5, which was an 18% reduction in land capability relative to croplands without a sorghum occurrence. Generally, areas with sorghum planting in the eastern region of the state have a lower cropland suitability compared to non-sorghum cropland in the same county. In contrast, the seven counties where sorghum cropland had an improvement in capability are in the southern and western tiers of the state, including Finney and Kearney, with a reduction of mean land capability score of >1 (Figure 2.8). Our findings support that sorghum is a crop choice in rainfed areas that can support increased cropping intensity under frequent water limitation. Thus, we accept the hypothesis that cultivation in soils with reduced land capability is a factor contributing to yield stagnation in the central and east regions of Kansas.

In addition to cultivation in soils with lower land capability, sorghum has had lower yield gains due to substantively less investment in crop improvement (i.e., number of breeding programs and resources provided to sorghum breeding programs) relative to other common summer crops like maize and soybean (Gizzi et al., 2016; Mayor et al., 2023). Nevertheless, sorghum has maintained a value chain, from input technologies to end-users, concentrated in water-limited production regions. As a mid-tier crop (<4 million ha), the vitality of sorghum cropping in the United States requires a stable planting area to sustain an industry with market capacity that delivers new crop input technologies and maintains end-use markets. Strategies for future improvement of sorghum current and water-limited yield potential include public investment in sorghum seed and input innovations, collaborations amongst private and public technology developers, and leverage of knowledge derived from other work in other crops.

Conclusion

Our study found that the sorghum yield gap in Kansas is 1.4 Mg ha⁻¹ relative to YG_a and 4.9 Mg ha⁻¹ relative to YG_w with current farmer yields representing 77% of maximum attainable yield and 49% of water-limited yield potential. Sorghum grain yields in Kansas rainfed systems appear to be stagnating due to a small gap between current and maximum attainable yield, a statewide shift in planting area toward regions with higher AWD that are more prone to water stress, and cultivation in soils with some production constraints, which is reflected by a mean land capability class of 2.5. Future research should focus on identifying and implementing strategies to increase exploitable yield in water-limited cropping regions.

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Table 2.1. Median growing season rainfall (GSR), current grain sorghum yield (Y_c), maximum attainable yield (Y_a), water-limited potential yield (Y_w), and yield gap relative to Y_a and Y_w for each Kansas region and district.

Region	District	GSR	Y_c	Y_a	Y_w	Y_c / Y_a	Y_c / Y_w
		mm	Mg ha ⁻¹			%	
West	SW	297	4.1	5.7	8.6	72	48
West	WC	279	4.6	6.3	9.6	73	48
West	NW	259	4.6	6.0	9.7	77	47
Central	SC	381	4.1	5.5	9.2	75	45
Central	C	355	5.1	6.2	10.0	82	51
Central	NC	370	5.8	6.9	10.8	84	54
East	SE	373	4.7	6.5	8.9	72	53
East	EC	366	4.7	6.6	8.4	71	56
East	NE	375	6.1	7.5	10.3	81	59
Kansas		328	4.7	6.1	9.6	77	49

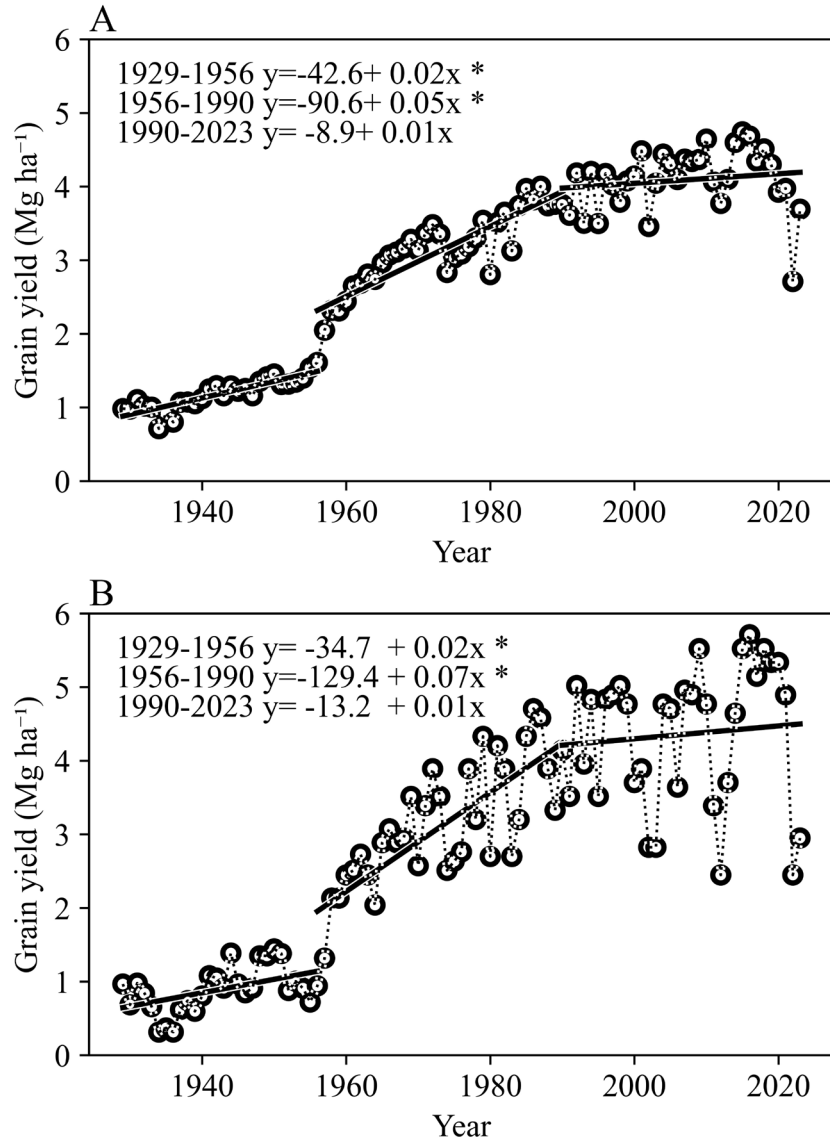


Figure 2.1. Time series of grain sorghum yield in the (A) United States and (B) Kansas. Trend lines were calculated for the pre-hybrid period 1929–1957, and two post-hybrid periods including 1957–1990 and 1990–2023. Sorghum grain yields were acquired from the United States Department of Agriculture National Agriculture Statistics Service. Note that asterisk (*) indicates statistical significance at $P < 0.05$.

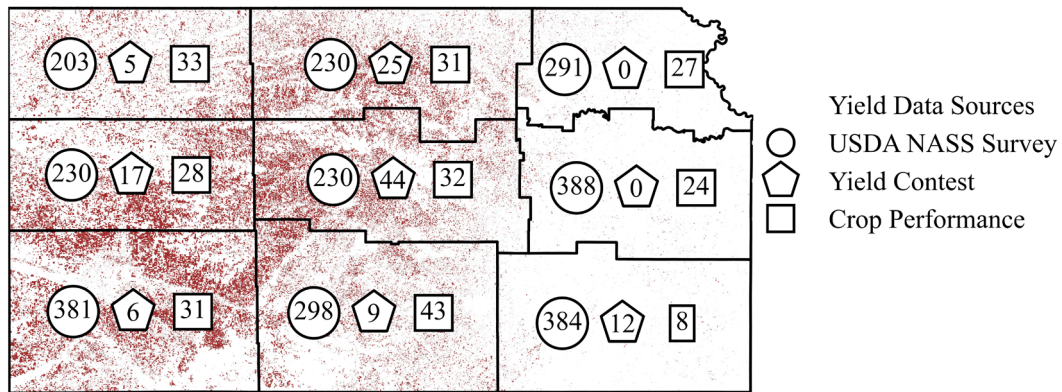


Figure 2.2. Source and number of site-years for each of the nine Kansas crop reporting districts. Yield observations were obtained from the USDA-NASS, the National Sorghum Yield Contest, and K-State Crop Performance Tests. The brown raster in the background represents grain sorghum fields at 30-m spatial resolution obtained from the USDA Cropland Data Layer for the years 2018–2020.

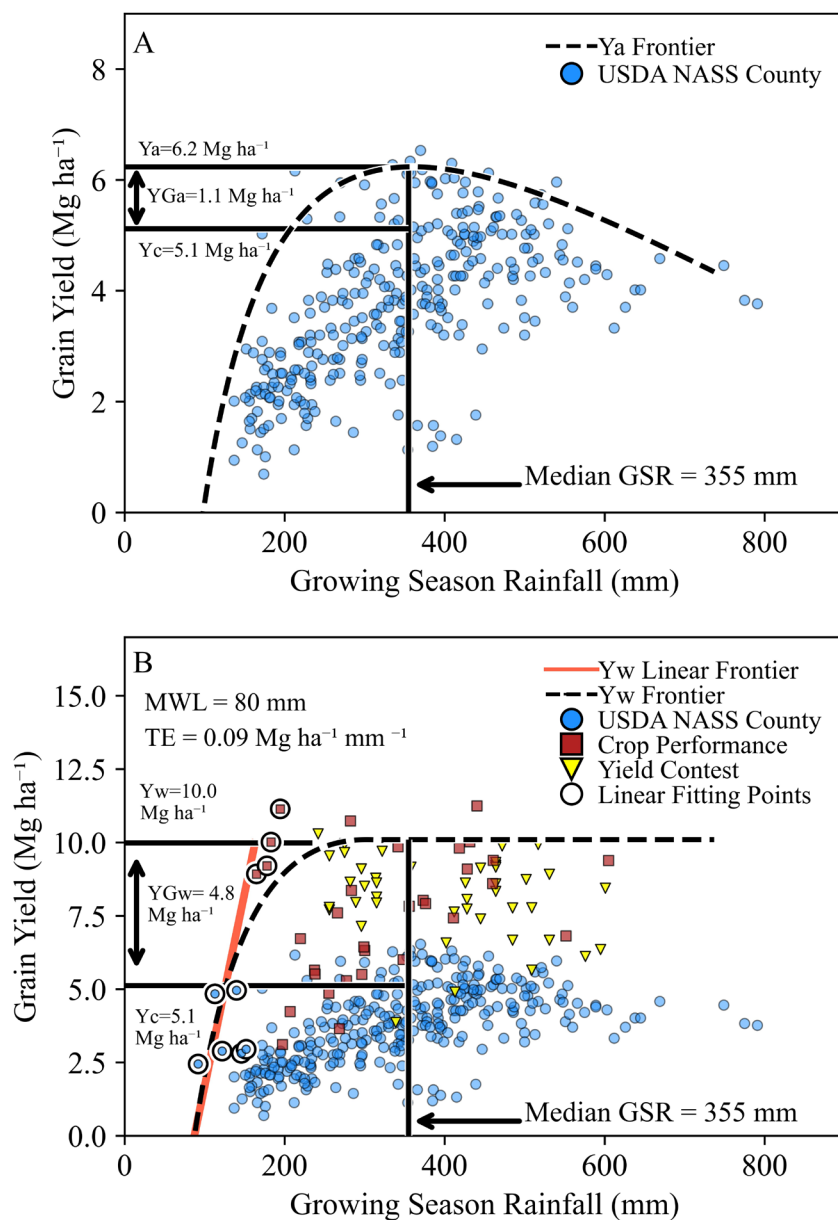


Figure 2.3. Example of yield gap calculations for the central crop reporting district showing (A) the attainable yield gap (Y_{Ga}) between maximum attainable yield (Y_a) and current yield (Y_c) at the typical growing season rainfall (GSR); and (B) the water-limited potential yield gap (Y_{Gw}) between water-limited potential yield (Y_w) and Y_c at the median GSR. The slope of the linear fit represents the transpiration efficiency (TE) and the x -intercept of the linear fit represents the minimum water loss (MWL).

