

Enhancing crop production in Kansas via in-silico studies and environmental characterization to
improve management decisions

by

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Abstract

Increasing climate variability and crop demand require sustainable intensification of rainfed cropping systems. This thesis addresses this challenge in Kansas by integrating crop growth model with environmental characterization to improve crop production strategies. Two complementary approaches were used: (1) evaluating the feasibility of intensifying rainfed wheat (*Triticum aestivum* L.) -based cropping systems by adding a summer crop using long-term in-silico simulations; and (2) characterizing rainfed maize (*Zea mays* L.) productivity environments across Kansas using long-term historical climate, yield and crop phenology data. Results from the simulations indicated that double-cropping can increase annual productivity, but success depends on crop specie, cycle length choice and sowing timing. Soybean (*Glycine max* L.) as a second crop after wheat consistently showed higher success rates and more stable yields than maize, with earlier summer planting maximizing yield (but increasing drought risk) and later planting avoiding drought (but increasing frost risk). Accordingly, wheat-soybean rotations were consistently more productive and profitable, whereas wheat-maize rotations showed greater yield variability and risk. In parallel, cluster analysis of the 1993–2021 climate and yield records delineated ten distinct rainfed maize production regions in Kansas, with average yields ranging from ~3.5 to ~7.5 Mg ha⁻¹. Correlation analysis revealed that extreme heat (daily accumulated degree-days > 35 °C) and high vapor pressure deficit during flowering stage were the primary yield-limiting climatic factors, with each additional degree-day > 35 °C around flowering reducing yield by ~46 kg ha⁻¹, with the stress being most severe in southeastern Kansas. These findings highlight that optimizing summer crop selection and planting schedule can enhance productivity in wheat-based systems, while spatial climate analysis enables region-specific management strategies. By combining long-term modeling with crop environmental characterization, this study provides insights to inform adaptive management strategies to improve crop productivity and resilience in Kansas. This regionalization approach could be easily extrapolated to other crops and regions.

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Dedication

I dedicate this to my parents, for shaping me into who I am, doing what they could with what they had.

To my sister, to whom I wish the very best on her journey.

And above all, to my grandparents, who always held on to the hope of seeing me well and hugging me again.

On March 28, 2022, I promised them we would see each other again.

When I came back, one of them was no longer there.

Se la dedico a mis viejos, por haberme formado tal como soy, haciendo lo que podían con lo que tenían a mano.

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El 28 de marzo de 2022 les prometí que nos volveríamos a ver.

Al regresar, me faltaba uno.

Chapter 1 - General Introduction

Increasing populations, fast growing demand in emerging economies, and existing resource intensive consumption patterns in developed countries (Tilman et al., 2011), create a need to maintain or increase crop productivity. In the past, the 'green revolution' addressed this concern through the introduction of new crop varieties, combined with increased use of inorganic fertilizers, pesticides and machinery, as well as better water management and larger field sizes. However, this period of agricultural intensification was accompanied by significant damage to the environment (Rockström et al., 2017). A defining challenge for society over the next half century will be to produce more food with lower environmental impact, under more variable climatic conditions (Godfray et al., 2010; Smith et al., 2013), and market volatility (Battisti & Naylor, 2009).

Increasing food production by expansion of existing cropland is not sustainable and has limited potential due to its negative environmental and social impacts (Ramankutty et al., 2002), thus, crop production needs to increase on existing cropland (Foley et al., 2005). Achieving this goal requires more than technological advances; it requires an integrated approach to decision-making that redefines how farming systems operate (Tilman et al., 2002). A key component of this strategy is optimizing crop management by carefully considering factors such as species selection, crop cycle length, planting date, nutrient management, and pest control. By tailoring these factors to local conditions, inefficiencies can be minimized while maintaining or even improving yields in a more sustainable manner (Shah & Wu, 2019).

The United States plays an important role as one of the main global crop producers, ranking first in maize, second in soybean, and fourth in wheat production (United States Department of Agriculture (USDA), 2025). Within the U.S., the Central Great Plains where

Kansas is located exhibits substantial spatial and temporal variation in environmental conditions and crop development factors (M. Kukal & Irmak, 2016a, 2016b). Kansas, in particular, is the world's leading producer of winter wheat (Smika, 1992), while also ranking seventh in maize and tenth in soybean production at the national level. The Kansas continental climate is marked by significant rainfall variability, ranging from 500 mm per year in the west to 950 mm in the east, and a frost-free period that extends from 155 days in the North to 205 days in the South (Goodin, 1995). This spatial and inter-annual climatic variability has profound implications for crop stability, with climate fluctuations accounting for 30–40% of the year-to-year yield variation in rainfed summer crops (M. S. Kukal & Irmak, 2018). While irrigation can partially mitigate these climatic constraints, this study focuses on rainfed cropping systems, as dryland farming is the predominant management practice in the region (Lanning-Rush, 2016).

Addressing this variability requires long-term studies capable of capturing both spatial and temporal patterns to support informed management decisions. However, evaluating multiple management strategies through long-term field experiments is both time-intensive and resource-demanding. To overcome these constraints, crop simulation models such as APSIM (Holzworth et al., 2014) provide an *in silico* approach to efficiently evaluate crop intensification strategies. At the same time, defining different environmental regions based on crop productivity and climate-related constraints requires extensive climate and phenological data. Identifying not only yield responses but also crop sensitivity across different crop growth stages allows for a more accurate characterization of production risks and opportunities.

The overall objective of this study is to provide information to support improved management decisions in the U.S. Central Great Plains, using Kansas as a case study due to its climate variability. This research is based on the premise of enhancing productivity within

existing rainfed cropping systems under a sustainable framework. Accordingly, the specific objectives are: i) evaluate the feasibility of rainfed wheat-based cropping systems intensification in Kansas through an in-silico approach (Chapter 2), ii) develop a methodology for characterizing crop-environments with similar productivity potential and climate-related constraints for summer crops, using maize in Kansas as a case study (Chapter 3).

Chapter 2 - Intensifying wheat-based rainfed systems: assessing summer crop alternatives using an in-silico approach in the U.S.

Central Great Plains

* Manuscript in preparation

2.1 Abstract

Double cropping improves productivity, land use efficiency, and profitability across the Central Great Plains region of the United States (US). However, limited research has evaluated the long-term productivity and economic viability of maize (*Zea mays* L.) and soybeans (*Glycine max* L.) as a summer crop following winter wheat (*Triticum aestivum* L.) for this key US producing region. The objective of this study was to evaluate the feasibility of incorporating summer crops (soybean and maize) into a wheat-based cropping system in the US Central Great Plains. Simulations were conducted under dryland conditions using the APSIM Classic model in Manhattan, Kansas. We evaluated two soybean maturity groups: 3.0 and 4.0, and two comparative relative maturity corn groups: 100 and 110; planted after winter wheat on four planting dates: 20 June, 1 July, 10 July and 20 July over a 30-year period (1993-2022). The analysis assessed crop success rates, yield trends, land equivalent ratio (LER) and gross margins across different sowing dates and crop cycle lengths. Early planting dates for summer double cropping maximized yields but increased the risk of water stress, while later dates improved crop establishment but increased the risk of frost. Soybean showed consistently higher success rates across all planting dates, while maize was more sensitive to water stress. Maximum LER values were observed on June 20th planting date for soybean, and July 10th for maize. Economic analysis showed that wheat-soybean systems provided more stable and profitable outcomes than wheat-maize, which exhibited higher variability and risk. These findings highlight the importance of selecting appropriate crops, cycle lengths, and planting dates to maintain productivity in double-cropping systems while balancing climate risks and profitability through adaptive management in wheat-based rotations in the Central Great Plains.

2.2 Introduction

Improving crop productivity is crucial for meeting the global demand for crop products while promoting environmental and social sustainability and enhancing farm profitability (Fischer et al., 2014). Increases in crop production can be achieved in three ways: i) increasing the area under cultivation by expanding the agricultural frontier, ii) increasing the yield per unit of area of a single crop by enhancing its yield potential through breeding or by minimizing the yield gap through improved crop management, or iii) increasing the number of crops harvested per year via crop intensification (Cassman, 1999). However, the availability of arable land to expand cropped area is limited and yield gains are below the levels required to meet this demand (Ray et al., 2013; Tilman et al., 2002). Therefore, the intensification of cropping systems is one of the viable alternatives to increase crop production levels (Waha et al., 2020). While some field crops in single crop-based systems often exhibit higher resource use efficiency, intensification through double cropping systems compensates through greater resource capture, resulting in higher overall productivity (Andrade et al., 2015).

The number of crops that can be grown in a crop sequence is constrained by factors such as the length of the growing season, which is related to the frost-free period (Cohn et al., 2016; Liu et al., 2013), and the availability of water to the crops (mainly as rainfed environments in the US Central Great Plains), which is related to the amount and distribution of precipitation (Arvor et al., 2014; Cohn et al., 2016; Liu et al., 2013). The U.S. Great Plains is one of the world's most important crop production region (Smika, 1992). Winter wheat (*Triticum aestivum* L.) is the dominant crop in the rainfed agricultural systems in the US Central Great Plains region (United States Department of Agriculture (USDA), 2015). This dominance is due not only to favorable environmental conditions for high yield potential (Lollato & Edwards, 2015; Greb et al., 1979), but also to limited crop alternatives (Biermacher et al., 2006). Among these states, Kansas has the shortest frost-free period, which limits early planting of summer crops (M. S. Kukal & Irmak, 2018) and presents the most challenging scenario for assessing the feasibility of increasing cropping frequency. In eastern Kansas, the wettest part of the region (>600 mm per year), grain wheat is produced from mid-October to mid-June (Patrignani et al., 2019). This creates a potential window to establish a summer crop that could grow until October (first frost date). However, precipitation is mainly concentrated in the spring (May–June), which limits water availability for summer crops during the hottest months of July and August but precipitation is

mainly concentrated in the spring (May - June), limiting water availability for summer crops during the hottest months of July and August (Massigoge et al., 2024).

Current experience with intensified cropping systems in North America has primarily involved summer legumes following winter cereals (Massigoge et al., 2024). However, given the high spatiotemporal variability in weather conditions, long-term studies are needed to assess the success rate of different intensification strategies. Nelson et al., (2010) and Kelley, (2003) analyzed the economic feasibility of wheat–soybean systems, while Rosenzweig et al. (2018) studied intensified cropping but excluded soybean and maize. More recently, Massigoge et al. (2024) evaluated the productivity and economic feasibility of wheat-soybean and wheat-maize double cropping, but their study was limited to a few years and did not consider variations in crop cycle length or planting dates, that could be considered to minimize/avoid the effect of climatic constraints on grain yields. Hence the long-term productivity and economic viability of double-cropping maize or soybean after winter wheat under different planting dates and crop cycle lengths, were the aims of this study.