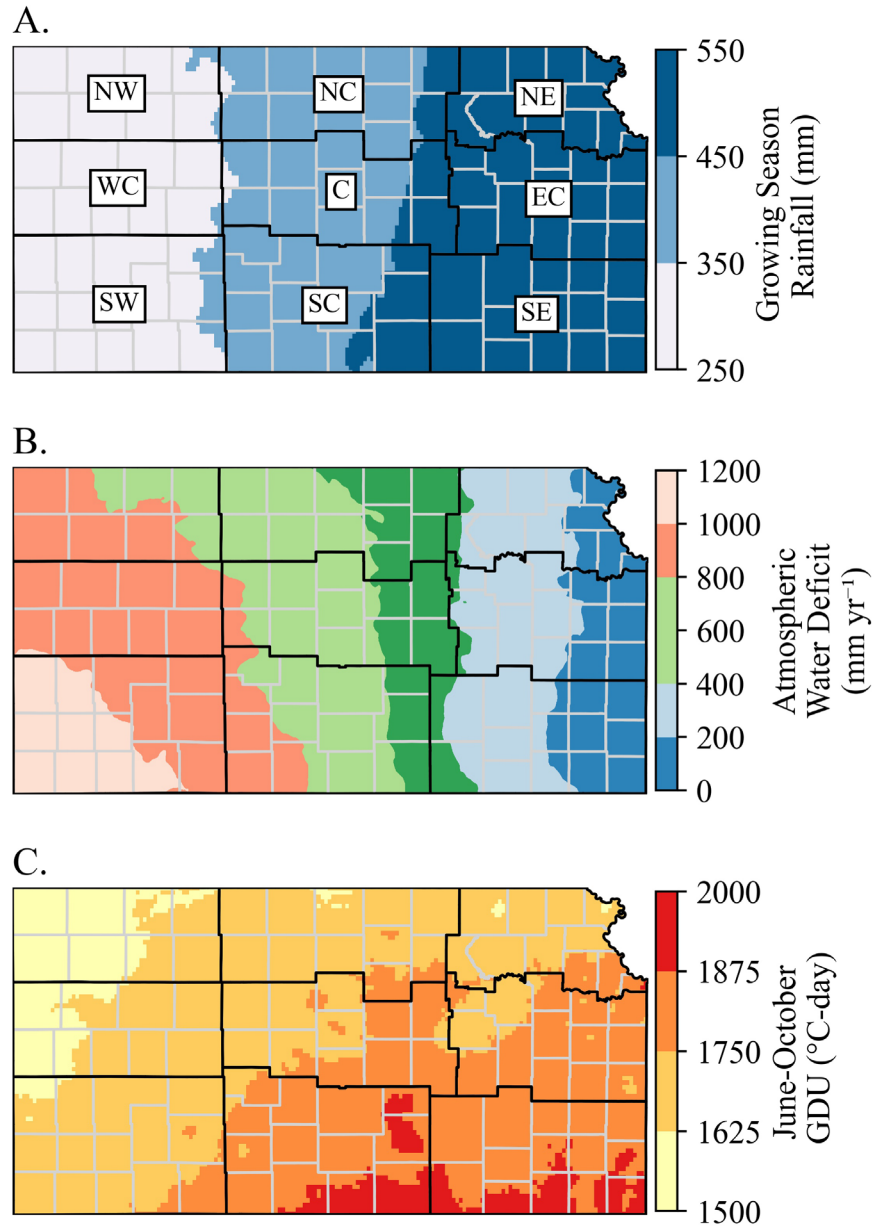


Figure 2.4. The nine crop reporting districts of northwest (NW), northcentral (NC), northeast (NE), westcentral (WC), central (C), eastcentral (EC), southwest (SW), southcentral (SC), and southeast (SE) outlined in black with (A) growing season rainfall (June–October), (B) atmospheric water deficit defined as annual reference evapotranspiration minus annual precipitation, and (C) cumulative growing degree units (GDU, $T_{base} = 10^{\circ}\text{C}$). Precipitation and air temperature were acquired from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) and reference evapotranspiration (ASCE Penman–Monteith) was acquired from TerraClimate gridded product. Atmospheric water deficit was computed for the entire year to reflect the conditions during both the growing season and fallow periods that usually contribute to soil water recharge.

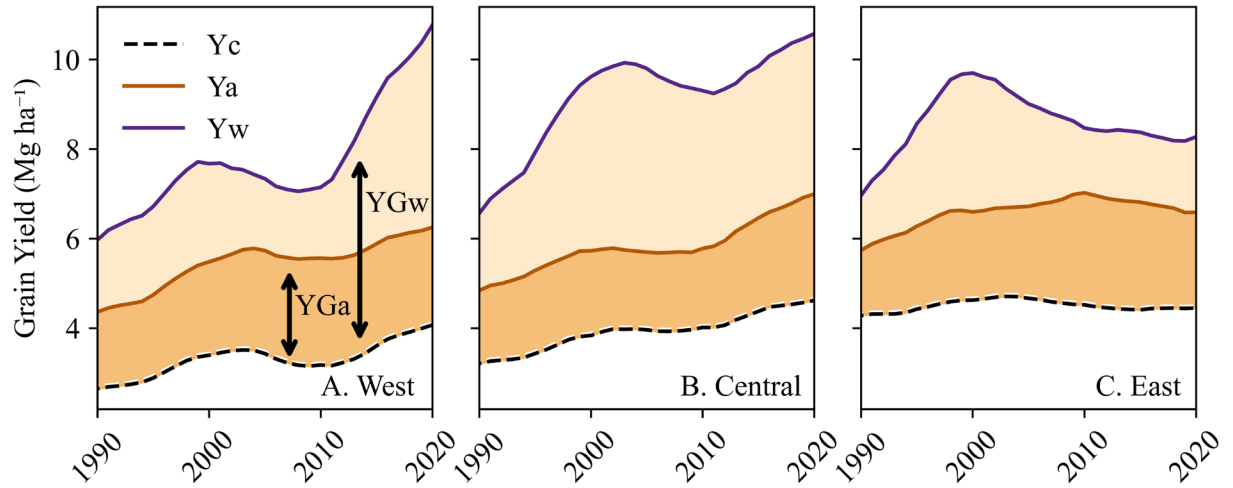


Figure 2.5. A time series of current farmer yields (Y_c), maximum attainable yield (Y_a), water-limited potential yield (Y_w), and gap between Y_c and Y_a highlighted in the dark brown area, and the gap between Y_c and Y_w represented by both the light and dark brown areas for (A) the west region, (B) central region, and (C) east region. The time series were calculated using a decadal yield rolling mean for the period 1980–2020.

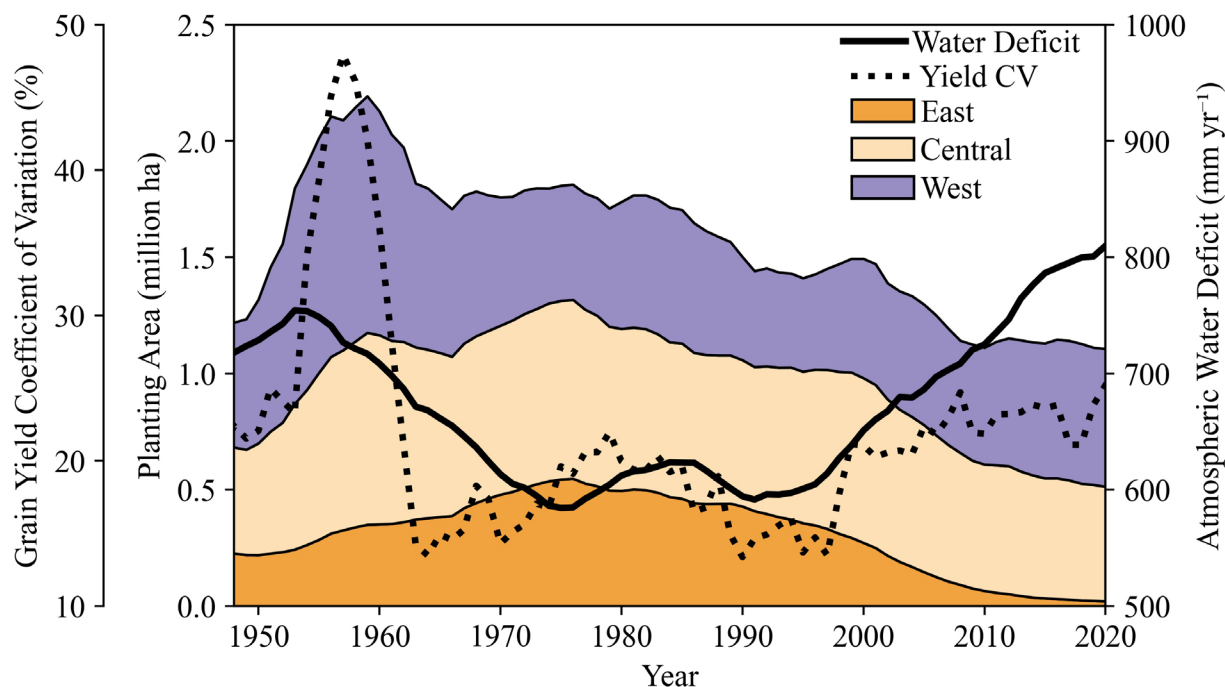


Figure 2.6. Decadal rolling coefficient of variation for grain yield in Kansas and decadal rolling mean of planting area for the crop reporting districts in the western, central, and eastern regions of Kansas shown in the stacked areas. A statewide decadal rolling mean atmospheric water deficit was calculated using county centroid values for atmospheric water balance with a mean weighted by sorghum planting area. Sorghum grain yields and planting area were acquired from the United States Department of Agriculture National Agricultural Statistics Service. Annual precipitation and reference evapotranspiration from 1991 to 2020 were obtained from TerraClimate.

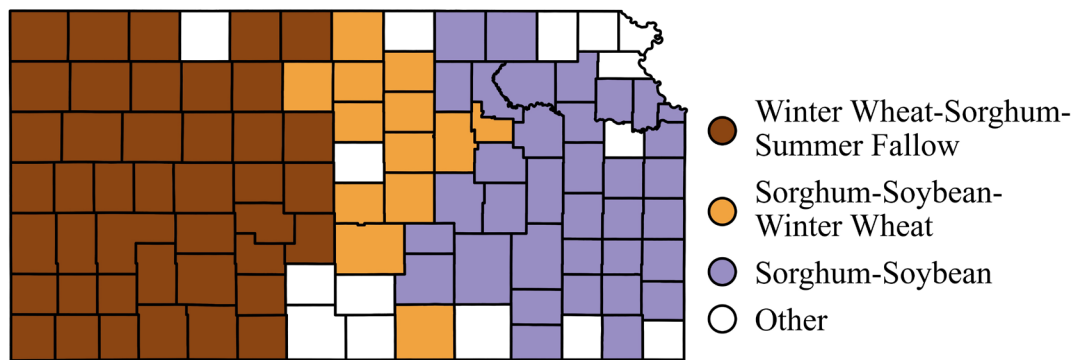


Figure 2.7. Typical sorghum-based crop rotations for Kansas calculated as the mode of all rotations in the period 2016–2022. Sorghum land cover data were acquired from United States Department of Agriculture Cropland Data Layer.

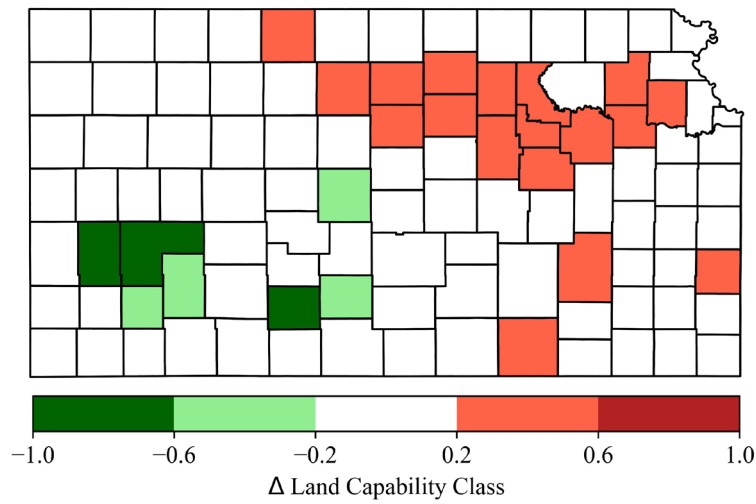


Figure 2.8. Difference in land capability class between farmland with and without grain sorghum. Negative values indicate an improvement of land capability in farmland with sorghum cropping. Land capability class data were acquired from the USDA-NRCS gridded Soil Survey Geographic database (gSSURGO) and sorghum land cover data were acquired from the USDA Cropland Data Layer for the period from 2008 to 2022.

Chapter 3 - Delineating Hierarchical Agro-Zones for Kansas

Cropping Systems

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Abstract

Agro-zones (AZs) are areas of relatively homogenous climate and soil conditions that are important for agricultural management and planning. Past AZs have largely excluded edaphic attributes and lack validation approaches that confirm correspondence of zones to homogenous spatial distribution of crop systems. The objectives of this study were to: 1) delineate hierarchical AZs for the state of Kansas and 2) validate the resulting AZs using external datasets of environmental causes of crop yield loss and land cover. The AZs were delineated using the *k*-means unsupervised clustering technique with macro-AZs derived from long-term (i.e., 30 years) gridded climatic features and nested micro-AZs based on soil physical attributes. Climate features included annual precipitation, reference evapotranspiration (ET_0), and mean annual temperature, while soil physical attributes included rootzone plant available water capacity, total soil organic matter for all horizons, and soil depth. The resulting AZs were validated using a multinomial regression model with a dataset of environmental causes of crop yield loss and land cover. The analysis resulted in three optimal clusters of relatively homogeneous climatic conditions that partitioned the state into northwest (AZ-NW), southwest (AZ-SW), and east (AZ-E), each with two nested micro-AZs based on soil physical properties. The multinomial model

had a validation test accuracy of 88% for the macro-AZs and 67% for the macro-micro-AZs. The AZ-NW was characterized by having the lowest annual precipitation of 583 mm yr⁻¹, which corresponded with drought conditions being the highest (54%) attributed cause of total crop yield losses. Similarly, AZ-SW had the highest annual ET_o of 1,421 mm yr⁻¹ and the highest fraction of crop losses attributed to heat and wind. AZ-E had the greatest occurrence of soybean land cover representing 12% of the dryland land area, and the highest precipitation (948 mm yr⁻¹) and temperature (13.2 °C). This study provides new, validated hierarchical AZs for the state of Kansas that can be used to devise agronomic practices, guide local breeding programs, and improve environmental monitoring.

Introduction

Agricultural zones (AZs) are regions characterized by homogenous environmental conditions that reflect similar crop production potentials and can be used to inform agricultural management, planning, and policy making. For instance, the delineation of regional AZs has been used to guide site selection for soybean variety trials (Gilbert and Martin, 2024), determine optimal planting dates for maize (Akinseye et al., 2016; Waongo et al., 2015), identify crop practices that benefit soil health (Wingeyer et al., 2015), develop plans for improved food security and resiliency (Delzeit et al., 2017; Hadebe et al., 2016; Rattalino et al., 2021), and inform agricultural land use (Hertel et al., 2019). Multiple AZs have been proposed at the global (Fischer et al., 2021; Kottek et al., 2006; van Bussel et al., 2015), national (Kala et al., 2012, 2008; Resende et al., 2020), and regional scales (Williams et al., 2008; Li et al., 2022) that primarily rely on climate features (van Wart et al., 2013). However, edaphic attributes, which are also crucial for assessing the potential crop productivity of a region (Lal, 2008; Oldfield et al., 2019), are less often included. One study that considered soil properties in the delineation of AZ was that by Williams et al. (2008), who included 14 soil features among 32 other input features to delineate AZs for the state of Iowa. Similarly, a total of 11 input features were used by both Liu and Samal (2002) for the state of Nebraska and by Nabati et al. (2020) for creating AZs in semi-arid regions of Iran. Because soil and topographic attributes tend to have greater spatial variability than atmospheric variables, incorporating numerous soil variables as input into AZ analyses can result in overly fragmented areas that undermine the goal of creating a manageable number of AZs.

Thus, new frameworks are needed to guide the selection and integration of climate, soil, and topographic input features that better balance the complexity of the input features and the

number of resulting zones, so that the resulting zones remain both practical and informative for decision-making. To address this challenge, an agglomerative hierarchical clustering framework may be key to effectively derive a manageable number of actionable agricultural zoning (Bruzzone and Carlin, 2006; Häme et al., 2020). For instance, macro-regions can be first delineated based on less spatially variable climate properties such as temperature and precipitation, and then each macro-region can be further subdivided into smaller micro-regions using more spatially variable soil attributes such as soil depth, organic matter content, and plant available water capacity (PAWC). This two-tiered hierarchical approach could account for the intrinsic variability of soil properties while maintaining the overarching structure and parsimony provided by climate-based macro-regions. Use-cases of hierarchical clustering include ecological classification, geological mapping, and landscape classification. In ecological classification, hierarchical techniques relate species interactions with environmental factors by addressing challenges related to high data dimensionality (Gauch and Whittaker, 1981; Rohlf, 1970). In French Guiana, researchers use hierarchical integration of radiometry data to improve mapping of rainforest areas with sparse ground observations (Martelet et al., 2006). In land cover classification, hierarchy created a basis for integration of user-knowledge to improve detection of changes in land cover with remote sensed satellite data (Häme et al., 2020).

An additional aspect of AZ delineation that previous studies have not addressed is the validation of the resulting zones using independent datasets. External validation with independent data allows for the testing of whether spatial variability of the salient environmental factors considered across zones corresponds to the observed variability in actual crop productivity (Di Vittorio et al., 2016). The hypothesis of this study is that the resulting hierarchical AZs delineated based on climate-based macro-regions and soil-based micro-regions

represent the observed spatial distribution of cropping systems. The objectives of this study were to 1) delineate hierarchical AZs encompassing macro-clusters based on climate features and nested micro-clusters based on soil physical attributes, and 2) validate the resulting AZs using a spatial dataset of environmental causes (e.g., drought, hail, heat) of crop yield loss and land cover information. This research presents a case-study scenario for the state of Kansas, which spans a wide range of climate and soil conditions and provides a model for delineation of AZs in a highly productive agricultural region.

Materials and Methods

Area description

The state of Kansas is centered on the U.S. Great Plains with nearly 190,000 km^2 of land area dedicated to row crops and rangeland vegetation and leads the U.S. in the production of grain sorghum [*Sorghum bicolor* (L.) Moench] and winter wheat (*Triticum aestivum* L.) and is third for beef cattle (*Bos taurus*) production (USDA NASS, 2023). The state of Kansas spans a broad range of environmental conditions with annual precipitation in the East-West direction ranging from 400 to 800 mm, mean annual air temperature in the North-South direction ranging from 10 to 15 °C, topographic conditions ranging from cropland areas with little to no change in elevation to the Flint Hills region with rolling terrain and slopes of up to 30%, and a wide range of soil types with prevalence of silt loam and silty clay loam textural classes.

Climate and Soil Datasets

For the climate features we considered mean annual precipitation, mean annual reference evapotranspiration (ET_0), and mean annual air temperature, which characterize the main

moisture and thermal regimes relevant to crop production in this region (Figure 3.1A-C). Long-term (1991 to 2020) mean air temperature and mean annual precipitation products were obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) gridded product at 4-km spatial resolution developed by the Climate Group at Oregon State University. The ET_o was obtained from the TerraClimate gridded global dataset (Abatzoglou et al., 2018) at 4-km spatial resolution, which is calculated using the ASCE Penman-Monteith equation (Allen et al., 1998) for short grass covering the normal period from 1981 to 2010. All climate variables were resampled to a common 800-m grid, merged, standardized, and transformed into reduced dimensionality of the first two principal components accounting for 95% of variance.

For the soil features we selected the sum of organic matter for all horizons of the soil profile, rootzone PAWC, and effective soil depth, which collectively characterize the main aspects of soil fertility, water holding capacity, and rooting depth relevant for agricultural production. Gridded soil datasets of organic matter, PAWC in the top 50 cm of the soil profile, and effective soil depth were obtained from the UC Davis Soil Resource Laboratory which developed a gridded version of the USDA-NRCS Soil Survey Geodatabase (SSURGO) (O'Green et al., 2017) (Figure 3.1D-F). The feature value used for effective soil depth was the lesser of depth to bedrock, depth to restricted layer, or effective root depth for temperate crops of 150 cm (Fan et al., 2016). In earlier stages of this study, other features including percent of sand, silt, clay, and elevation were pruned to minimize multicollinearity. All soil features were resampled to a common 800-m grid, merged, and standardized. A principal component analysis for 95% variability retained all components.

Clustering Method

The *k*-means unsupervised clustering technique (Lloyd, 1982) was used to classify the climate and soil datasets into hierarchically nested AZs (Figure 3.2). The nesting approach consisted of separately applying the *k*-means method to first generate macro-AZs based on climate features and subsequently applying the *k*-means method again to generate micro-AZs based on soil physical properties within each macro-AZ. The optimal number of clusters for the macro-AZs and macro-micro-AZs was selected based on the Silhouette scores for a range of possible cluster numbers between 2 and 15. The Silhouette method evaluates the inter- and intra-cluster similarity based on the Euclidean distance results in scores between -1 and 1, where higher values indicate the optimal number of clusters (Wang and Xu, 2019).

Validation of Agro-Zones

The resulting AZs from the *k*-means unsupervised clustering were validated using two independent validation datasets comprised of land cover data and crop insurance records for environmental causes of crop yield loss. Two unique validation models were conducted, one for macro-AZs alone, and a second validation model for the macro-micro-AZs. The first validation dataset consisted of land cover data obtained from the gridded Cropland Data Layer (CDL) at 30-m spatial resolution for the period from 2013-2022 developed by the USDA National Agriculture Statistics Service (NASS) (Figure 3.3). Land cover frequency (LCF) was computed for each pixel as the number of occurrences of a unique land cover over the ten-year period from 2013 to 2022 (i.e., decadal frequency). The LCF was computed for major land cover types based on the 2022 CDL with a minimum reported area of 20,000 hectares, which included grassland, winter wheat, corn (*Zea mays* L.), soybeans (*Glycine max* L.), summer fallow, grain sorghum,

wheat-soybeans double crop, alfalfa (*Medicago sativa* L.), hay, triticale (*Triticosecale* Wittmack), and cotton (*Gossypium hirsutum* L.) (Figure 3.3). The second validation dataset was county level crop insurance records for the period from 2017 to 2021 obtained from the USDA Risk Management Agency (RMA) Summary of Business database, which provides a unique record for each insurance loss event denoting the cause of yield loss, the estimated affected area by each biotic or abiotic factor causing the yield loss, and the county (Figure 3.4). The designation of cause for a loss event occurs with a trained and licensed insurance adjuster evaluating the field site and discussing the insurance claim with the farmer. Using these county level crop insurance records, the loss cause ratio (LCR) was computed as the area of each cause of yield loss over the total area of realized indemnity yield losses for a given county. Because our study is focused on rainfed agriculture, irrigated areas were removed using a mask obtained from the Kansas Biological Survey, and causes of loss directly attributed to irrigation infrastructure (e.g., failure of irrigation equipment or supply) were excluded from the analysis. Additionally, general “other” categories, decline of price, wildlife, and natural disasters like earthquakes, tornadoes, and cyclones were excluded from the analysis. The validation data set, comprised of LCF and LCRs, were resampled to a common 800-m grid. Validation data was masked to remove non-crop areas denoted by CDL (i.e., forests, urban, and water).

A multinomial logistic regression model was developed with the AZ labels as the dependent categorical features and a dataset of LCR and LCF as the independent features. For each validation, 75% of the dataset was used as the training set and 25% held from model training as a test set to evaluate model performance. Pruning of predictors and selection of model parameters was done with a ten-fold cross validation grid search with the training dataset. Model performance was assessed with a ten-fold cross validation using the testing dataset. The

multinomial validation model to compute the probability of AZ label i given the probability of AZ label z was defined as follows:

$$\ln\left(\frac{P_i}{P_z}\right) = \beta_{0i} + \beta_{1i}X_1 + \cdots + \beta_{ki}X_k \quad (1)$$

where z equals the total number of predicted categories, and i may be equal to any category in the range of 1 to $z-1$, and k is the total number of independent predictors. To evaluate the multinomial model we used the metrics of precision, recall, and F1-score. Precision assesses the accuracy with recall capturing sensitivity, and the F1-score is a single score that balances scores of precision and recall by penalizing for discrepancy between the scores.

Results

Delineation of Agro-Zones

Clustering of climate features resulted in three optimal (Silhouette score = 0.59) macro-AZs of relatively similar area for the state of Kansas (Figure 3.5). The clusters represent AZs in the northwest (AZ-NW), southwest (AZ-SW), and east (AZ-E) portions of the state. The largest spatial extent belongs to the AZ-E with a total of $87,000 \text{ km}^2$, while the spatial extent of AZ-NW was $65,000 \text{ km}^2$ and AZ-SW was $60,000 \text{ km}^2$. The resulting AZs represent the major spatial patterns in annual precipitation, thermal regime, and atmospheric demand, with the AZ-NW having the lowest mean annual precipitation of 583 mm yr^{-1} and the AZ-E having the highest mean annual precipitation of 948 mm yr^{-1} . The AZ-NW has the lowest mean annual temperature at $11.6 \text{ }^\circ\text{C}$ (Table 2.1). The area of highest atmospheric demand was AZ-SW with a mean annual ET_o of $1,421 \text{ mm yr}^{-1}$ (Table 2.1).

Clustering of the previous climate-based macro-AZ using soil physical features resulted in two nested micro-AZs for each of the macro-AZs. The spatial extent of the resulting micro-

AZs was balanced in the AZ-NW with each micro-AZ occupying 48% and 52% of the area, and imbalanced in the other two macrozones with the micro-AZs occupying approximately 67% and 33% of the area. In AZ-NW, soil depth largely explained the separation of the micro-AZs, with deeper soils (>1490 mm) concentrating in AZ-NW2 compared to a depth of 630 mm in AZ-NW1 (Table 2.1). In AZ-E2, differences in both soil depth and soil organic matter are the main distinctions of the micro-AZs. For instance, AZ-E2 (light-green area in Figure 3.5) overlays the Flint Hills region which is dominated by shallow and rocky soils and grassland vegetation and has an average soil depth of 780 mm and a mean organic matter of 19.4 kg m². In contrast, AZ-E1 had a soil organic matter of 28.5 kg m² and a soil depth of 1030 mm. In the AZ-SW, the main differentiating factor between micro-AZs was soil texture, where the AZ-SW2 is characterized by sandy soils of the Arkansas River basin that have distinctive low soil organic matter with values as low as 10.6 kg m² and low PAWC with values as low as 63 mm in the top 500 mm of the soil profile (Table 2.1).