Given the complexity and multiple factors influencing the performance of a cropping system, the use of field experiments over long periods of time is necessary but requires considerable time and resources. In contrast, crop simulation models are emerging as valuable tools to evaluate the adoption of different agronomic management practices (Chenu et al., 2017) and crop sequences (Andrade et al., 2015; Caviglia et al., 2013; Salado-Navarro & Sinclair, 2009; Q. Yu et al., 2006), offering a cost-effective approach for long-term farm management study (Cao et al., 2015; Thorburn et al., 2005). The Agricultural Production Systems sIMulator (APSIM) (Holzworth et al., 2014) has been widely used to simulate cropping systems worldwide, providing insights into system dynamics and adaptation strategies. Therefore, analyzing the frequency of events over a long period of time can help refine crop management decisions and assess the feasibility of intensifying wheat-based systems. In cropping systems with two or more crops per year, reduced yields of individual crops may be offset by an overall increase in total annual grain production (Evans, 1993). Therefore, the evaluation of cropping systems requires not only yield comparisons, but also an assessment of the economic profitability. The land equivalent ratio (LER) is a valuable metric for comparing the land use efficiency of double-cropping and monocropping systems (Martin-Guay et al., 2018; J. Yu et al., 2025). Agronomic assessments acquire practical relevance when integrated with economic

evaluations, as profitability and cost-effectiveness are central to farm decision-making (Meyeraurich et al., 2006).

Following this rationale, the aims of this study were to: i) evaluate the feasibility of soybean and maize genotypes with different cycle lengths as summer double-crop options following winter wheat, ii) analyze the crop failure risk associated with frost and drought of these genotypes, and iii) determine the optimal combination of summer crop species, crop cycle length, and planting date based on grain yield, LER, and gross margin.

2.3 Materials and methods

This study evaluated a crop sequence in which winter wheat (*Triticum aestivum* L.) was followed by a summer crop as a potential double-crop system. To achieve this, four sowing dates were analyzed for two maize genotypes (comparative relative maturities 100 and 110) and two soybean genotypes (maturity groups 3 and 4), each with different cycle lengths. The analysis considered both productive and economic perspectives through an in-silico approach using the crop simulation model APSIM Classic v7.10 (Holzworth et al., 2014). Simulations were performed independently, with each run covering two calendar years but restarting annually over a 30-year period. Crop sequence schemes were structured as a factorial combination of summer crop species, crop cycle length, and sowing date (Figure 2.1). In the subsequent analysis, we used the model output to make comparisons, whereas in the case of yield, the model provides dry basis yield.

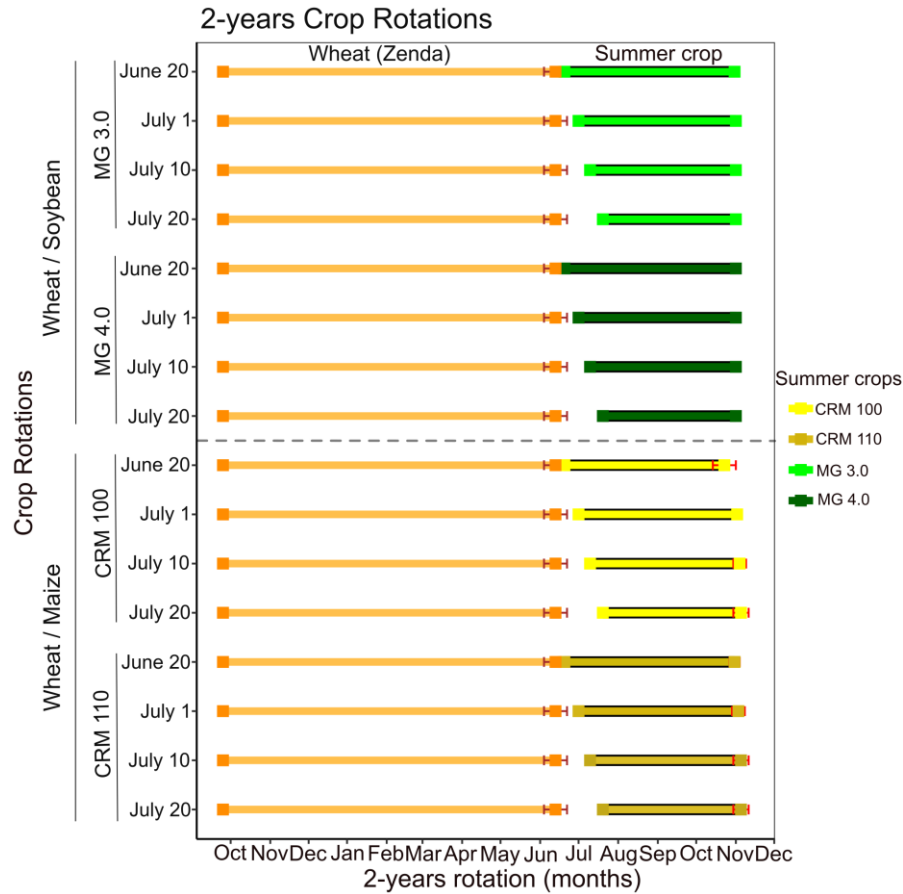


Figure 2.1: Two-year crop rotation schemes including wheat (cultivar 'Zenda') and a summer crop, either soybean or maize. Wheat is always sown on September 25th of the first year, followed by a summer crop with different sowing dates (June 20th, July 1st, July 10th, and July 20th). Soybean genotypes include MG 3 and MG 4, while maize genotypes include CRM 100 and CRM 110. The x-axis represents the months over a two-year period.

2.3.1 Crop Simulation model

2.3.1.1 Crop simulation model evaluation

Summer crop options included maize hybrids with Comparative Relative Maturities (CRM) of 110 or 100, soybean cultivars with Maturity Groups (MG) 4 or 3, and the 'Zenda' cultivar for winter wheat. The cycle length of the summer crops and the selected winter wheat cultivar, which is characterized by a medium-early maturity, are in line with typical crop sequences in the region. Cultivar parameters for maize CRM 100 and soybean MG 4 were obtained from Balboa et al., (2019), while those for the wheat cultivar Zenda were obtained from

Evers (2022). For maize CRM 100 and soybean MG 3, the generic cultivar parameters available in APSIM were used. Model evaluation was performed at the individual crop level using an independent dataset of experiments with phenological and yield observations (Figure A.1, A.2 and A.3).

2.3.1.2 Cropping system simulations

2.3.1.2.1 Double-crop simulations

The summer crops of the double-cropping systems were sown on four different dates: June 20th, July 1st, July 10th, and July 20th. The winter wheat (cultivar 'Zenda'), the first crop in the cropping sequence, was always sown on September 25th in the prior year, the earliest recommended sowing date for the region (Shroyer et al., 1996). Summer crop sowing dates before June 20th were excluded because winter wheat was not harvested early enough to allow planting in more than 50% of the years evaluated. While wheat sowing after the summer crop was not simulated, as it was beyond the scope of this analysis, all simulations were designed to conclude by November 1st, the last day within the recommended wheat planting window for this region.

Crop management practices followed regional agronomic recommendations. Fertilization rates were set at 107 kg N ha⁻¹ at sowing for maize, 90 kg N ha⁻¹ at tillering (Z2.5) for wheat, and no nitrogen application for soybean. Plant populations were set at 200 plants m⁻² for wheat with a row spacing of 19 cm, 7.0 plants m⁻² for maize, and 40 plants m⁻² for soybean, both with a row spacing of 76 cm. The maximum soil profile depth explored was set at 2.4 m for maize and soybean and 2.0 m for wheat. Simulations were initialized with 30% of the soil water available for the crop (upper limit - lower limit) on June 1st before wheat sowing.

APSIM Classic does not include a grain dry-down module to simulate the transition from maturity to harvest at commercially acceptable moisture levels. Therefore, we have included a custom module for each crop based on published equations. The maize dry-down module was adapted from Martinez-Feria et al., (2019), with corrections from Chazarreta et al., (2023) The soybean dry-down module was developed following Da Silva et al., (2024). Since no published equation was available for wheat, we estimated its dry-down rate using weekly USDA-NASS

crop reports from the past 10 years and established that 225 GDD (using a base temperature of 0 °C) was required from maturity to harvest.

Daily water stress was retrieved from the APSIM Classic v7.10 model using *swdef(photo)*, a factor that regulates physiological processes related to photosynthesis. It is derived from the water availability ratio, calculated as the actual soil water supply relative to the potential soil water supply. *Swdef(photo)* ranges from 1 (no stress) to 0 (complete stress). In the model, water stress affects crop growth by influencing leaf expansion and senescence, which reduce the leaf area index (LAI), limit radiation interception, and ultimately constrain biomass accumulation. In addition to water stress, frost damage was assessed based on whether the first frost event (minimum temperature $\leq 2^{\circ}\text{C}$) interrupted the crop cycle, impacting final growth and yield.

2.3.1.2.2 Monocrop simulations

These simulations included winter wheat (cultivar 'Zenda') sown on October 15th at a density of 270 plants m^{-2} with a row spacing of 19 cm and 90 kg N ha^{-1} applied at tillering (Z2.5); maize (CRM 110) sown between April 5th and May 15th at a density of 7 plants m^{-2} with a row spacing of 76 cm and 200 kg N ha^{-1} applied at sowing; and soybean (MG 4) sown between May 10th and June 1st at a density of 40 plants m^{-2} with a row spacing of 76 cm and no nitrogen application.

2.3.1.3 Soil and weather data sources

The soil profile was developed based on in situ soil samples collected in Manhattan, Kansas, US, followed by laboratory analysis, and then incorporated into APSIM. The soil was classified as silty clay loam (Wymore series, fine mesic Aquertic Argiudoll) (United States Department of Agriculture (USDA), 2014). The simulated soil profile had a depth of 2.4 m, and the hydraulic properties were estimated following Saxton & Rawls (2006). Daily weather data were obtained from a National Oceanic and Atmospheric Administration (NOAA) weather station located less than 10 km from Manhattan, Kansas (Figure A.4).

2.3.2 Crop success rate

The feasibility of the different summer crop options in double-crop systems was assessed by calculating the crop success rate, defined as the proportion of years within the 30-year simulation that resulted in a harvestable crop. The crop success rate was determined for each combination of crop cycle duration and sowing date. A crop was considered harvestable when it reached at least 50% of the grain-filling duration in terms of thermal time (Growing degree days, GDD), depending on each crop species and genotype. For maize, the threshold in GDD from flowering (silking) to physiological maturity to be considered harvestable was 491 for CRM 110 and 458 for CRM 100. For soybeans, it was 535 and 514 GDD for maturity groups (MG) 4 and 5, respectively. Thus, in soybean photoperiod effects were accounted for using a monthly photoperiod value calculated in R using the Suncalc package Thieurmél & Elmarhraoui (2017) based on the latitude and longitude of the site. A base temperature of 8°C for maize and 10°C for soybean was used for the GDD calculation. Crops that experienced severe water stress in the early stages that affected their establishment, or crops that were affected by a late frost before reaching 50% of grain fill, were considered to be unharvestable. The sum of the percentage of years with one of these events was counted as the percentage of crop failures. On the other hand, harvestable conditions were divided into unripe crops when frost events occurred after the 50% seed filling threshold but before physiological maturity, and ripe crops when physiological maturity was reached with measurable yield, with both categories combined in the total crop harvest.