Validation of Agro-Zones

The validation of macro-AZ labels used a multinomial model trained on an independent dataset of environmental causes of crop yield loss and land cover frequency resulted in a class-weighted average for precision, recall, and F1-score of 88% for all three metrics. We accept the hypothesis that macro regions represented by unique climate conditions are characterized by unique crop systems. Differences in predictions between the test labels (Figure 3.6A) and predicted labels (Figure 3.6A) concentrate in the transition between macrozones. Precision, recall, and F1-score were >75% for all macro-AZs, with the AZ-SW having the lowest performance (Table 2). This relative lower performance for AZ-SW could be in part explained

by an imbalance of AZ-SW labels in the dataset (24% of the total) because of removing irrigated areas compared to AZ-E (33% of the total) and AZ-NW (43% of the total). Macrozone means for LCR and LCF elicit the specific crop system dynamics of the macrozones (Figure 3.7). For example, in AZ-E, excess moisture caused 49% of yield losses, the highest for all macrozones and the highest contributor to losses in AZ-E. This corresponds to differences in the crop rotation including having the lowest percentage of land cover area with summer fallow (0.07%) and highest land cover area to soybeans (12%). The SW-AZ had the highest percentage of losses attributed to heat (4%) and wind (4%) corresponding to the highest land area to wheat (24%) and lowest to corn (1.7%) and beans (1.5%). The AZ in the NW region has concurrence of the greatest land area cover relative to other macrozones in corn (9.6%), sorghum (7.1%) and summer fallow (10%), which provides context to the region's overall strategy in managing water-limitations (highest drought LCR, 54%) by using summer fallow in a rotation.

The validation of macro-micro-AZ labels (i.e., second validation approach) using a multinomial model trained on independent datasets of environmental causes of crop yield loss and land cover resulted with an accuracy of 67% in the test set, and weighted average scores for precision, recall, and F1-score of 67%, 67%, and 66%, respectively. Thus, we accept the hypothesis that macro-micro regions represented by unique climate and soil conditions are characterized by unique potential for crop production. The validation performance of the six macro-micro-AZs is on average 22% lower for metrics relative to the macrozone validation. The AZ-SW2 has the lowest recall scores of 25% (Table 2) and correspondingly the smallest fraction of test data with 7% of observations. All but two micro-AZs exceed 60% for F1-score, with E1-AZ at 57% and SW2-AZ at 25%. For both E1-AZ and SW2-AZ, a lower recall score relative to precision downwardly weighed the F1-score, indicating the validation model performed better

with accuracy of positive predictions, e.g., positive predictions were indeed actual positive observations, but the model missed identifying observations that were positive labels for the AZ.

Discussion

Delineation of Agro-Zones

This research demonstrates a workflow to delineate regional AZs using a hierarchical clustering approach that partitioned the state of Kansas into macro-AZs using climate features and nested micro-AZs with soil physical properties. The hierarchical approach of subdividing climate-based macro-clusters using soil physical characteristics provided a greater level of spatial detail while preserving cluster parsimony. Hierarchy allows for selection of climate features that drive processes of crop growth (Fick et al., 1988) with subsequent delineation of soil physical features that regulate processes of soil and nutrient resource cycling (Cichota et al., 2021; Wimalasiri et al., 2020). Typically, in AZ delineation the decision of whether to utilize expert-knowledge or quantitative methods is evaluated in a competing paradigm (Fischer et al., 2000). Here, we integrate these competing approaches, resulting in a simple, yet powerful method to leverage expert knowledge in a quantitatively objective framework. While limited in application, the analytical hierarchy process has been used in studying tailored AZ questions such as groundwater use in agriculture (Razandi et al., 2015), agricultural suitability for specific bio-physical contexts (Zolekar et al., 2015), and zoning vulnerable environments (Nguyen et al., 2016). Other research context may require AZs for a specific crop, e.g., a sorghum breeding program defining a target population of environments. In these cases, system specific climate and soil physical features may be utilized within the same hierarchical model framework. For example, growing degree days may be used in place of mean annual temperature. The same

nested framework would benefit from a user guided hierarchical prioritization to select crop specific climate features followed by selection of soil physical features.

Validation of Agro-Zones

In previous studies the validation of AZs resulting from cluster analysis has mostly relied on the same datasets used in the clustering process (Arshad et al., 2020; Gupta et al., 2019). However, many predictive models are evaluated with independent datasets as observed in models predicting soil fertility with NIR data and historical yields and validated by soil samples (Helfer et al., 2020) or predicting maize yields with inputs of satellite and crop model data and validation from yield monitors (Deines et al., 2021). Our study demonstrates the use of independent external validation datasets that are spatially aligned with the clustering input variables. To our knowledge this is the first study demonstrating leverage of landscape production data for external validation of AZs. The LCF and LCR datasets capture the dominant land use and environmental phenomena that causes crop yield loss and are ultimately related to crop yield potential across the state. Our validation performance of 88% is close to the 93% achieved for AZs in the Vellore production region of India (Anitha & Acharjya, 2018) and higher than the performance of ~22% to 72% observed in a study validating AZ based on fluctuations of groundwater level (Mohapatra et al., 2021).

Application of Delineated AZs

Examples of AZ application include site selection for research farms or breeding stations (Packwood et al., 1998), development of coordinated plans for improvement of nation-state agricultural productivity (Chanda, 1988), and understanding of crop-environment interactions

(Carcedo et al., 2022). Solutions leveraging AZs have been implemented to evaluate crop adaptation (Abbas et al., 2023), model climate change shifts in production agriculture for the continent of Africa (Kala et al., 2008), and characterize groundwater interactions with agriculture in India (Mohapatra et al., 2021). These types of investments in agricultural planning and management are finite, highlighting the importance of defining high impact AZs for extrapolation of site-specific observations to a zone's areal extent.

These AZs for the state of Kansas may be applied to a multitude of key land management and planning contexts. For instance, the Kansas Mesonet network can leverage these AZs for placement of new station sites to improve coverage of environmental monitoring. Guidance of site selection extends to location placement for the K-State Crop Performance trials which evaluates regional performance of crop varieties. Breeding programs may leverage these AZs to establish selection sites that best capture the genetic and environmental interactions of a zone's areal extent. Kansas has a rapidly growing dairy sector which would benefit from leveraging these AZs to evaluate suitability of new forage systems. Further, agronomy management questions are more readily addressed with AZs, such as regional recommendations for planting dates and soil fertility.

Conclusion

This study demonstrated the use of a hierarchical clustering method to delineate homogeneous agricultural zones that capture the salient environmental conditions across the state of Kansas. The state of Kansas can be divided into three macro-AZ that capture the main climate features and each macro-AZ can be additionally subdivided into two micro-AZs that capture the salient soil physical features. The resulting AZs from the hierarchical clustering method

corresponded well (88% for precision, recall, and F1-score) with two independent datasets of environmental causes of crop yield loss and land cover. This external validation confirms the correspondence of homogenous AZs of environmental conditions to homogenous spatial distribution of crop systems.

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Table 3.1. Mean and coefficient of variation (CV) for Kansas soil and climate features for the resulting macro-AZs and micro-AZs. Soil features include plant available water capacity (PAWC) in the top 50 cm of the soil profile, organic matter (OM) in the soil profile, and soil depth. Climate features include Annual precipitation (P), annual grass reference evapotranspiration (ET_o), and air temperature (T_{air}). Mean climate features were computed for the period 1991 to 2020.

		PAWC		OM		Soil Depth		P		ET_o		T_{air}	
		mm		kg m ⁻²		mm		mm yr ⁻¹		mm yr ⁻¹		°C	
		Mean	CV	Mean	CV	Mean	CV	Mean	CV	Mean	CV	Mean	CV
Kansas		87	17	20.0	32	950	41	743	27	1283	11	12.6	7
E	E	82	13	23.9	27	900	34	948	11	1193	8	13.1	5
	E1	88	9	28.5	17	1030	31	952	11	1193	8	13.1	5
	E2	77	13	19.4	20	780	30	945	11	1193	8	13.0	6
NW	NW	97	10	19.1	22	900	47	583	17	1285	6	11.6	4
	NW1	96	11	19.0	22	630	28	623	14	1261	6	11.7	4
	NW2	100	7	19.4	22	1490	4	500	11	1336	4	11.3	4
SW	SW	83	22	16.2	35	1080	38	622	19	1421	4	13.2	5
	SW1	94	9	19.4	20	980	39	615	18	1414	4	13.1	5
	SW2	63	19	10.6	34	1250	32	634	19	1433	4	13.4	4

Table 3.2. Performance of the multinomial validation model based on precision, recall, and F1 score calculated for each macro-AZ and each macro-micro-AZ.

	Precision	Recall	F1 Score
Macro Validation Model			
E	0.92	0.94	0.93
NW	0.89	0.89	0.89
SW	0.79	0.76	0.78
Weighted Mean	0.88	0.88	0.88
Macro-Micro Validation Model			
E1	0.62	0.53	0.57
E2	0.60	0.71	0.65
NW1	0.78	0.87	0.82
NW2	0.72	0.69	0.70
SW1	0.66	0.67	0.66
SW2	0.56	0.25	0.34
Weighted Mean	0.67	0.67	0.66

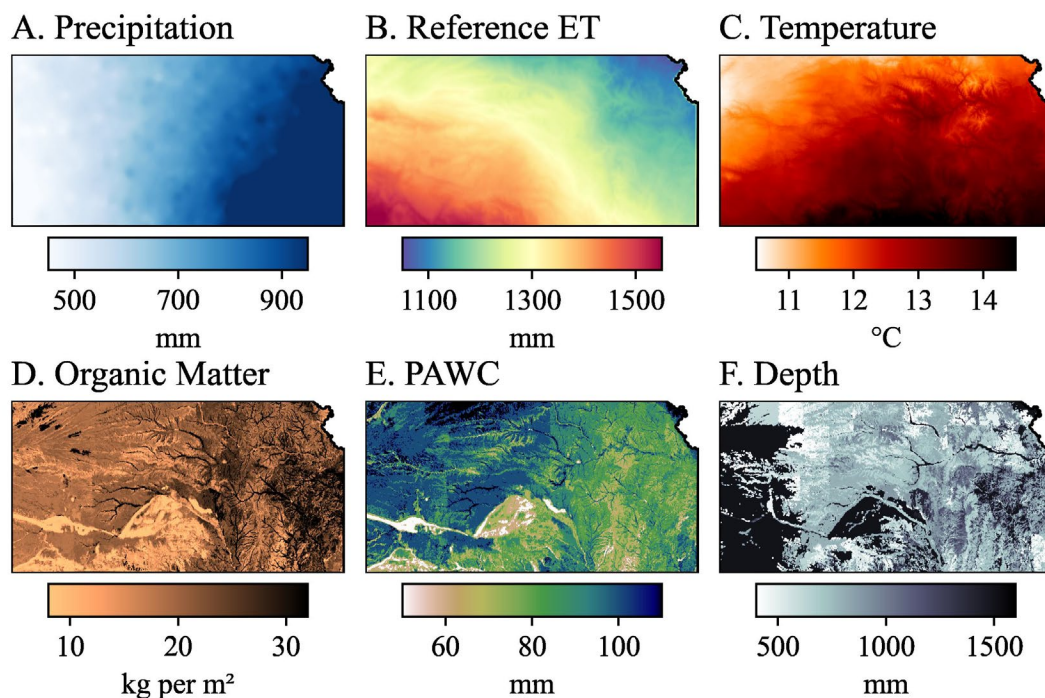


Figure 3.1. Kansas climate and soil physical features including A) annual precipitation from 1991-2020, B) annual reference evapotranspiration from 1981-2010, C) mean annual air temperature from 1991-2020, D) sum of organic matter for all horizons of the soil profile, E) plant available water capacity (PAWC) in the 0-500 mm layer, and F) depth to restrictive layer for plant growth. Temperature and precipitation data were acquired from Parameter-elevation Regressions on Independent Slopes Model (PRISM) from the Climate Group of Oregon State University Climate Group, reference ET was acquired from TerraClimate, and soil data were developed by USDA NRCS and acquired from UC Davis Soil Resource Laboratory.

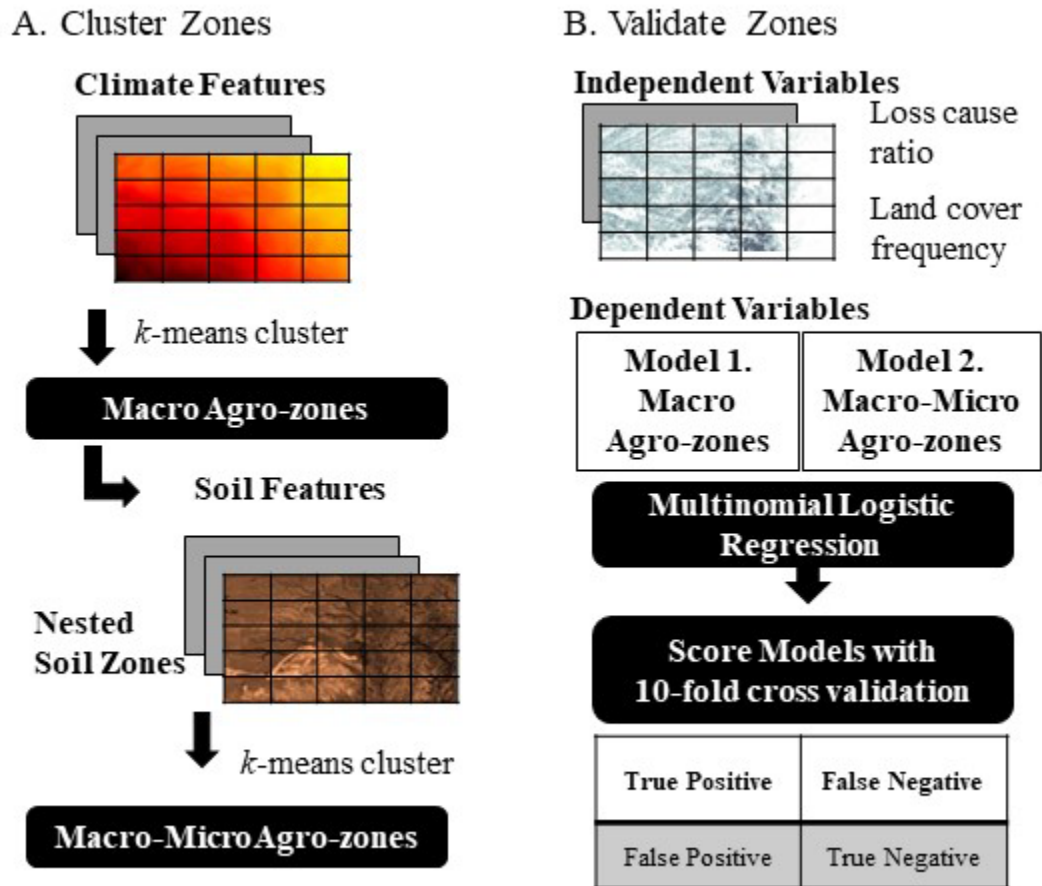


Figure 3.2. Diagram of Clustering and Validation. Agro-zones (AZ) are modeled (A) with application of *k*-means algorithm in a nested framework with climate features determining macro-AZs, and soil physical features determining micro-AZs. AZs are validated (B) with multinomial logistic regression using an independent dataset comprised of loss cause ratio (LCR) and land cover frequency (LCF) information.

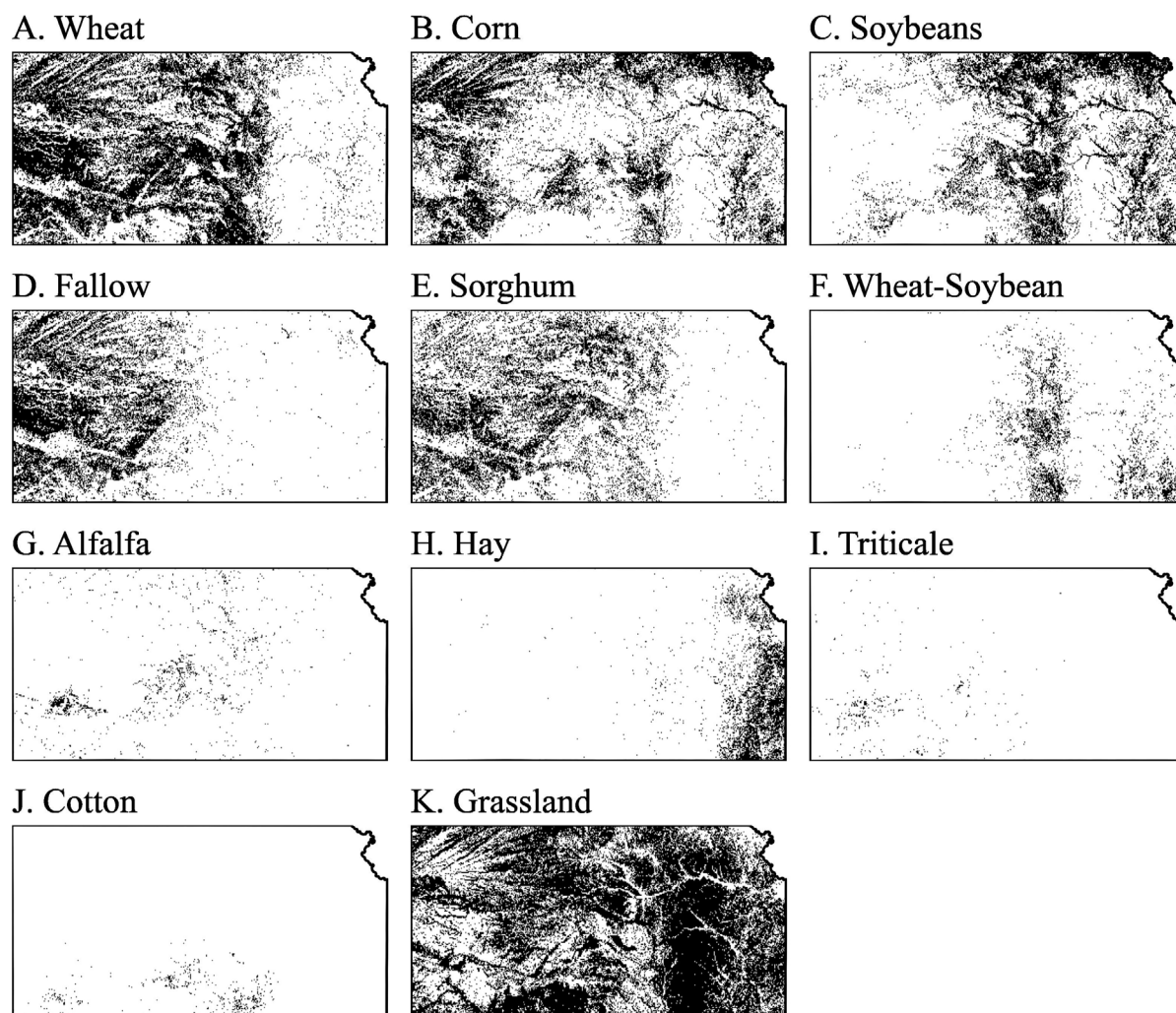


Figure 3.3. Predominant land covers across the state of Kansas obtained from the USDA Cropland Data Layer (CDL). Pixels represent the land cover frequency (LCF) from 2013 to 2022 for (A) wheat, (B) corn, (C) soybeans, (D) fallow, (E) sorghum, (F) wheat-soybean double crop, (G) alfalfa, (H) hay, (I) triticale, and (J) cotton. Additional landscape data derived from USDA CDLs are areas with (K) grassland.

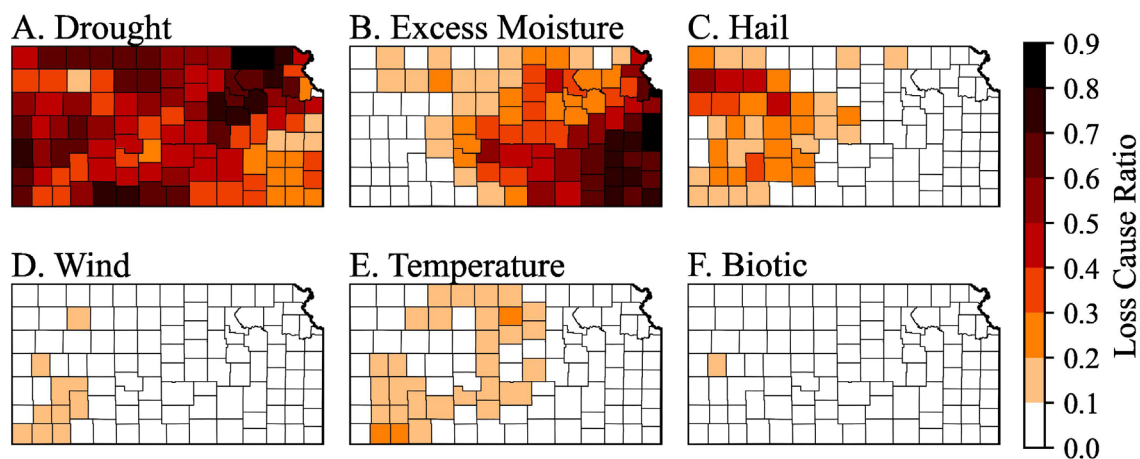


Figure 3.4. Loss Cause Ratios. The 13 unique causes of crop loss areas are calculated for their area fraction relative to the total area of yield loss in the period of 2017 to 2021, where 0 represents a cause which accounts for 0% of losses in a county and 1 indicates a cause which accounts for 100% of a county's loss area. Unique loss records are with a county spatial designation from USDA Risk Management Agency. The LCR are calculated for the loss causes of (A) drought, (B) excess moisture which is the sum of unique factors: excess moisture and flood, (C) hail, (D) wind which is the sum of unique factors: hot wind and wind, (E) temperature which is the sum of unique factors: heat, cold winter, freeze and frost, and (F) biotic which is the sum of unique factors: insects and plant disease.

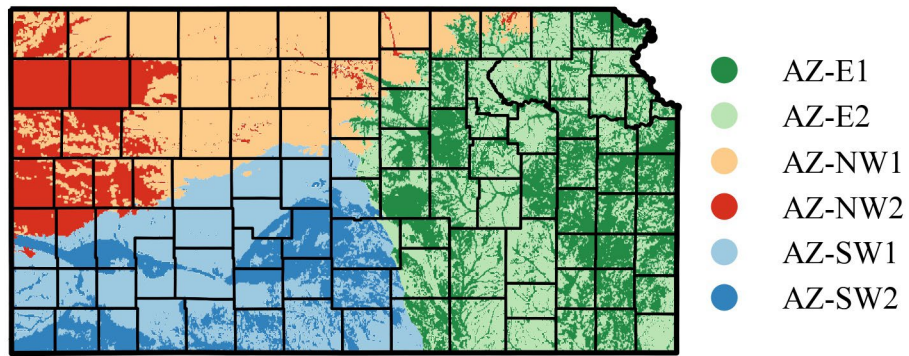


Figure 3.5. Map showing the resulting macro-AZs (AZ-E, AZ-NW, and AZ-SW) and the nested micro-AZs. Areas with the same color (i.e., green, blue, and red) are areas of AZ-E, AZ-NW, and AZ-SW, and six micro-AZs of AZ-E1, AZ-E2, AZ- AZ-NW1, AZ-NW2, AZ-SW1, and AZ-SW2.

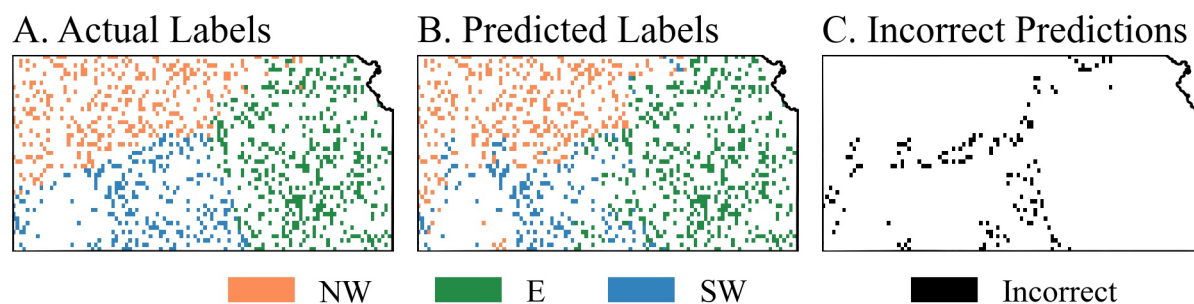


Figure 3.6. Independent validation of the resulting macro agro-zones using a multinomial logistic model and a dataset consisting of dominant land cover types and causes of crop loss. The multinomial model was trained using 75% of the dataset and then tested using the remaining 25% of the dataset. The actual and predicted labels in (A) and (B) are from the test set. Incorrect predictions (C) between the actual and predicted labels were mostly located along the transition lines of the macro agro-zones.

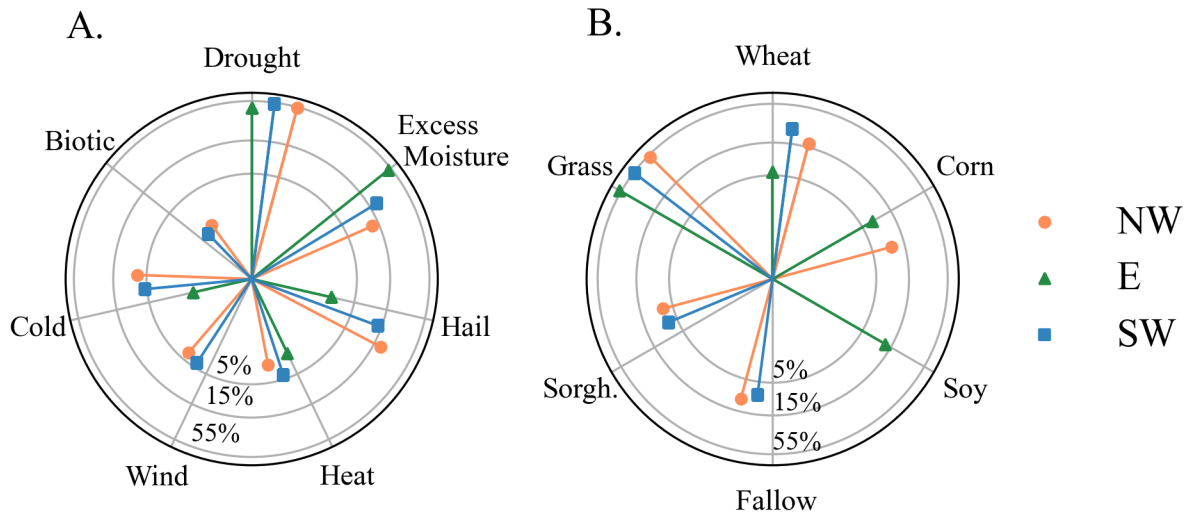


Figure 3.7. Mean percent values of loss cause ratio (LCR) and land cover for each macro agricultural zone. LCR (A), which is calculated as a percent of loss area for a unique cause relative to the total area of yield loss in the period of 2017 to 2021 and obtained from USDA Risk Management Agency. Causes of yield loss representing <1% of the total losses were not included. Land cover frequency (LCF) (B), which was calculated as a percent of land area for a unique land cover over all dryland land area in the period of 2013-2022 with areas less than 5% not included in the figure. Crop frequency and area data were obtained from USDA Cropland Data Layer.