2.3.3 Land equivalent ratio (LER)

In order to evaluate the double cropping system alternatives across different sowing dates, crop cycle lengths and species, dry matter yield comparisons were carried out alongside the calculation of the land equivalent ratio (LER) (Giménez et al., 2018; Monzón et al., 2014). The LER was used to assess the relative productivity of the double-cropping systems compared to single-cropping, providing a measure of land use efficiency. It was estimated as the sum of the relative yields of the component crops in the double-cropping system, expressed relative to the longest CRM or MG full-season crop best adapted to the region (Equation 2.1).

$$LER = \frac{Yield_1, d}{Yield_1, m} + \frac{Yield_2, d}{Yield_2, m}, \quad (2.1)$$

where $Yield_{1, m}$ and $Yield_{2, m}$ represents the reference full-season monocrop wheat and summer crop yields under optimal conditions for the region (monocultures in our study), assuming maximum attainable rainfed yield at an optimal planting date. Similarly, $Yield_{1, d}$ and $Yield_{2, d}$ correspond to wheat and the respective summer crop yields in the double cropping system under varying planting dates. A LER value greater than 1 indicates that the double cropping system provides a productivity advantage over full-season cropping.

2.3.4 Economic analysis

The economic analysis of the different cropping systems was based on the gross margins of the different species, sowing dates, and crop cycle length alternatives. All the variables and fixed costs and incomes were obtained from the Kansas Farm Management Association (KFMA, <https://www.agmanager.info/kfma/kfma-enterprise-reports>) in the annual ProfitLink summary from 2013 to 2022. Gross margin calculations were based on historical grain prices, cost inputs, and simulated yield values. Prices were obtained from enterprise reports (citation) covering 10 years and indexed to November 2024 (US\$) using the Consumer Price Index inflation calculator (https://www.bls.gov/data/inflation_calculator.htm). Thus, an average indexed price was used for each input and output variable applied across all years. Yield data, expressed at 15.5% grain moisture for maize and 13.5% for soybean and wheat, were derived from 30 years of simulations, capturing annual variability while keeping economic inputs and outputs constant based on 10-year averages. Margin, expressed in USD per hectare, was defined as the difference between revenue and total costs, where revenue was calculated as the product of unit crop price and simulated yield. Costs included seed, fertilizer, herbicide/insecticide, drying and opportunity costs as 25% of revenue in all systems.

Crop-specific cost calculations considered differences between monoculture and intercropping systems. For wheat, costs were consistent across systems as its management was not affected by crop sequence, and drying costs were assumed to be negligible as crops always reached commercial moisture at harvest in our cases. Soybean costs varied between monocrop and double-crop systems, with herbicide, insecticide and drying costs derived from farm data, while seed costs remained constant. Maize costs followed a similar approach, but herbicide and insecticide costs for double-crop maize were not available, so they were estimated using a conversion factor of 0.65 applied to monocrop maize costs. This factor was derived from the cost

ratio observed in double-cropped and monocropped soybean systems. Fertilizer costs were determined based on the urea price for the previous October, taken from the World Bank Commodity Markets Outlook (World Bank, 2025).

2.3.5 Data analysis

A linear model was used to analyze the effect of planting date and genotype, including their interaction, on maize and soybean grain yield. Type III analysis of variance (ANOVA) was conducted using the car package (Fox & Weisberg, 2019) to assess the significance of main effects and interactions. Post-hoc multiple comparisons were performed using estimated marginal means, followed by pairwise comparisons with no adjustment for multiple testing. The multcomp package (Hothorn et al., 2008) assigned letter groupings to facilitate the interpretation of treatment differences.

The effects of sowing date, crop cycle length, crop species, and their interaction on gross margin were evaluated using a linear mixed model. Sowing date, crop cycle length, crop species, and their interaction were considered as fixed factors, while crop cycle length nested within species and year was considered as a random effect. These models were fitted using the lme4 package (Bates et al., 2015), and the effects of the fixed factors on the variables of interest were assessed using a likelihood ratio test (LRT) under a χ^2 distribution. Post-hoc multiple comparisons were performed using the emmeans package (Lenth, 2022). All statistical analyses were performed using R software (R Core Team, 2023).

2.4 Results

2.4.1 Maize and soybean double-crop yields

Yield reduction due to delayed sowing in maize and soybean as summer crops in a double-crop system, did not vary with the genotype (the crop cycle length) (specie-genotype-sowing date interaction, $p = 0.2385$). However, a significant interaction between crop and sowing date was found (crop $\times$ sowing date interaction, $p < 0.001$), indicating that the effect of sowing date on yield differs between maize and soybean. Therefore, separate analyses were conducted for each species.

In soybean, yield loss due to delayed sowing date did not differ between the short and long genotypes (MG 3 and 4, respectively) ($p = 0.2948$) (Figure 2.2A). For both soybean

genotypes, the highest mean yields were achieved when the sowing date was on June 20 (2.5 and 2.4 Mg ha⁻¹ for MG 4 and 3, respectively), while the lowest mean yields were obtained at the latest sowing date (0.6 and 1.1 Mg ha⁻¹ for MG 4 and 3, respectively). It should be noted that the MG 3 soybean genotype had more harvestable years than that of MG 4 (28 vs. 14, respectively), and almost twice as many successful years at the latest sowing date (Figure 2.2A). In maize, as in soybean, the yield reduction due to a delay in sowing date did not differ between the short and long genotypes (CRM 100 and 110, respectively) ($p = 0.275$) (Figure 2.2B). In maize i) low harvestable years were obtained at the earliest sowing date for both CRM100 and CRM110, ii) the highest mean yield was simulated when sown on July 10th (6.1 and 5.4 Mg ha⁻¹ for CRM 100 and 110, respectively), iii) yield decreased sharply at the latest sowing date, with more harvestable years for CRM100 (14) than CRM110 (4). It is worth noting that more harvestable years were obtained for soybean than for maize at all sowing dates and that the interannual yield variability was greater for maize than for soybean (coefficients of variation of 111 and 47% for maize and soybean, respectively) (Figure 2.2 A and B).

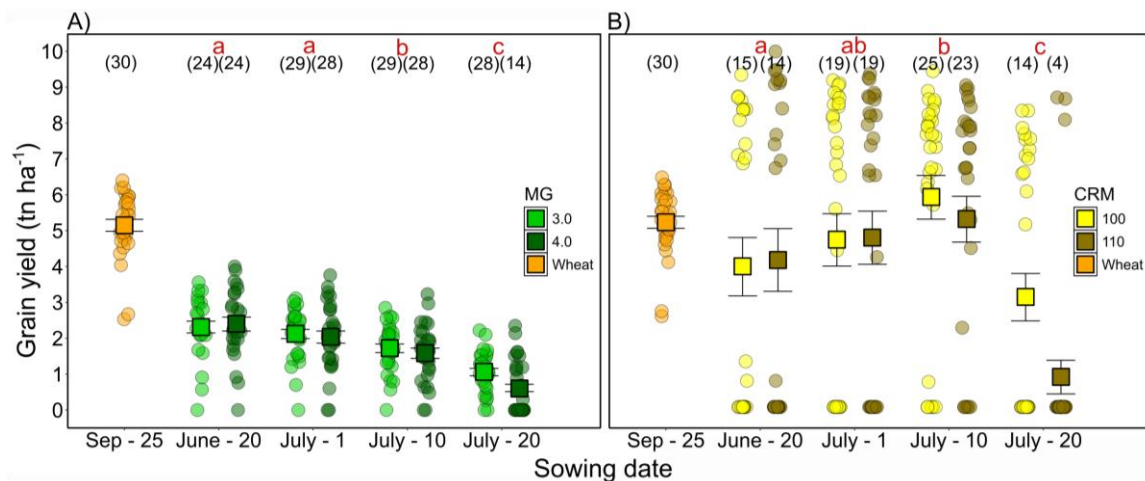


Figure 2.2: Simulated crop dry-basis yield for A) wheat-soybean and B) wheat-maize double-crop systems across different sowing dates. In (A) soybean genotypes correspond to MGs 3 and 4 while in B) maize genotypes correspond to CRMs 100 and 110. Circles represent each simulation year, while large squares represent the mean yield for each sowing date and genotype. Error bars indicate the standard error. Different letters indicate differences between sowing dates across genotypes (at $\alpha = 0.05$). Numbers in parentheses indicate the number of harvestable years for each sowing date and genotype.

2.4.2 Maize and soybean double-crop yield limiting factors: water stress and frost damage

Both summer crops in the double-crop system experienced greater water stress when sown earlier than when sown later (Figure 2.3 A and B). Delaying the sowing date reduced both the intensity (lower water stress factor in Figure 2.3) and duration (time during which the water stress factor was <1) of water stress in maize and soybean (Figure 2.3 A and B). Furthermore, in maize, water stress always overlapped with R1 and at least part of the grain filling period at all sowing dates (Figure 2.3B). In contrast, in soybean, the occurrence of water stress during grain filling decreased as the sowing date was delayed (Figure 2.3A). Overall, soybean experienced less severe water stress than maize. However, within each crop, genotypes reached similar water stress intensity (minimum water stress factor value) for each sowing date (Figure 2.3 A and B). In the worst-case scenario (i.e. the earliest sowing date for both crops), the maximum water stress intensity (lower water stress factor) was ~ 0.7 and 0.9 for soybean genotypes MG 3 and 4, respectively, across the lower and upper yield terciles (Figure 2.3A). In maize, CRM 100 and 110 genotypes reached maximum water stress intensities of 0.6 and 0.55 , respectively, for the lower and upper yield terciles (Figure 2.3B). Moreover, as planting was delayed, the critical period shifted closer to the first frost date (indicated by the dotted line). The first average frost date occurred on October 6th, shortening the interval between R1 in maize and R5 in soybean to the first frost. For crops sown on June 20th, this period was approximately 35 days longer compared to those sown on July 20th.

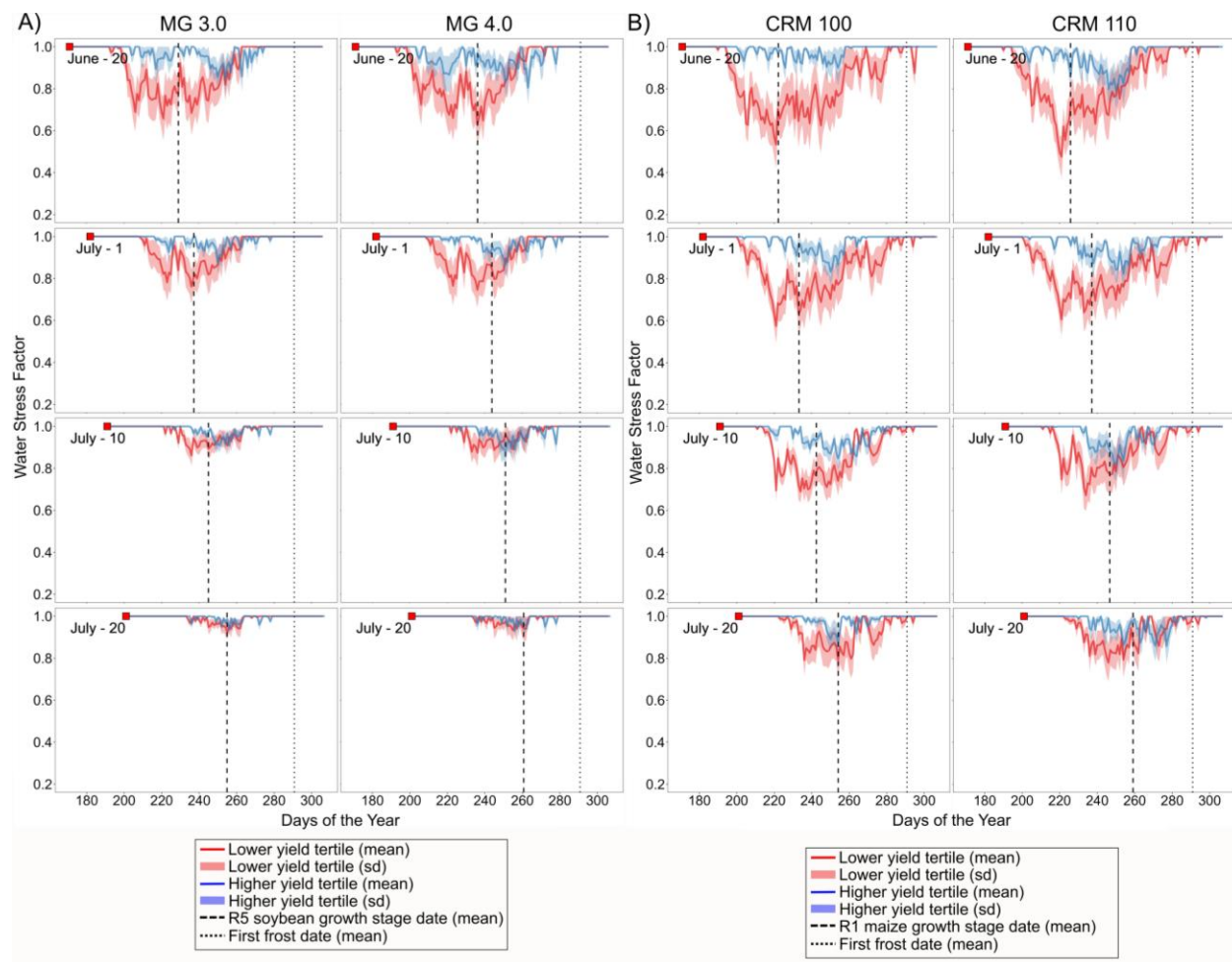


Figure 2.3: Simulated water stress factor (1 = no stress; lower values indicate greater stress) for photosynthesis in soybean A) and maize B) following wheat in double-crop systems across different planting dates and crop cycle length. The red squares indicate the planting date for each genotype. The blue and red solid lines represent the mean daily water stress factor for the upper yield tertile (30% of years with the highest yield) and for the lower yield tertile (30% of years with the lowest yield), respectively. The shaded areas show the standard deviation. The dashed vertical line indicates the average date of the midpoint of the critical period for each crop (R5 in soybean and R1 in maize), while the dotted vertical line indicates the mean first frost date (Minimum temperature of 2 °C) over the last 30 years.

2.4.3 Crop success ratio

After July 1st, summer crops could always be sown after wheat (30 out of 30 years), but their success rate of reaching a harvestable condition varied by crop species and genotype across sowing dates (Table 2.1). Soybean genotypes showed high percentages of harvestable crop condition, exceeding 80% of the years at most sowing dates for both maturity groups, except in the case of MG 4 sown on July 20th, where the harvestable crop condition was 47%. On the

other hand, maize fails to reach harvestable crop condition in more than 80% of the years, reaching a maximum of 80% and 74% for genotypes CRM 100 and 110, respectively, at the July 10th sowing date. The percentage of harvestable crops dropped to 43% (CRM 100) and 10% (CRM 110) for the July 20th sowing date. The cause of crop failures varied between crop species and sowing dates. While early water stress affected maize in ~40% of the years in the earliest sowing dates (June 20th and July 1st), early frost became the more relevant limiting factor at the latest sowing date, reaching 80% and 47% for the CRM 110 and CRM 100 genotypes, respectively, when sown on July 20th. Contrarily, water stress hardly affected the percentage of harvestable crop in soybean (only 3% of the years), but early frost became relevant for MG 4 sown on July 20th (crop failure in 40% of the years). Except for the last planting date, where the short-cycle genotypes achieved twice the harvestable condition in soybean and four times in maize compared to the long-cycle genotypes, harvestable conditions were similar between short- and long-cycle genotypes at all other planting dates (Table 2.1).

Table 2.1: Crop success rate for soybean and maize genotypes as second crops across different sowing dates in a double-cropping system.

Crop	Crop cycle length	Planting date	Effectively sown	Crop failure		Crop failure (total)	Harvestable		Crop harvest (total)
				causes ¹			conditions ²		
				Early water stress	Early frost		No maturity crop (yield)	Crop maturity (yield)	
Soybean	MG 3	June 20	83%	3%	0%	3%	23%	57%	80%
		July 1	100%	3%	0%	3%	63%	34%	97%
		July 10	100%	3%	0%	3%	87%	10%	97%
		July 20	100%	3%	3%	6%	94%	0%	94%
	MG 4	June 20	83%	3%	0%	3%	57%	23%	80%
		July 1	100%	3%	3%	6%	84%	10%	94%
		July 10	100%	3%	3%	6%	94%	0%	94%
		July 20	100%	3%	50%	53%	47%	0%	47%
Maize	CRM	June 20	83%	36%	0%	36%	0%	47%	47%
	100	July 1	100%	40%	0%	40%	17%	43%	60%

	July 10	100%	20%	0%	20%	67%	13%	80%
	July 20	100%	13%	44%	57%	43%	0%	43%
	June 20	83%	40%	0%	40%	3%	40%	43%
CRM	July 1	100%	40%	0%	40%	40%	20%	60%
110	July 10	100%	23%	3%	26%	67%	7%	74%
	July 20	100%	13%	77%	90%	10%	0%	10%

1 Crop failure causes include early water stress (preventing establishment) and early frost (interrupting grain filling before 50%), with total crop failure representing their sum.

2 Harvestable conditions are defined as years in which the crop reached at least 50% of the thermal time for effective grain filling. The total harvestable percentage results from the sum of no maturity crop with yield (frost occurring after this threshold), and crop maturity with yield (crops reaching full physiological maturity before harvest), minus crop failure cases.

2.4.4 Land equivalent ratio

The LER was greater than 1 in most years for most crop combinations, crop cycle lengths and sowing dates (Figure 2.4). In addition, more than 50% of the cases exceeded an LER of 1.5, except for the maize genotypes CRM 100 and 110 and the soybean genotype MG 4 sown at the latest sowing date (July 20th) (Figure 2.4). In the soybean double cropping systems, LER decreased with later soybean sowing dates, as reflected by the leftward shift of the distributions. The median LER of the MG 3 changed from 2 on June 20th to 1.5 on July 20th and from 2.1 to 1.1 in the MG 4 soybean genotype. For the mid tercile of the maize double-cropping system did not show a clear pattern across planting dates as in soybean. The July 10th sowing date consistently presented higher LER values with a median of 1.9 and 1.8 for the CRM 100 and 110 maize genotypes, respectively. For the other terciles LERs did not show a clear pattern across planting dates. In three out of four years, the LER obtained for maize was lower than that obtained for soybean (Figure 2.4).

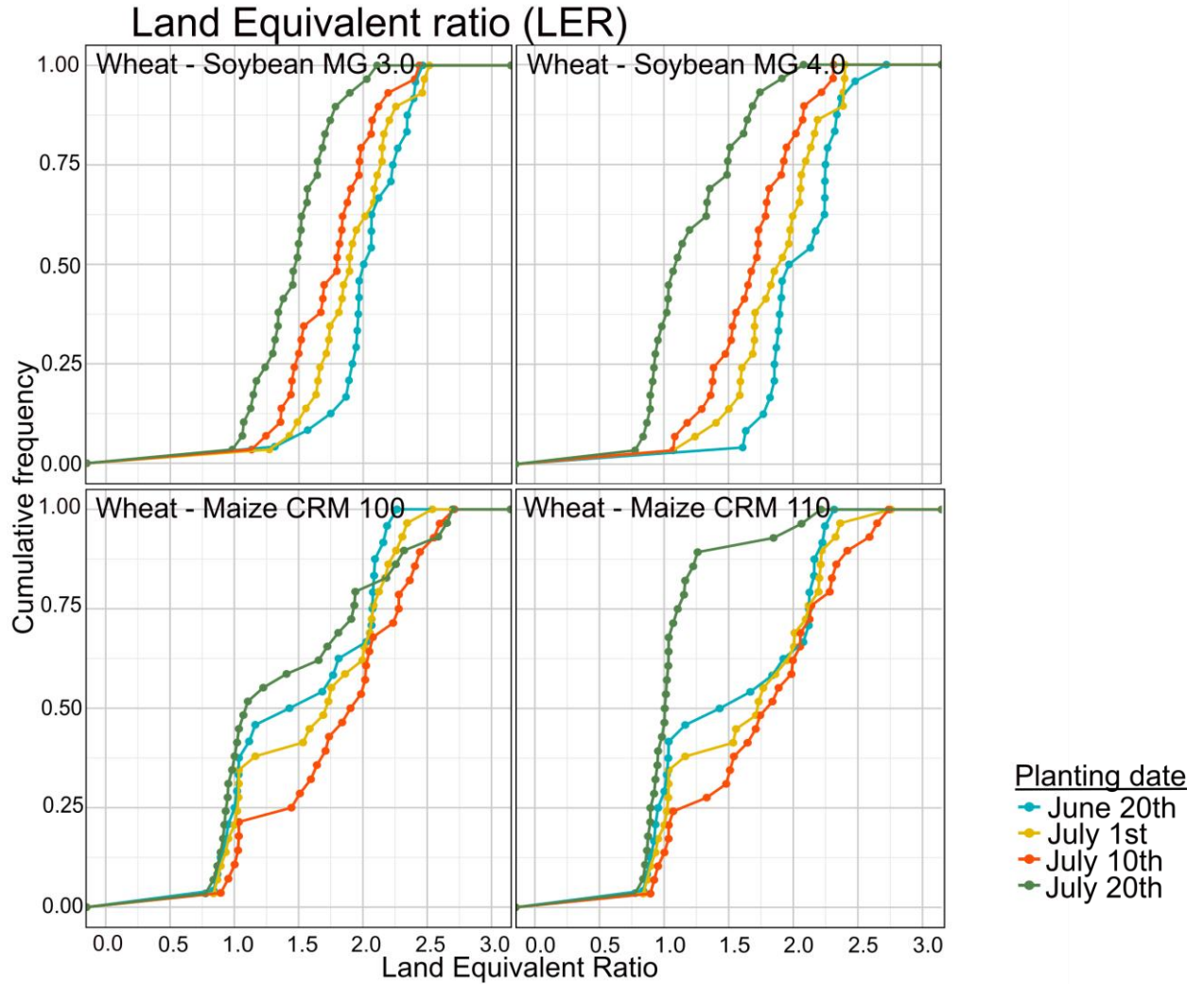


Figure 2.4: Cumulative frequency distributions of the Land Equivalent Ratio (LER) for different double cropping systems: wheat-soybean (left panel), A) MG 3 B) MG 4, wheat-maize (right panel), C) CRM 100 , and D) CRM 110. Blue, yellow, red, and green lines correspond to the sowing dates June 20th, July 1st, July 10th, and July 20th, respectively.