Chapter 4 - Grain Sorghum Maintains Yield Superiority Over Maize in Water-Stressed Conditions

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Abstract

Maize and sorghum are both warm-season, C₄ plants that share U.S. production environments and are cultivated for food, feed, and biofuel. This paper re-examines the study by Rotundo et al. (2024) to better understand the advantage of maize yields relative to sorghum yields in water-limited environments using a dataset from the USDA Risk Management Agency (RMA) that correctly computes county-level yields by discriminating maize and grain sorghum yields by irrigation practice. Our re-analysis revealed that grain sorghum has an advantage over maize in 41% of U.S. counties in a semi-arid climate where both crops share planting area. At the regional level, grain sorghum also showed an advantage over maize in terms of water use efficiency, defined as grain yield divided by crop actual evapotranspiration, in 35% of the counties in the state of Kansas. We found that reporting county-level yields computed by combining irrigated and non-irrigated yields (as done by Rotundo et al., 2024) resulted in a four-fold greater yield advantage of 2,774 kg ha⁻¹ for maize yield over grain sorghum. Our revised analysis showed that grain sorghum still has advantage over maize yields in water-limited rainfed environments concentrated in the U.S. Great Plains, which is supported by the continued cropping of grain sorghum in this region. Moreover, this work emphasized the importance of

reporting county-level yields by irrigated and non-irrigated practices in national-level agriculture statistics.

Introduction

Maize (*Zea mays* L.) and grain sorghum [*Sorghum bicolor* (L.) Moench] are among the top five globally produced cereals, accounting for 40% and 2% of the total production, respectively (FAO, 2024). Maize and grain sorghum are both warm-season, C₄ plants that are widely utilized for feed, fuel, and food. In the United States (U.S.), maize production is concentrated in the Midwest Corn Belt, with the states of Iowa (5.3M ha) and Illinois (4.5M ha) leading the maize planted area (USDA NASS, 2024). Grain sorghum is typically planted in non-irrigated areas of the southern Great Plains, with the states of Kansas (1.2M ha) and Texas (0.7 ha) accounting for most of the sorghum planted area (USDA NASS, 2024). However, in recent decades, the development of improved drought-tolerant maize hybrids has led to an increase of maize planted areas in traditionally sorghum-dominated states like Kansas and Texas, reaching a planted area similar or exceeding grain sorghum. In 2024, the state of Kansas had 2.5M ha and Texas had 0.9M ha planted with maize (USDA NASS, 2024).

The broad adaptation of grain sorghum to water-stress is largely attributed to persistent selection in water-limited environments deriving traits which include escape strategies such as stay-green (Borrell et al., 2014), reduced transpiration with leaf rolling and waxy bloom (Kadioglu and Terzi, 2007), and increased root water uptake (Goche et al., 2020). On the other hand, maize has greater water-sensitivity with high yield potential under favorable water conditions, attributed to greater photosynthetic capacity with erect leaves in dense crop canopies (Li et al., 2021; Loomis and Amthor, 1999; Messina et al., 2022b) and sensitivity to water stress during anthesis (Cooper et al., 2014; Edmeades et al., 2000; Turc et al., 2016). The rate of genetic gain for maize has outpaced grain sorghum (Demarco et al., 2022) with a dwindling gap between the rate of maize improvement in water-stressed environments relative to improvement

in water-sufficient environments (Messina et al., 2023). In the 1970s, maize improvement concerted selection for yield under drought (Campos et al., 2004; Duvick 1977; Duvick 2005); results of which culminated with improved drought-tolerant hybrids as exemplified by the release of AquaMax[®] (Cooper et al., 2014).

In a recent study evaluating maize and grain sorghum yields across multiple decades and a wide range of production environments in the U.S., Rotundo et al. (2024) found that the shared production area of the two crops exhibited a decreasing trend from the 1960s to the 2020s, which was mainly attributed to the dwindling planting area of grain sorghum. The study by Rotundo et al. (2024) concluded that maize outyields grain sorghum and has an undisputed dominance in U.S. production environments, with the greatest yield advantage identified in the areas with the highest water stress. However, upon careful examination of the methodology used by Rotundo et al. (2024), we found that the dataset obtained from the U.S. Department of Agriculture (USDA) National Agriculture Statistics Service (NASS) included county-level yields that averaged both irrigated and non-irrigated maize or sorghum cropland. Historically, USDA-NASS intermittently reported yields by practice (i.e., irrigated and non-irrigated), which was recently discontinued. County-level yield reporting began in the 1920s, with specific start dates for maize and grain sorghum varying by state. From 1980 to 2007, and again in 2009, county-level yields were reported separately for irrigated and non-irrigated cropland, ensuring reliable data during this period. After 2009, practice-specific sorghum yield reporting was discontinued, and maize yields were reported by practice for a limited number of states until 2018, after which this was also discontinued. As a result, recent USDA-NASS county-level maize and sorghum yield data include mixed management practices, likely biasing some of the conclusions drawn by Rotundo et al. (2024). Hence, the objective of this study was to re-examine the advantage of maize yields

relative to grain sorghum yields in water-limited environments using an alternative dataset that correctly discriminates maize and grain sorghum yields by irrigation practice.

Materials and Methods

Yield and planting area datasets

The dataset used by Rotundo et al. (2024) consisted of county-level maize and sorghum yield data from the USDA-NASS for the period 1960 to 2020. To address the lack of distinction between irrigated and non-irrigated yields of the USDA-NASS dataset, we conducted our analysis using a source of non-irrigated county-level yields obtained from the USDA Risk Management Agency (RMA) Actuarial Data Master Directory (USDA RMA, 2024). The USDA-RMA is a federally subsidized crop insurance program with enrollment of ~200 million hectares. The USDA-RMA receives unique yield reports and management information for each insured parcel of land with fraudulent reports prosecutable by the USDA Office of Inspector General. Starting in 2019, USDA-RMA published a county-level yield which discriminates crop yields by irrigated and non-irrigated practice. Thus, our study re-examined the maize and sorghum yield analysis using 1) the USDA-NASS dataset, which combines irrigated and non-irrigated yields, and 2) the USDA-RMA that distinguishes between irrigated and non-irrigated yields. The analysis covered the period from 2019 to 2023, during which both datasets overlap. While this comparison is limited to only five years, the extent of the datasets is sufficient to illustrate the perils of using USDA-NASS reports from recent years in which irrigated and non-irrigated farm yields were combined in the computation of county-level yields. To evaluate the magnitude of yield differences using combined practice and non-irrigated yield reports, we also obtained non-irrigated yields for maize and grain sorghum in years when practice specific yields

were available in the USDA-NASS. A missing piece of information in the USDA-RMA dataset is the percentage of maize and sorghum land area that is irrigated and non-irrigated at the county-level. To solve this problem, we obtained the areal extent of irrigated and non-irrigated maize and grain sorghum from 2019 to 2023 from the USDA Farm Service Agency (FSA) (USDA FSA, 2024), which was corroborated with a regional office of the USDA. As a result, the new dataset used in this study contained county-level yield and land area for non-irrigated maize and sorghum.

Calculation of water use efficiency

For maize and grain sorghum, water use efficiency (WUE) was calculated as the amount of biomass assimilated (grain yield per hectare) per unit of water use (actual crop evapotranspiration) over a time period (growing season) (Sinclair et al., 1984). The calculation of WUE was limited to the state of Kansas, which is the U.S. state with the greatest overlap between the planting of these crops. A county-level mean total growing season crop evapotranspiration (ET_c) was estimated for each corresponding county-level yield report. The county-level growing season ET_c was estimated for each crop and year as the mean total ET_c between the USDA-NASS reported mean state-level planting and harvest dates obtained from the OpenET platform (Melton et al., 2022), which has a spatial resolution of 30-m. Fields planted with maize or grain sorghum were identified from the gridded USDA-NASS Cropland Data Layer (USDA NASS CDL, 2024) with a spatial resolution of 30-m. Irrigated areas were removed from the analysis using an irrigated lands mask obtained from the Kansas Biological Survey (Gao et al., 2017). To quantify the potential for water stress corresponding to Kansas production environments, we used the atmospheric water deficit (AWD), which is defined as the annual

reference evapotranspiration minus the annual precipitation for each county (Purcell et al., 2003). To identify counties in semi-arid production regions we calculated the aridity index, which is defined as the ratio of annual precipitation to annual potential evapotranspiration, with semi-arid regions having an index between 0.2 and 0.5 (Trabucco & Zomer, 2018). To calculate the aridity index we used long-term (i.e., 1991–2020) mean annual reference evapotranspiration, mean annual potential evapotranspiration, and mean annual precipitation from the TerraClimate dataset (Abatzoglou et al., 2018).

Results

The USDA-RMA dataset was aligned with the USDA-NASS dataset for counties with low ($\leq 25\%$ irrigation area) (Figure 4.1). The USDA-RMA also correctly discriminated yield values in counties that have $>25\%$ of maize or sorghum area under irrigation (Figure 4.1). In other words, Figure 4.1 clearly shows that aggregating grain yields from irrigated and non-irrigated maize or sorghum cropland results in skewed yields, as the higher yields from irrigated land inflate the average yield. For instance, in 2020, Finney County, Kansas resulted in a mean maize yield of $9,810 \text{ kg ha}^{-1}$ when using USDA-NASS, but only $2,797 \text{ kg ha}^{-1}$ when using USDA-RMA. This difference is primarily due to 60% of the maize area in Finney County, Kansas, being under irrigated conditions compared to 5% of the grain sorghum area. Similarly, for the same county, grain sorghum yield resulted in $4,965 \text{ kg ha}^{-1}$ when using the USDA-NASS dataset whereas the yield was $3,423 \text{ kg ha}^{-1}$ when using the USDA-RMA dataset. In other words, the choice of yield dataset resulted in an overstatement of $7,013 \text{ kg ha}^{-1}$ for maize and $1,542 \text{ kg ha}^{-1}$ for grain sorghum. In another situation, in Ochiltree County, Texas, during the period from 2019 to 2023, the USDA-FSA reported an irrigated percentage of 88% for maize and 19% for

grain sorghum. For this county and period, the mean grain yields reported by the USDA-NASS for maize and grain sorghum respectively were 12,304 kg ha⁻¹ and 3,415 kg ha⁻¹. However, in this region non-irrigated maize is a high-risk crop and consequently, USDA-RMA does not offer federal insurance for non-irrigated maize insurance nor report a yield. The reported USDA-RMA mean yield for grain sorghum was 2,767 kg ha⁻¹ which represented an overstatement of yield for grain sorghum of 648 kg ha⁻¹.

From 2019 to 2023, across the U.S., 46% of counties that planted maize also planted grain sorghum. However, in these counties, grain sorghum constituted only 7% percent of the corn area. Where both crops are planted, irrigation occurs on 25% of the maize area compared to 10% of the sorghum area (Figure 4.2). We found that the total area in the U.S. where grain sorghum has a yield advantage has dwindled; nevertheless, grain sorghum has a persistent yield advantage relative to maize in areas prone to high frequencies of drought. Concentrated in the High Plains of Texas and the surrounding region, there are a total of 123 counties where USDA-RMA insured and reported yields for non-irrigated grain sorghum but did not insure nor report non-irrigated maize, indicating that maize does not have adequate drought adaptation for these areas. Based on USDA-RMA non-irrigated yield reports, the mean yield advantage of maize to sorghum was 2,347 kg ha⁻¹ with grain sorghum having a yield advantage in 14% of reported counties (Figure 4.3). This non-irrigated yield advantage narrows in counties with a semi-arid climate, with a yield advantage of 423 kg ha⁻¹ of maize to sorghum and 41% of the counties with an overall yield advantage for grain sorghum.