2.4.5 Economic analysis

Double cropping systems had higher mean gross margins than monocrops (Figure 2.5). Wheat-soybean showed the highest mean value (1,146 USD ha⁻¹) followed by wheat-maize (891 USD ha⁻¹), soybean monocrop (541 USD ha⁻¹), maize monocrop (531 USD ha⁻¹), and lastly wheat monocrop (750 USD ha⁻¹) ($p < 0.01$). Double crop wheat-soybean margins decreased as the planting date was delayed in both maturity groups. The median gross margin decreased from 1,385 USD ha⁻¹ on June 20th to 620 USD ha⁻¹ on July 20th, and from 1,450 USD ha⁻¹ to 828 USD

ha⁻¹ in MG 4 and 3, respectively. In the case of double crop wheat-maize, the best performance was observed on July 10th, with a median of 1,260 USD ha⁻¹ for CRM 110 and 1,427 USD ha⁻¹ for CRM 100. The worst performance occurred when maize was planted on July 20th, with a median margin of only 93 USD ha⁻¹ and 141 USD ha⁻¹ for CRM 110 and 100, respectively.

The wheat-soybean double cropping systems consistently showed lower variability in economic margins than the wheat-maize systems. The interquartile range (the difference between Q75 and Q25) of the gross margin was lower for both soybean maturity groups compared to maize, except for CRM 110 maize sown on July 20th, which had the lowest variability but extremely low margins.

Low gross margins (Q25) were consistently higher for soybean than for maize across all sowing dates and maturity groups, except for the CRM 100 maize sown on July 10th. The Q25 margins for all sowing dates and maturity groups were above 420 USD ha⁻¹, with a minimum average of 306 USD ha⁻¹. In comparison, the wheat-maize double crop had a lower minimum average (-259 USD ha⁻¹), with Q25 values starting at 302 USD ha⁻¹. Conversely, the double-cropped wheat-maize had the highest maximum economic margins. The Q75 average across all planting dates and both genotypes were 1,420 USD ha⁻¹, with 1,295 USD ha⁻¹ for CRM 110 and 1,546 USD ha⁻¹ for CRM 100. The average maximum economic margin across all sowing dates was 1,876 USD ha⁻¹ for the maize double crop, with maximum values reaching 1,903 USD ha⁻¹ for CRM 110 and 1,848 USD ha⁻¹ for CRM 100. In both maize and soybean double cropping systems, the longest genotypes (CRM 110 for maize and MG 4 for soybean) achieved the highest maximum margins.

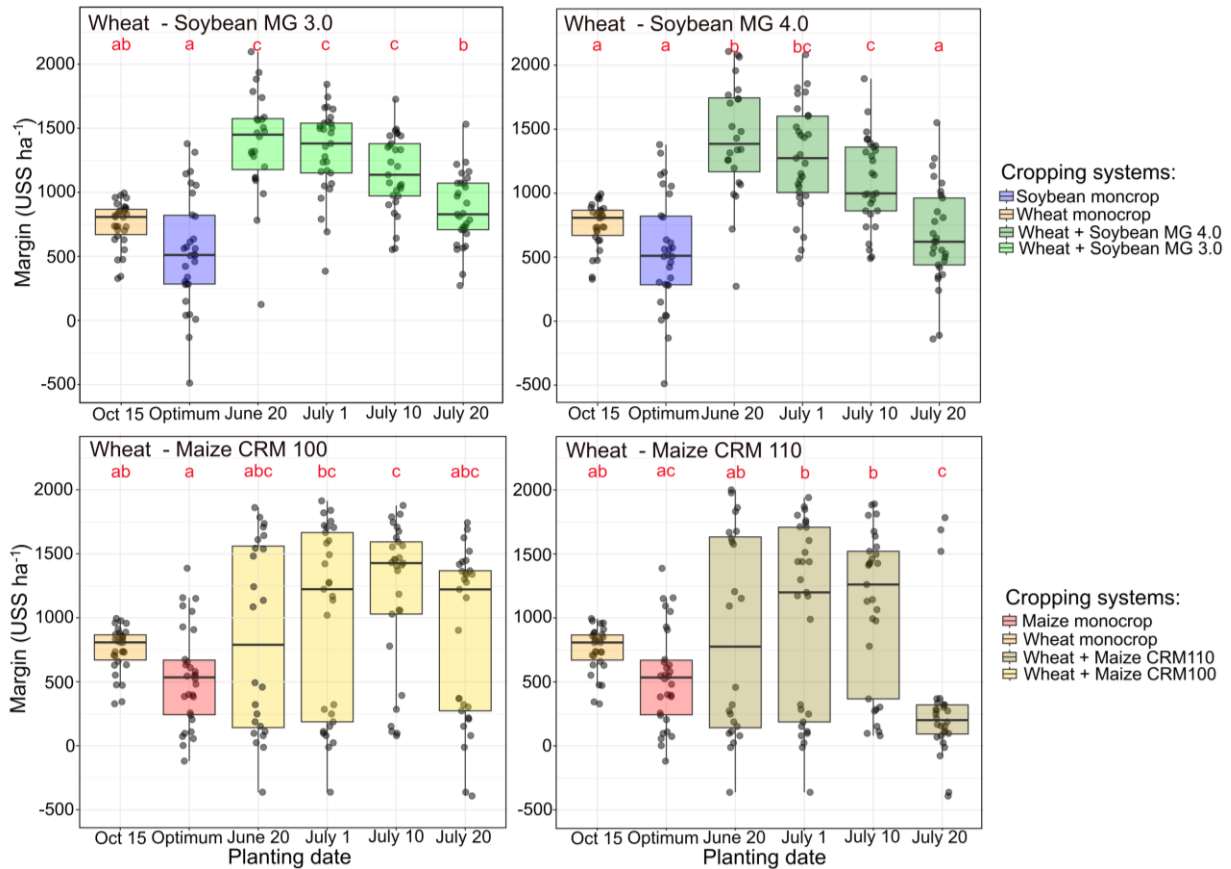


Figure 2.5: *Economic margin (US\$ ha⁻¹) for different cropping systems across sowing dates. Panels show double-crop combinations: A) Wheat – Soybean MG 3.0, B) Wheat – Soybean MG 4.0, C) Wheat – Maize CRM 100, and D) Wheat – Maize CRM 110 separately due to significant interaction crop and genotype for double cropping systems. Boxplots display margin distributions, with black dots representing individual data points. Red letters indicate mean comparisons within each sowing date for a given genotype × summer crop species combination, including monocrop wheat, monocrop maize or soybean, and double-crop systems.*

2.5 Discussion

This study provides new insights utilizing an in-silico approach to investigate the feasibility of crop intensification from rainfed wheat-based monocropping to double cropping systems. This study focused on the wheat-maize (versus wheat-soybeans) double cropping system and compared them across a wide range of sowing dates and varying summer crop cycle lengths. Beyond simulated grain yield performance, we examined LER and economic feasibility to explore how planting date, crop species, and genotype combinations respond to limiting

factor. These insights contribute to refining double-crop strategies and advancing sustainable intensification in wheat-based systems.

From the land use perspective, Caviglia et al. (2011) reported similar LER results for the wheat-soybean sequence in the Pampas of Argentina, with those values ranging from 1.58 to 1.82 using MG 3 soybeans. Although some studies did not explicitly report LER, their productivity comparisons support our findings. For example, in a global review, Santos Hansel et al. (2019) observed that double-cropped soybean after winter wheat yielded 61% of the full-season soybean yield. Similarly, Kyei-Boahen & Zhang (2006) reported a slightly higher relative yield of 60–90% in the Mid-South USA. For wheat–maize cropping systems, studies from other temperate regions, such as the Argentine Pampas and northwest Italy, suggest similar yield penalties maize as double crop compared to full-season maize, although LER was not explicitly reported. In our study, double-cropped maize yielded 50–60% of the monocropped maize. Mercau & Otegui (2015) reported that maize double-cropped after wheat compared with monocropped maize sown at the same date yielded 14–47% less. Similarly, Blandino et al. (2023) observed that maize double-cropped after wheat in north-western Italy yielded 47% less than monocropped maize.

Double-cropped summer crops are sown later than full-season crops, often under conditions of reduced available resources (Blandino et al., 2023; Santos Hansel et al., 2019; Caviglia et al., 2011). In soybean, delayed sowing shortens the growth cycle due to photoperiod sensitivity (Egli & Bruening, 2003) and increases the risk of early autumn frosts during seed filling (Seifert & Lobell, 2015; Calviño et al., 2003). As a result, the crop has less time to accumulate biomass and produce seed because radiation capture is reduced by the compressed growing season (Egli, 2011). In maize, delayed sowing date from spring to early summer shifts maize grain-filling period into a phase of progressively declining photo-thermal conditions (Bonelli et al., 2016), but can be counterbalanced by reduced water constraints around flowering (Maddonni, 2012). In our study, the earliest planting date of maize in double-cropping system after wheat had high water stress values during late vegetative stages and flowering, affecting simulated leaf expansion, radiation interception and grain yield as was reported in manipulative experiments (Çakir, 2004). Particularly, water stress around flowering results in high spikelet abortion due to poor synchrony between pollen shed and silk exposure (Otegui et al., 1995), reduced pollen production (Hall et al., 1982), slower silk elongation (Westgate & Boyer, 1985b)

and disruption of reproductive development (Westgate & Boyer, n.d., 1985a), leading to drastic penalties in crop yield as was simulated for early sowings. The highest mean yields, with higher crop success rates were simulated when maize was sown on July 10th (6.1 and 5.4 Mg ha⁻¹ for CRM 100 and 110, respectively), due to lower water constraints determined by a longer fallow period.

In the Central Great Plains region of the US, wheat monocropping is often used as a risk-mitigating strategy. Moderately risk-averse farmers favor wheat-based rotations, and more risk-averse farmers focused on winter wheat monocropping (Williams et al., 2000). Among double-cropping strategies, the wheat-soybean system was the most stable, with consistently higher minimum margins, consistent with findings from the southeastern Great Plains (Kyei-Boahen & Zhang, 2006). Conversely, wheat–maize cropping systems exhibited greater yield and economic margin variability, including potential economic losses due to crop failure. However, for the July 10th and July 20th sowing dates, wheat–maize achieved the highest upper quantile economic margins, particularly for the shortest cycle length maize genotype, suggesting that while wheat–maize carries greater financial risk, it also offers greater profit potential under optimal conditions.

While our findings provide valuable insights, certain limitations must be acknowledged. Although this study was based on simulations, a fundamental step in testing the productive and economic feasibility of a cropping system, these need to be verified through field experiments. On the other hand, the economic margin calculations did not consider several potential outputs, such as crop insurance, government subsidies, or market fluctuations, which could affect profitability. In particular, wheat-maize double-cropping systems face higher climate-related risks, as evidenced by high crop failure rates in maize, making their success more dependent on seasonal conditions and management strategies.

2.6 Conclusion

This study highlights the potential of double-cropping systems to intensify wheat-based production in the U.S. Central Great Plains. Simulations demonstrated that wheat-soybean systems consistently outperformed wheat-maize in terms of stability, crop success rates, and economic margins. Early planting dates maximized yield but increased water stress, while later sowings improved establishment but heightened frost risk. Soybean showed greater resilience,

achieving higher harvestable rates across planting dates, whereas maize exhibited greater variability and risk. The land equivalent ratio (LER) exceeded 1.5 in most years, indicating superior land use efficiency in double-cropping systems compared to monocropping. Economic analysis reinforced wheat-soybean double crop as the most stable and profitable option, though wheat-maize provided higher margins under optimal conditions. These results underscore the importance of crop selection, planting date, and cycle length to balance productivity, risk, and profitability. Future research should validate these findings through field trials to refine double-crop strategies under real-world conditions.

Chapter 3 - Environmental characterization for rainfed maize production in the US Great Plains region

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3.1 Abstract

Identifying regions with similar productivity and yield-limiting climatic factors enables the design of tailored strategies for rainfed maize (*Zea mays L.*) production in vulnerable environments. Within the United States (US), the Great Plains region is susceptible to weather fluctuations, particularly in Kansas, where rainfed maize production is a significant agricultural activity. This study aims to delimit environmental regions with similar crop growth conditions and to identify the main climatic factors limiting rainfed maize yield, using the state of Kansas as a case study. For this purpose, databases encompassing the period from 1993 to 2021 period, including NOAA weather station data (n = 208), USDA county maize yield data, and crop phenology reports at the agricultural district scale, were compiled for analysis. Four periods based on crop phenology data were defined: fallow period, vegetative period, critical period around flowering (± 15 days), and grain filling period, each with reported climatic variables. A Fuzzy c-means clustering algorithm identified ten productive regions. Grain yields range from ~ 3500 to ~ 7500 kg ha⁻¹, spanning South-West to North-East regions. Within each region, correlation analysis was carried out between detrended yields and climatic anomalies to identify the most relevant seasonal climatic factors over 29 years. Extreme degree days (i.e., accumulating maximum air temperature above 35 °C) and vapor pressure deficit during the critical period are the main climatic drivers of rainfed maize yield across regions. In Kansas, extreme degree days exhibit a west-to-east and south-to-north increase. Yield decreased by 46 kg ha⁻¹ per °Cd of extreme degree days during the critical period across regions, with maximum yield penalty in the south-east region. This methodology contributes to the knowledge of the most relevant climatic drivers of rainfed maize, with the potential for application in other regions for the development of adaptive management strategies and policies.

3.2 Introduction

Maize (*Zea mays* L.) is one of the most widely cultivated grain crops, with 205 M ha harvested area globally and more than 34.5 M ha in the United States (US) during the 2021 season (FAO, 2023). In the US, 85% of the total maize production is concentrated in the Corn Belt region (USDA-NASS, 2019). Within the Central Great Plains region, Kansas is ranked as the seventh largest state for maize production nationwide. Within the state, 72% of the maize area is produced without irrigation (USDA-NASS, 2018; Lanning-Rush, 2016), thus increasing its risk of drought (Zambreski, 2016) and climate variability (Anderson et al., 2016). Maize productivity varies from western to eastern Kansas, roughly ranging from 4100 to 7300 kg ha⁻¹ under rainfed conditions from 1993 to 2021 period (USDA-RMA: United States Department of Agriculture Risk Management Agency, 2023). This spatial variation is closely aligned with the precipitation pattern observed in the region (Goodin, 1995). Although radiation and temperature defines the potential productivity of the crop, water supply imposes an upper limit for rainfed crop grain yield (Van Ittersum & Rabbinge, 1997). Through these conditions, climate exerts considerable control over actual yields, with maize having a larger sensitivity compared to other summer crops (Lobell & Field, 2007). Furthermore, the vulnerability of maize, in terms of yield, to extreme climatic conditions varies according to the ontogenic stage of the crop (Kiniry & Ritchie, 1985). It defines the stage around flowering (R1, Ritchie (2005)) as the most susceptible to yield reductions (i.e., critical period) due to the definition of the number of kernels per unit area (Otegui & Bonhomme, 1998). In Kansas cropping systems, maize flowering usually occurs during early July (USDA-NASS, 2022), which coincides with the period of highest atmospheric water demand (M. S. Kukal & Irmak, 2023). Furthermore, this stressful condition related to high temperatures may continue during the grain filling period and can affect grain weight and several intrinsic attributes of maize kernels related to hardness (Mayer et al., 2014, 2019) relevant to obtain valuable end-use products. Thus, understanding the main climatic factors influencing maize productivity is required to develop climate adaptative strategies for sustainable food production (Asseng et al., 2009).

Given the state of large climate variability in Kansas, it is advantageous to focus on regions with similar agroecological characteristics in order to identify yield-limiting climatic conditions that affect crop yields (Bailey, 2009; Mourtzinis et al., 2020; Omernik, 1995; Sivakumar & Valentin, 1997; Waltman et al., 1999). In addition, examining historical trends in

crop yields and climatic variables across spatial and temporal scales helps to understand the main factors underpinning yield formation and the timing of their impact (Lu et al., 2017). This analysis identifies the primary drivers of grain yield variability across regions and also determines which regions experience high year-to-year fluctuations in crop production due to weather extremes (Ben-Ari & Makowski, 2016; M. S. Kukal & Irmak, 2018; Leng et al., 2016). Furthermore, evaluating the impact of climatic variables focusing on crop vegetative and reproductive periods has greater explanatory capacity (Ye et al., 2017;Çakir, 2004). These approaches help to understand the interaction between climatic variables and crop yields with a probabilistic approach (Giménez et al., 2018; Maddonni, 2012). Consequently, it allows the development of management strategies that are tailored to the specific realities of each area (Rattalino Edreira et al., 2018).

Extensive studies have been focused on US environmental characterization (Lobell et al., 2013, 2014; Löffler et al., 2005; Rattalino Edreira et al., 2018; Seifert et al., 2017). The improvement of maize varieties for cultivation in drought-prone environments provides a clear illustration of the US targeting of selection in breeding programs with the objective of enhancing water use efficiency (Cooper et al., 2014; Gaffney et al., 2015; Messina et al., 2018, 2009). In a different approach, Munaro et al. (2020) used variance component analysis and conditional inference trees to explore the interaction of winter wheat (*Triticum aestivum* L.) variety traits with management for the US Great Plains region. Recently, Couëdel et al., (2021) proposed a method to characterize environments for maize, soybean (*Glycine max* L.), and wheat crops based on a static spatial framework and using simulated data to obtain the frequency of environment types.

This study aims to develop a comprehensive environmental characterization approach using historical climatic variables, crop phenology, and grain yield data of rainfed maize crops from 1993-2021 period to i) delimit maize productive regions for the state of Kansas, and ii) identify the most relevant climatic variables limiting rainfed maize yields within each productive region outlined in i).

3.3 Materials and Methods

The methodology employed in this study, encompassing data collection, integration of climate and phenology variables, determination of regions based on productivity and weather

patterns, and subsequent analyses, is comprehensively summarized in the conceptual workflow (Figure 3.1).

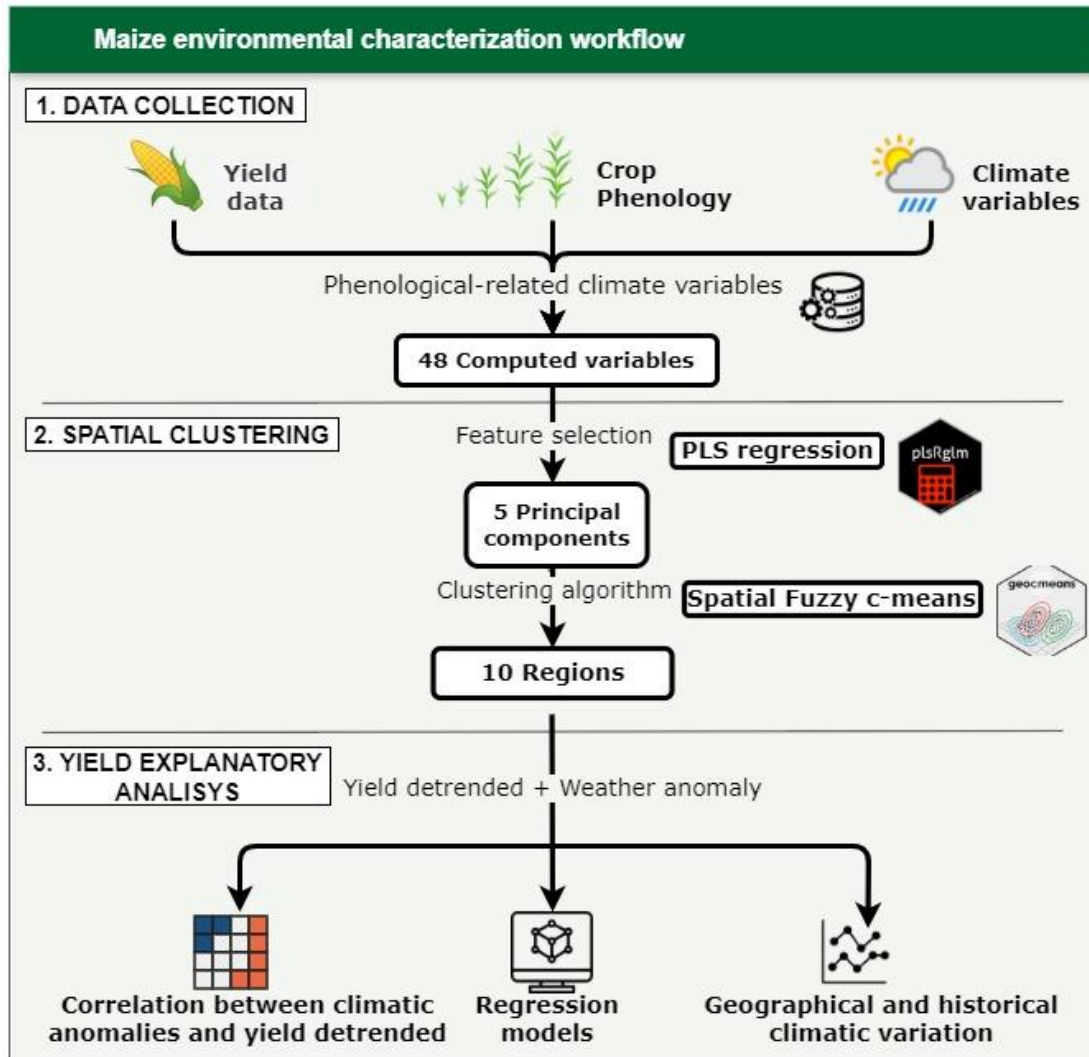


Figure 3.1: Conceptual workflow of the overall data collection, processing, and analysis for the characterization of rainfed maize environments in Kansas, US. The process is dissected in three sections, 1. Data Collection, 2. Spatial Clustering, and 3. Yield Explanatory Analysis.

3.3.1 Data Collection

3.3.1.1 Historical climate variables

The focus of this work was the state of Kansas, in the Central Great Plains region of the United States for the period between 1993 and 2021. Kansas State is characterized by a continental climate, with average temperatures ranging from 0 °C in January to 26 °C in July and

a West-East precipitation gradient from 500 to 950 mm yr⁻¹, concentrated in late spring and summer (Goodin, 1995). The frost-free period also presents a West-East gradient, ranging from ~155 to ~205 days; respectively. As latitude increases, the annual average daily solar radiation decreases (17 to 15.7 MJ m⁻² day⁻¹).