For grain sorghum in the period of 2019 to 2023, mean growing season ET_c across the state of Kansas was 501 mm, ranging from 335 mm in Rawlins County in 2022 to 595 mm in Linn County in 2023 (Figure 4.4). Conversely, maize had a mean growing season ET_c of 571

mm, with a minimum of 353 mm in Logan County in 2022 and a maximum of 713 mm in Meade County also in 2022. The highest growing season ET_c was observed in 2023 for both maize and grain sorghum while both crops had the lowest mean growing season ET_c in 2022. Maize had a typical statewide WUE of $9.9 \text{ kg ha}^{-1} \text{ mm}^{-1}$, while grain sorghum had a WUE of $8.5 \text{ kg ha}^{-1} \text{ mm}^{-1}$ (Figure 4.5). On average, 65% of the 105 counties in Kansas have a maize WUE advantage relative to grain sorghum, however, there is substantial year-to-year variability, with a minimum of 49% of counties having a maize advantage in 2022 to a maximum 74% in 2020 (Figure 4.6). Maize had the greatest WUE efficiency advantage in eastern Kansas, which corresponds to the areas of highest yield potential for non-irrigated maize. We found that Kansas counties with a relative advantage in maize WUE had a mean county-level AWD = 434 mm, while counties with a sorghum WUE advantage were characterized by drier conditions with a mean AWD = 878 mm.

The use of USDA-NASS yields, as done by Rotundo et al. (2024), resulted in an overstated maize advantage to sorghum by $2,774 \text{ kg ha}^{-1}$ (Figure 4.6) when compared to USDA-NASS non-irrigated reported yields in the period of 1990 to 2010. Moreover, the use of USDA-NASS yields (Figure 4.6A) fails to capture the magnitude of year-to-year swings of the maize to grain sorghum relative advantage, as demonstrated in the drought-stressed production year of 2011 when the percent of counties with a maize to grain sorghum advantage was 22% (Figure 4.6B). The method used by Rotundo et al. (2024) resulted in the greatest magnitude of yield advantage in the region that overlays southwest Kansas and the High Plains of Texas and Oklahoma (Figure 4.7A). Thus, the discrepancies between USDA-NASS and USDA-RMA reported yields are greatest in water-limited environments where maize is commonly irrigated (Figure 4.7B).

Discussion

Our study provides strong evidence that grain sorghum still holds a yield advantage over maize in certain water-limited environments of the U.S., although this yield advantage has dwindled over time. Our revised estimations showed that grain sorghum has an advantage over maize in water-limited environments (concentrated in the Great Plains), which is supported by the continued cropping of grain sorghum in this region. We also found that the conclusion of Rotundo et al. (2024), stating that “*Maize today has an undisputed dominance in U.S. agriculture, outperforming sorghum widely*” may be a stretch, as their analysis was based on a skewed dataset that included both irrigated and non-irrigated yields, inflating some values and affecting their conclusions. Our findings that grain sorghum has an advantage for yield stability and WUE in water-limited environments are consistent with field studies in the grain sorghum production region. As an example, field studies have identified planting grain sorghum as a viable strategy to reduce fallow periods and build soil organic matter in water limited environments (Schlegel and Havlin, 1997; Simon et al., 2022). Researchers have attributed the yield stability of grain sorghum under water stress to traits such as stay-green, retention of green leaf at maturity (Tolk et al., 2013; Xu et al., 2008), and in-season stress adaptation with growing season plasticity of seed number set (van Oosterom and Hammer, 2008; Demarco et al., 2022) or tillers (Abreha et al., 2021). Yet, the genetic gain advantage of maize relative to grain sorghum is undisputed and well-documented with maize’s rate of gain being four-fold the rates of genetic gains in grain sorghum (Duvick 2005; Mayor et al., 2022; Pfeiffer et al., 2019; Smith et al., 2014). Improvements in maize genetics have targeted drought-tolerant traits (Cooper et al., 2014; Campos et al., 2004) which resulted in maize hybrids with native drought-tolerant traits like AQUAmax[®] (Gaffney et al., 2015; Messina et al., 2022a) and Artesian[®] (Hao et al., 2019)

marketed by Corteva AgriScience and Syngenta respectively, and transgenic traits including DroughtGuard® (Nuccio et al., 2018; Wang et al., 2015) introduced by Monsanto in 2011. However, multi-year field trials at sites including Akron, Colorado and Bushland, Texas did not find appreciable change in the crop water use of these improved drought-trait maize hybrids (Marek et al., 2020; Nielsen and Schneekloth, 2018; Schwartz et al., 2022). It may be, as suggested by others (Nielsen and Schneekloth, 2018; Pester, 2009), that the improvement of drought tolerance in maize diminishes under severe water stress conditions.

Moreover, this work emphasized the importance of national-level agriculture statistics by crop practices, such as irrigated and non-irrigated practice. In April 2024, USDA announced a discontinuation of county-level crop yield estimates, further eroding accessibility to public national agriculture statistics. The use of USDA-NASS yield statistics at the county-level resulted in a four-fold overstatement of the advantage of maize relative to sorghum in counties with both irrigated and non-irrigated practice. Accurate discrimination between irrigated and non-irrigated practices in USDA-reported data is crucial for reliable calculations of water use efficiency and yield trends at both county and regional levels. Discontinuing these reports or aggregating the data across different management practices risks impairing scientific research, leading to increased likelihood of skewed conclusions about crop performance across production environments.

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Statistician for the USDA-NASS office in Kansas, and information regarding USDA Risk Management Agency data from Jeff Darrow, Deputy Director for the Topeka Regional Office, USDA-RMA and team members of the USDA-RMA Service Desk. This work was partially supported by the USDA National Institute of Food and Agriculture through the Agriculture and Food Research Initiative Competitive Grant no. 2019-68012-29888 and through Multistate project W5188.

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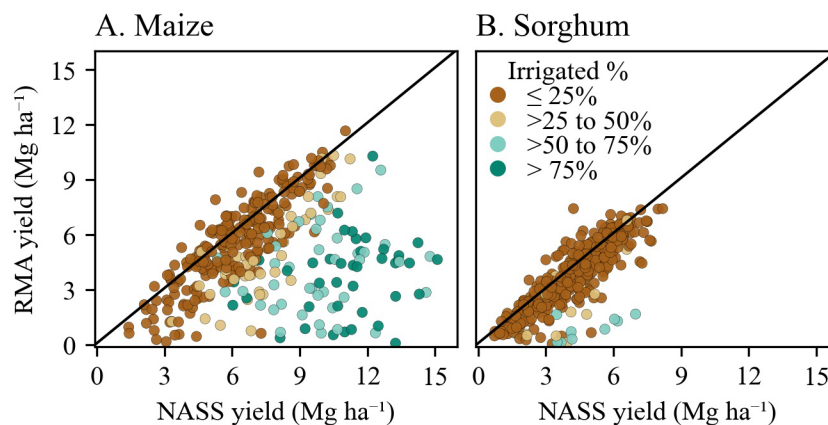


Figure 4.1. County-level maize (A) and sorghum (B) yields reported by the USDA National Agriculture Statistic Service (NASS) compared to county-level non-irrigated yields reported by the USDA Risk Management Agency (RMA) from 2019 to 2023. The dataset obtained from the USDA-NASS combines yield for all practices, meaning that yield averages for each county and year were calculated using yields under irrigated and non-irrigated cropland.

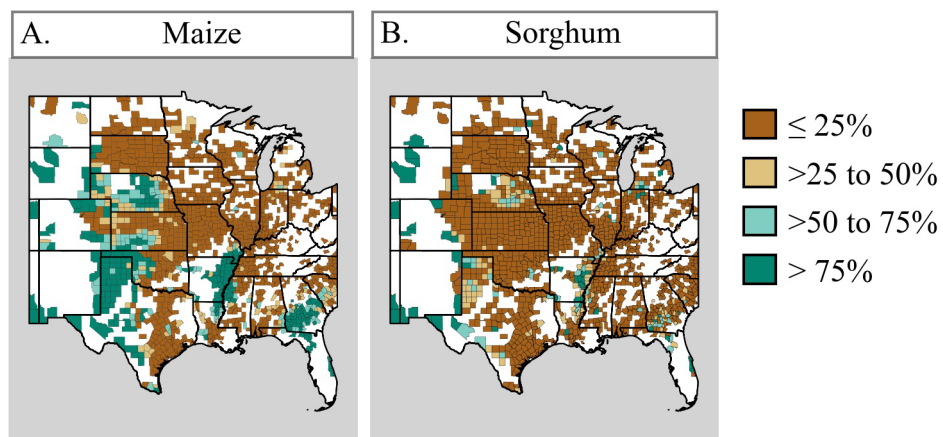


Figure 4.2. The percent of irrigated maize and sorghum area relative to total county-level planted area for each crop obtained from the USDA Farm Service Agency crop acreage report data as the mean from 2019 to 2023.

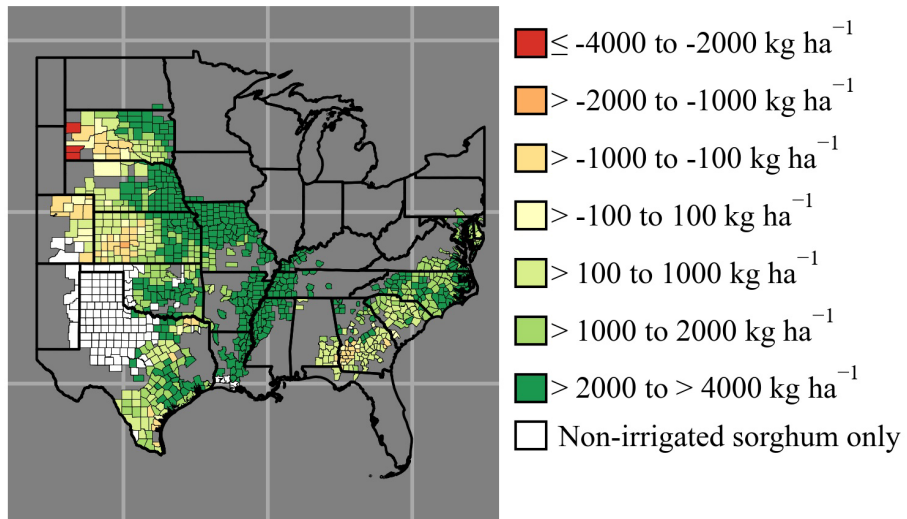


Figure 4.3. Maize to sorghum yield difference calculated as the difference between the mean value of all counties with reported non-irrigated yield for maize and sorghum from 2019 to 2023. Counties with negative values (reddish colors) represent an advantage of grain sorghum over maize yields. Yield data was obtained from the USDA Risk Management Agency.

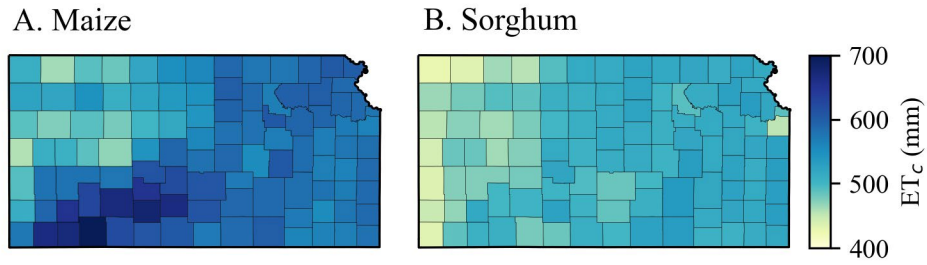


Figure 4.4. Estimated growing season crop evapotranspiration (ET_c) for non-irrigated maize and sorghum in Kansas, United States. ET_c was calculated as the county-level mean value for the growing seasons from 2019 to 2023. The growing season period is calculated between the planting date and harvest date. Land area for maize and sorghum was acquired from the USDA Cropland Data Layer, planting and harvest dates for each crop was obtained from USDA National Agricultural Statistics Service, and ET_c was acquired from the OpenET platform.

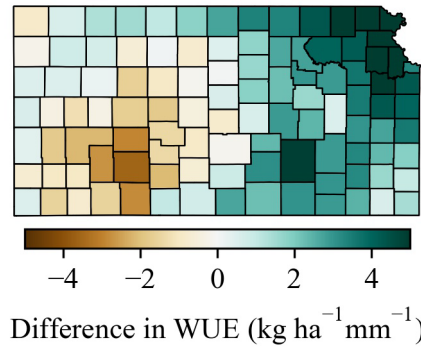


Figure 4.5. Difference in water use efficiency (WUE) for non-irrigated maize and sorghum was determined as the grain yield per hectare divided by the growing season evapotranspiration for the growing seasons of 2019 to 2023. Counties with negative values (brownish colors) represent a WUE advantage of grain sorghum over maize. Land area for maize and sorghum was acquired from the USDA Cropland Data Layer, yield data were acquired from the USDA Risk Management Agency, and growing season evapotranspiration was acquired from OpenET.