Daily climate data (Table 3.1) were obtained from the Global Historical Climatology Network (GHCNd) (Chamberlain & Hocking, 2023). The US component of GHCNd is an integrated version of the National Centers for Environmental Information (NCEI or NOAA) daily surface observations, including the US Cooperative Observer Network, the Automated Surface Observing System, and other observing systems. This study involved 208 long-term weather stations across the state of Kansas, covering data from the 29 agricultural growing seasons studied. Considering the inclusion of the preceding fallow period, the weather data spanned from September 28, 1992, to December 31, 2021. The weather stations were selected based on data availability and station continuity (Figure B.1). Daily minimum (Tmin) and maximum (Tmax) temperature and precipitation were retrieved from those weather stations. The coordinates of the selected weather stations were employed to obtain solar radiation, and relative humidity daily data from NASA-POWER (Sparks, 2018). Daily Evapotranspiration (ET_o) was computed using the Hargreaves and Samani (1985) methodology detailed in Correndo et al., (2021). This method relies on temperature data and requires critical coefficients: the solar constant provided by Cobaner et al., (2017) and a radiation adjustment coefficient (Samani, 2004). Furthermore, the vapor pressure deficit (VPD) was calculated using daily air temperature and daily relative humidity data from NASA as detailed by Correndo et al., (2021) rather than hourly data. A previous comparison between daily and hourly data for this calculation revealed only a small difference, with an RRMSE of 0.08 (Figure B.2). Daily thermal amplitude and frost-day (days with minimum temperatures (Tmin) lower than 2°C; Miedema et al., (1987) were calculated. Furthermore, the occurrence of heat stress was computed by accumulating maximum air temperature above 35 °C (Commuri & Jones, 2001; Berry & Bjorkman, 1980). Hereafter, this variable is referred to as extreme degree days (EDD).

Table 3.1: Descriptions of climate, phenology, and maize grain yield data sources, variables, frequency of determination, and spatial resolution of those factors used in the overall analysis.

Type	Source	Variables	Frequency Spatial resolution
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Climate	Global Historical Climatology Network daily (GHCNd)	Minimum Temperature Maximum Temperature Precipitation	Daily	Stations
	NASA-POWER	Radiation Relative humidity		50km x 50km
	USDA NASS Crop Progress Reports (NASS-CPR)	Planting, seedling emergence (VE), silking stage (R1), physiological maturity (R6), and harvest date.	Weekly	Agricultural statistic district
Maize grain yield	USDA, Risk Management Agency (RMA)	Maize yield	Yearly	County
	USDA, National Agriculture Statistics Service (NASS)	Maize yield		County

3.3.1.2 Crop phenology

The crop phenology data were obtained from the National Agriculture Statistics Service Crop Progress Reports (NASS-CPR) of the US Department of Agriculture (USDA) published weekly at the Agricultural statistic district level accessible at https://www.nass.usda.gov/Statistics_by_State/Kansas/Publications/Crop_Progress_and_Condition/index.php (Table 3.1). During the crop season, NASS reports crop phenology progress weekly as the percentage of maize planted area in planting date, seedling emergence (VE), silking stage (R1), kernel dough stage (R4), kernel dent stage (R5), physiological maturity (R6), and harvest. Crop stages were defined as described in Ritchie (2005). For this study, the dates of occurrence of planting, VE, R1, R6, and harvest were recorded when the crop advance reached 50% progress in each district. The VE for all districts was missing from 1993 to 1997. This gap was estimated employing a thermal time (TT) model (Ritchie & Nesmith, 2015):

$$TT (^{\circ}Cd) = \sum(Tm - Tb), \quad (3.1)$$

where Tm is the mean air temperature of a day (the average of the minimum and the maximum air temperature), and Tb is the base temperature. The emergence date was determined when TT from the planting date was ca. 100 $^{\circ}Cd$ with a base temperature of 10 $^{\circ}C$ (Padilla et al., 2004).

Lastly, to account for potential frost damage, the occurrence of $Tmin$ below 2 $^{\circ}C$ after the estimated seventh leaf (V7) stage onwards was considered detrimental to maize productivity (Maddonni, 2012). Since the USDA-NASS CPR does not report the V7 stage, days to reach V7 from emergence were calculated from TT required to expand seven leaves estimated from the phyllochron (41.5 $^{\circ}Cd$ leaf $^{-1}$), mean air temperature and a Tb of 8 $^{\circ}C$ (Otegui & Melón, 1997).

3.3.1.3 Yield data

Data of non-irrigated maize grain yields in the state of Kansas for the period ranging from 1993 to 2021 were obtained from distinct units within the USDA, the Risk Management Agency (RMA) accessible at <https://webapp.rma.usda.gov/apps/RIRS/AreaPlanHistoricalYields.aspx> and the NASS (<https://quickstats.nass.usda.gov/>) (Table 3.1). Both data sources reported annual maize yields at the county level, with RMA reporting maize yields in more counties compared to NASS (Zulauf et al., 2016). Therefore, we designated RMA as the primary data source for maize yield, while NASS was employed to fill data gaps (or identify outliers) occurring between 1993 and 1997 period. The maize yield data derived from RMA presented an overestimation close to 25% relative to yield data from NASS (72% remained, Figure B.3). A model to estimate RMA maize yield was performed using NASS yield and the county-year interaction as explanatory variables (Figure B.4). The predictions resulting from this model were employed to fill the missing data gap.

3.3.1.4 Phenological-related climate variables

Climatic variables were computed for different maize periods to evaluate their impact on grain yield (Table 3.2). Four periods based on phenology data were defined: fallow period, vegetative period, critical period, and grain filling period. The fallow period involved the time elapsed from the harvest of the previous crop to maize sowing in the next season. The vegetative crop period spanned from emergence (VE) to 15 days before R1. The critical period was defined

as ± 15 days around R1 (Otegui & Bonhomme, 1998). Lastly, the grain filling period encompassed from 15 days after R1 to R6. All data entries were spatially adjusted to the sites of the NOAA's weather stations and temporally to annual steps standardize for both spatio-temporal resolutions.

Table 3.2: Description of the variables employed in this study, created by the convergence between climate and crop phenology.

Variable	Period	Acronym	Description	Unit
Radiation (RD)	Vegetative	RD_VEG	Accumulated solar radiation	MJ m ⁻²
	Critical period	RD_CP		
	Grain filling	RD_GF		
	Whole crop cycle	RD_CS		
Precipitation (PP)	Vegetative	PP_VEG	Accumulated rainfall precipitation	mm
	Critical period	PP_CP		
	Grain filling	PP_GF		
	Fallow period	PP_FP		
Reference evapotranspiration (ET0)	Vegetative	ET0_VEG	Average reference evapotranspiration	mm day ⁻¹
	Critical period	ET0_CP		
	Grain filling	ET0_GF		
Vapor pressure deficit (VPD)	Vegetative	VPD_VEG	Average daily vapor deficit pressure	kPa
	Critical period	VPD_CP		
	Grain filling	VPD_GF		
Extreme degree days (EDD)	Vegetative	EDD_VEG	°C accumulated over 35 °C	°Cd
	Critical period	EDD_CP		
	Grain filling	EDD_GF		
Daily thermal amplitude (DTA)	Vegetative	DTA_VEG	Daily difference between Tmin and Tmax	°C
	Critical period	DTA_CP		
	Grain filling	DTA_GF		
Growing degree days post emergence	Whole crop cycle	GDD_postemergence	Growing degree days accumulated from emergence to physiological maturity (R6) above 8 °C.	days

Accumulated days from planting to emergence	Vegetative	days_to_emergence	Accumulated days from sowing to emergence	days
Frost free period	Vegetative	frost_free_days	Number of days of the period between the last occurrence of min < 2°C in spring and the first occurrence of Tmin < 2°C in the subsequent fall.	days
Frost early days	Reproductive	FE_days	Number of days with Tmin < 2°C from V7 to R1	days
Frost late days	Frost late days	FL_days	Number of days with Tmin < 2°C from R1 to R6	days

Note: Vegetative period (VEG); Critical period (CP); Grain filling period (GF); Crop cycle (CP); Fallow period (FP).

3.3.2 Spatial Clustering

3.3.2.1 Feature reduction

Each climatic variable was condensed through two measurements per site: mean and standard deviations of historical data. Due to the substantial number of variables (mean and standard deviation of 24 variables = 48), a dimensionality reduction was performed (Córdoba, 2014; Hernández et al., 2021). For this purpose, a Partial Least Squares regression (PLSr) was applied using the *pls* R-Package (Liland et al., 2023). The PLSr is a multivariate statistical technique that combines features of principal component analysis (PCA) and multiple linear regression. It aims to find the latent factors, known as components, that best explain the covariance between the predictor variables (variables listed in Table 3.2) and the response variable (maize yield). By utilizing these components, PLSr effectively reduces the dimensionality of the data while retaining the essential information for predictive modeling (Maitra & Yan, 2008). For the PLSr model, five components were selected, which explained 76% of the variation, and presented a root mean square error of prediction of 0.33.

The variable importance in projection (VIP) scores of the model were calculated employing the *plsVarSel* R-package (Mehmood et al., 2012). The VIP scores quantified the relative importance

of the predictor variables in explaining the variability in the response variable (maize yield), across all model dimensions (Figure B.5).

3.3.2.1 Clustering algorithm

Spatial datasets have intrinsic characteristics, such as spatial autocorrelation and spatial heterogeneity, that must be considered. Therefore, a spatial weighting matrix was constructed based on a distance threshold of 55 km to define spatial relationships between data points. The minimum distance to ensure each data point had at least one neighbor within this range. This step was carried out employing *spdep* R-package (Pebesma & Bivand, 2023).

The sites were grouped into regions with similar yields explained by climate variables using the spatial fuzzy c-means (FCM) clustering algorithm (Bezdek et al., 1984), with the *Geocmeans* R-package (Gelb & Apparicio, 2021). The final number of clusters chosen for regionalization was 10, based on the Xie-Beni and Fukuyama-Sugeno index (Figure B.6).

3.3.3 Yield explanatory analysis

3.3.3.1 Yield detrending

Detrending is the process of eliminating the trend from a time series. In this work, the method was employed to remove the effects of non-climatic variables on maize yields, such as non-stationary changes progressively with the time of genetic improvements, and management practices (Lobell, 2007; Lobell & Field, 2007; Tao et al., 2008; Zhang et al., 2015). This study carried out the detrending per site (weather station) using *pracma* R-package (Brochers, 2022). This function calculates the difference between the data and a straight line, or a composite line fitted to the relationship between grain yields and years by least-squares to the data.

3.3.3.2 Climatic anomalies

In each region, climatic variable anomalies of each year were calculated at the county level according to the following equation:

$$a(t) = w(t) - \bar{w}(t), \quad (3.2)$$

where $a(t)$ represents the anomaly in the year t , $w(t)$ represents the value of the variable for the year t , and $\bar{w}(t)$ the mean value of the variable from weather stations within a county for 29

years. If $a(t) > 0$, then the value in year t is higher than average, while $a(t) < 0$ represents a value in year t lower than the average.

3.3.3.3 Correlation analysis

A correlation analysis was conducted to examine the relationships between anomalies of climatic variables at different maize stages and detrended yields within each region. Specifically, the Pearson correlation coefficient (r) and p-values for these correlations were computed using the 'rcorr' function from the *Hmisc* R-package (Harrell, 2023). Subsequently, the results were visualized as a heat map, allowing for comparisons between climatic variables at different crop stages, and their geographical locations to determine their associations with grain yield. This analysis considered the average of all the weather stations within a county. Each county was considered a repetition within each region. Finally, the variable with the highest correlation coefficient (r) value were selected per region to continue with the analysis.