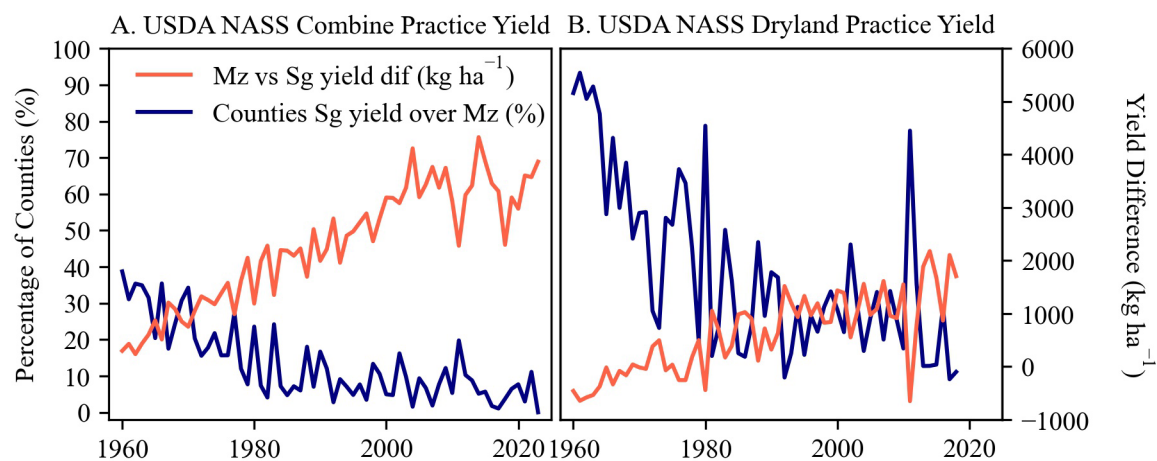
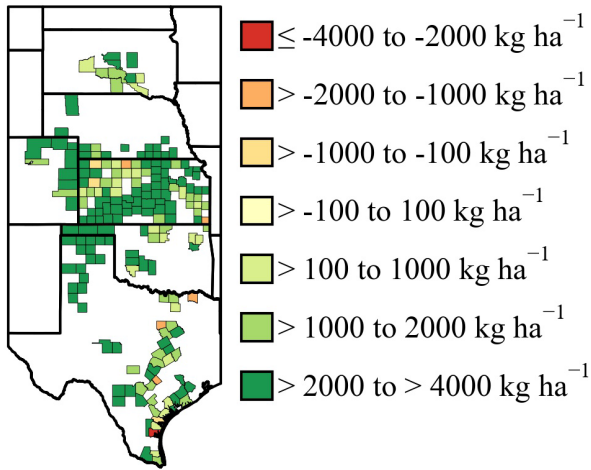


Figure 4.6. The advantage in yield for maize to sorghum and the percentage of counties with a sorghum yield advantage for counties with reported non-irrigated and combined irrigated and non-irrigated with A) combined practice yield report and B) yield report from non-irrigated cropland. Yield data was retrieved from the USDA National Agriculture Statistic Service (NASS).

A. Maize to Sorghum Yield Advantage



B. Difference in Yield Advantage

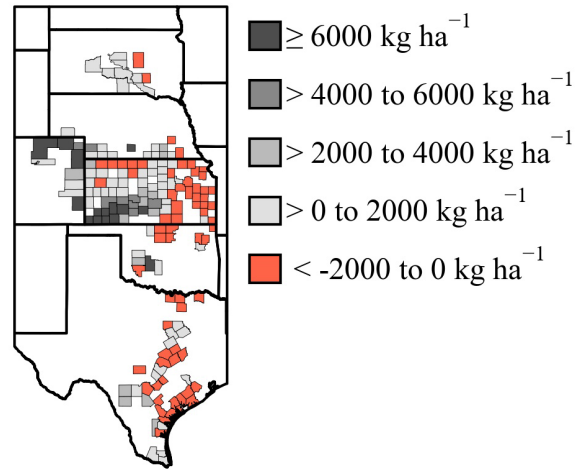


Figure 4.7. Maize to sorghum yield difference calculated from 2019 to 2023 with A) USDA-National Agriculture Statistic Service (NASS) irrigated and non-irrigated combined practice yield and B) the difference between USDA-NASS combined yield and USDA- Risk Management Agency non-irrigated yields.

Chapter 5 - General Conclusions:

Grain sorghum plays a key role in rainfed areas of the U.S. Southern Great Plains due to resilience in the water-limited environments and utilization for feed and ethanol production. In this region, the state of Kansas has the highest concentration of sorghum production with ~50% of the national planted area. The objectives in this dissertation were to i) quantify the magnitude of the yield gap and determine the causes of yield stagnation for grain sorghum in Kansas; ii) delineate crop production agro-zones for the state of Kansas and validate resulting agro-zones with an external dataset of environmental causes of crop yield loss and land cover; and iii) re-examine and understand the advantage of maize yields relative to grain sorghum yields in water-limited environments .

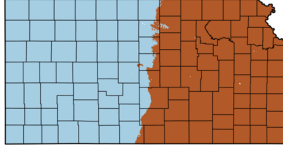
In the first chapter, we evaluated the magnitude of yield gaps for grain sorghum in the state of Kansas and tested the multiple working hypotheses that i) grain sorghum yields are stagnating due to a small exploitable yield gap, ii) grain sorghum yields are stagnating due to a shift in production area from wetter to drier regions, and iii) grain sorghum yields are stagnating due to cultivation in poor soils. We found that the yield gap in Kansas is 1.4 Mg ha^{-1} relative to YG_a and 4.9 Mg ha^{-1} relative to YG_w with current farmer yields representing 77% of attainable yield and 49% of water-limited yield potential. Furthermore, we identified that shifts in the land area planted to sorghum have intensified atmospheric water deficit by 30% since 1980s and the lands planted to sorghum have a mean land capability of 2.5, which was an 18% reduction in land capability relative to croplands without a sorghum occurrence. Statewide stagnation was not caused by a closure of the exploitable yield gap and instead was primarily attributable to the onerous of acres shifting to higher intensity of atmospheric water deficit and secondarily attributable to cultivation in poor soils.

In our second chapter, we delineated the macro and micro crop production agro-zones (AZ) for the state of Kansas. The analysis resulted in three optimal clusters of relatively homogeneous climatic conditions that partitioned the state into northwest, southwest, and east, each with two nested micro-AZs based on soil physical properties. The hierarchical approach of subdividing climate-based macro-clusters using soil physical characteristics provided a greater level of spatial detail while preserving cluster parsimony. Validation was conducted with a multinomial model of these zones with an external dataset of environmental causes of loss and landcovers and resulted in a validation test accuracy of 88% for the macro-AZs and 67% for the macro-micro-AZs. To our knowledge this is the first study demonstrating leverage of landscape production data for external validation of AZs.

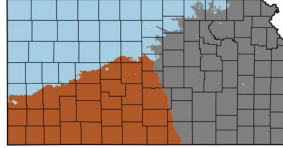
In our final study, we explored a recent conclusion that maize has a yield advantage in all production systems, including the most water stressed environments of the Southern Great Plains. We found that the use of yield reports from mixed irrigated and non-irrigated practices, resulted in a four-fold overstatement of maize yield advantage relative to sorghum. The areas of greatest overstatement are in the Southern Great Plains, where the proportion of maize and sorghum irrigated was 25% and 10%, respectively. The water use efficiency of these crops in the state of Kansas was $9.9 \text{ kg ha}^{-1} \text{ mm}^{-1}$ for maize and $8.5 \text{ kg ha}^{-1} \text{ mm}^{-1}$ for sorghum. The balance of counties with an advantage for maize WUE was 68 of the 105 total counties, however in years with severe drought conditions, such as 2022, the number of counties with a maize WUE advantage dropped to 51 counties. After excluding county-level yields from irrigated cropland, we found that sorghum outperforms maize in water-limited areas prone to frequent and severe drought conditions.

Appendix A – Supplemental Material for Chapter 3

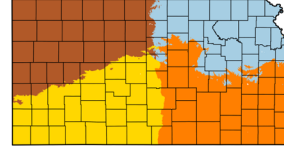
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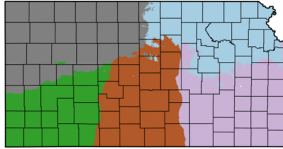
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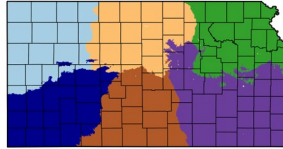
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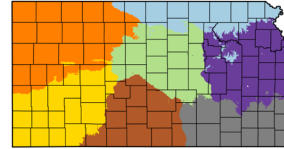
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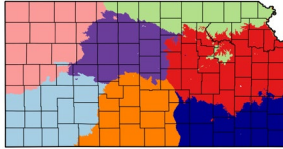
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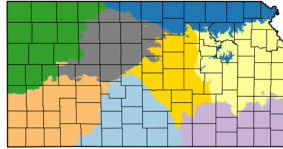
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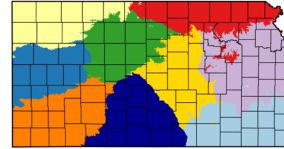
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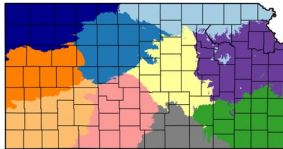
Cluster Number: 9
Silhouette Score: 0.52



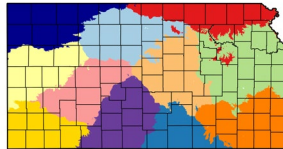
Cluster Number: 10
Silhouette Score: 0.54



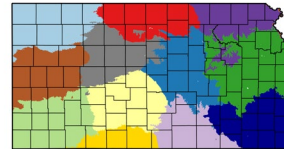
Cluster Number: 11
Silhouette Score: 0.55



Cluster Number: 12
Silhouette Score: 0.56



Cluster Number: 13
Silhouette Score: 0.57



Cluster Number: 14
Silhouette Score: 0.56



Cluster Number: 15
Silhouette Score: 0.56



Figure A1. Maps showing the state of Kansas divided into 2 to 15 clusters and their corresponding Silhouette scores, which represents a measure of inter- and intra-cluster performance in the range of -1 (worst performance) to 1 (best performance).

Appendix B – Supplemental Material for Chapter 4

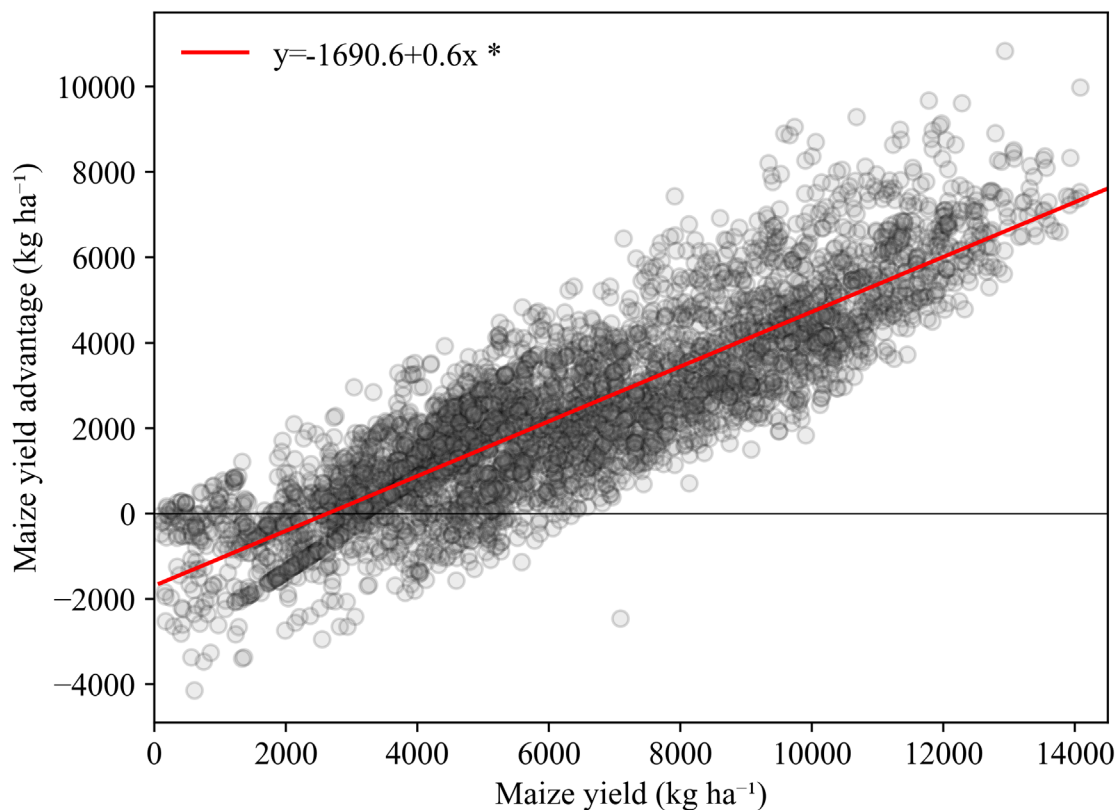


Figure B1. Maize yield advantage calculated as the difference between maize to sorghum grain yield relative to maize yield. The figure shows non-irrigated county-level grain yields observed from 2019 to 2023. Yield data was obtained from the USDA Risk Management Agency. Note that asterisk (*) indicates statistical significance at $P < 0.05$.