3.3.3.4 Regression models

For each region, linear and linear-plateau models were employed to elucidate the association between detrended yields and the most highly correlated climatic variable. These models were individually fitted and subsequently chosen based on the F-test in ANOVA. Additionally, to compare the response of detrended grain yield to the same climatic variable across regions, the slope and intercept values of the fitted linear functions were compared using the *emmeans* (Lenth, 2022). Besides, to facilitate comparisons among regions, the response of detrended grain yield to climatic variables was expressed as a percentage based on the mean regional detrended yields.

3.3.3.5 Geographical and Historical Climatic Variations

A distribution map of the climatic variable that exhibited the highest overall correlation with grain yields was constructed using the *ggvoronoi* package (Garrett et al., 2018) to enhance comprehension of the factors most strongly linked to maize yield. Additionally, the historical variation of those variables was examined by analyzing their annual anomalies relative to the region-specific adjusted mean. The analysis evaluates potential trends, such as increases,

decreases, or cyclic behavior, and whether these variables displayed similar patterns across the different environments.

3.4 Results

3.4.1 Environmental characterization

The clustering process defined ten distinct regions for rainfed maize production in Kansas (Figure 3.2), showing the variation in crop productivity by specific climatic variables within each region. Mean maize grain yield and climatic variables of the regions are compared in Table 3.3. Grain yields spanned from a minimum of $\sim 3500 \text{ kg ha}^{-1}$ to a maximum of $\sim 7500 \text{ kg ha}^{-1}$, from the southwest to the northeast regions. The frost-free period was longer in southern and eastern regions than in northern and western regions, with the longest period (186 days) in the southeastern region and the shortest period (153 days) in the northwestern region. Annual precipitation also showed a perceptible increase from West to East, ranging from 495 mm in the southwest to 1132 mm in the southeast, and this is replicated during the maize growing season. In contrast, the highest mean temperature during maize seasons was estimated in the southeast region (22.1°C) and the lowest (19.9°C) towards the northwestern. Similarly, daily solar radiation during the maize growing season decreased from the southeast ($18 \text{ MJ m}^{-2} \text{ day}^{-1}$) to the northwest ($16 \text{ MJ m}^{-2} \text{ day}^{-1}$) region.

Additionally, dates of planting and silking stage occurred earlier in the East regions than in the other regions. These dates, in turn, remained mostly the same in the central regions during the study period (Figure B.7). In the eastern regions, both dates were shifted earlier (i.e., early sowing), where in the western regions the planting date was delayed without affecting the flowering date, suggesting a shift to a shorter maize vegetative period.

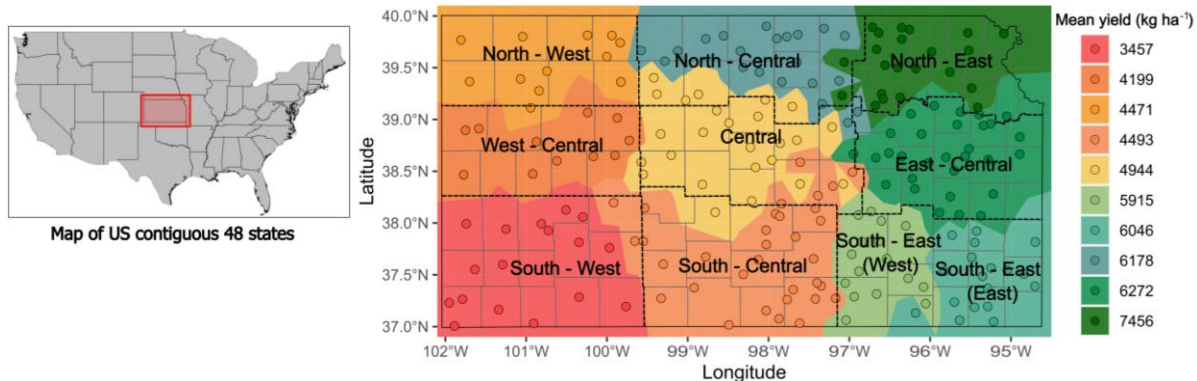


Figure 3.2: Delineation map of ten environmental regions for rainfed maize cultivation in the state of Kansas, US. NOAA weather stations (solid circles), county boundaries (grey line), and Agricultural statistic districts (dashed line) are inserted. Colors indicate varying maize productivity levels across the state.

Table 3.3: Grain yield (kg ha⁻¹), climatic conditions (mean of 29 years), and mean dates of crop phenology of 10 regions for rainfed maize production in Kansas described in Fig. 1. Region data were presented in descending order of average maize yields. Climatic conditions: frost-free period (days), air temperature during the growing season (minimum, maximum, and mean, expressed in °C), annual and seasonal rainfall (mm), and solar radiation (MJ m⁻² day) during the growing season and the entire year. Mean values are provided, with corresponding standard deviations enclosed in brackets. Maize crop phenology is described by the mean planting date and silking date per region obtained for the period 1992-2022.

Region	Grain yield (kg ha ⁻¹)	Frost-free period (days)	Growing season (04/01 - 10/30)					Annual		Maize crop phenology
			Mean minimum air temperature (°C)	Mean maximum air temperature (°C)	Mean season air temperature (°C)	Mean solar radiation (MJ m ⁻² day ⁻¹)	Accumulated solar radiation (MJ m ⁻²)	Rainfall (mm)	Rainfall (mm)	
South - West	3457 (331)	168 (17)	13.4 (6.8)	29.1 (7.6)	21.3 (6.8)	24.1 (0.8)	3669 (115)	327 (107)	495 (141)	9-May 20-Jul
West - Central	4199 (235)	160 (19)	12.8 (7.0)	28.2 (7.8)	20.5 (7.1)	23.6 (0.8)	3585 (125)	357 (110)	536 (138)	14-May 23-Jul
North - West	4471 (296)	153 (19)	12.2 (7.1)	27.6 (7.9)	19.9 (7.2)	23.3 (0.9)	3542 (129)	368 (117)	541 (144)	15-May 27-Jul
South - Central	4493 (484)	183 (18)	15.5 (6.9)	28.7 (7.1)	22.1 (6.7)	22.6 (1.0)	3438 (152)	495 (155)	802 (194)	2-May 11-Jul
Central	4944 (349)	173 (18)	14.6 (7.0)	28.4 (7.5)	21.5 (7.0)	22.6 (0.9)	3438 (138)	464 (136)	717 (177)	2-May 12-Jul
South - East (West)	5915 (215)	185 (19)	15.7 (6.7)	27.8 (6.6)	21.8 (6.4)	21.8 (0.9)	3320 (140)	592 (178)	993 (211)	21-Apr 4-Jul
South - East (East)	6046 (213)	186 (20)	15.9 (6.5)	27.6 (6.5)	21.8 (6.3)	21.5 (0.9)	3265 (140)	637 (183)	1132 (236)	22-Apr 4-Jul
North - Central	6178 (510)	169 (17)	14.3 (7.0)	27.5 (7.4)	20.9 (6.9)	22.2 (0.9)	3370 (142)	486 (143)	747 (182)	6-May 16-Jul
East - Central	6272 (409)	179 (17)	15.3 (6.7)	27.0 (6.8)	21.2 (6.5)	21.4 (1.0)	3252 (145)	588 (169)	982 (209)	1-May 10-Jul
North - East	7455 (706)	170 (16)	14.6 (6.9)	26.9 (7.0)	20.7 (6.7)	21.4 (0.9)	3246 (140)	561 (159)	893 (206)	4-May 14-Jul

3.4.2 Correlation between crop yields and climatic variables

The correlations between crop yields and climatic variables were explored in previously defined regions during different maize periods (Figure 3.3). The highest correlation values were obtained when climatic variables were computed during the critical period. For instance, extreme degree days during the critical period (EDD_CP) had the highest correlation with grain yield in 8

of 10 regions (average $r > 0.9$, and $p\text{-value} < 0.001$), except for the North-Central region, where it emerged as the second variable after vapor pressure deficit during the same period (VPD_CP). This climatic variable has the second-order of correlation value with grain yield in 7 of 10 regions (average $r > 0.88$, and $p\text{-value} < 0.001$). In some regions, both climatic variables also presented a high correlation with grain yield when they were computed during the grain-filling period. Thus, EDD during the grain filling (EDD_GF) has ranked as the second most important in the North-East and South-East (East) regions, while VPD during the grain filling (VPD_GF) was the most important climatic constrain for grain yield in the North-West region.

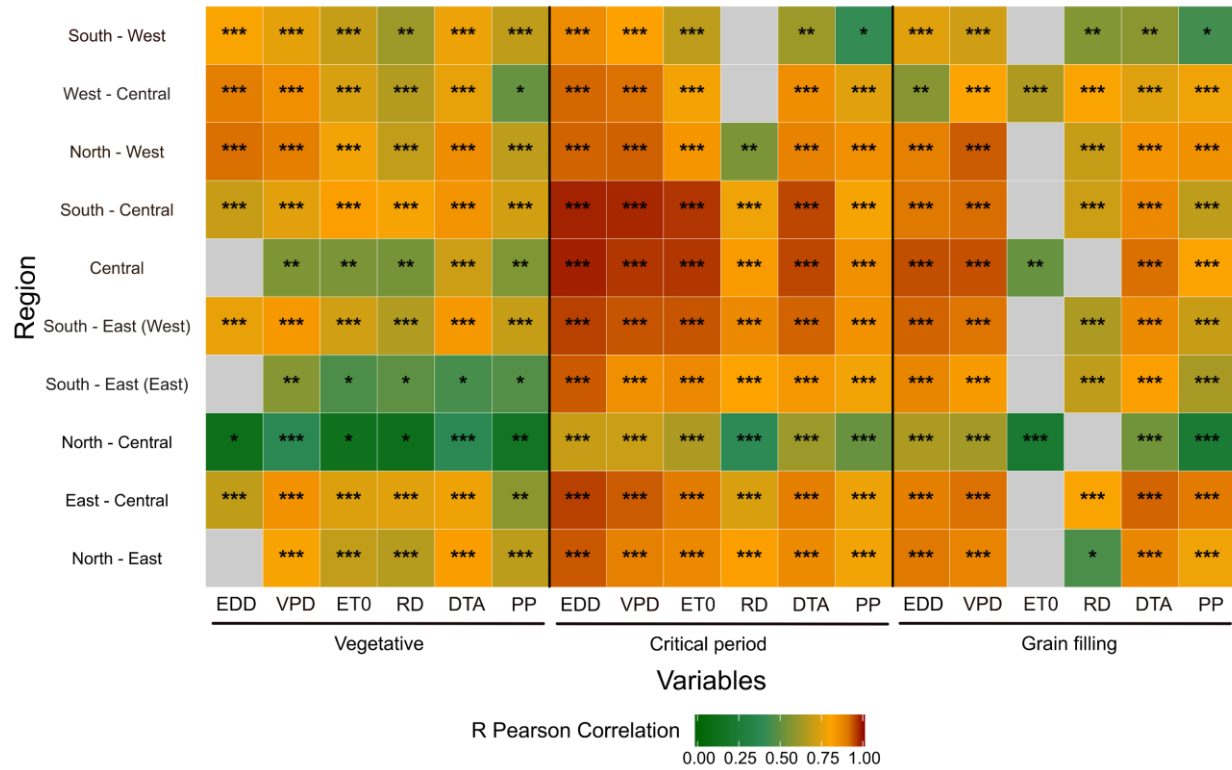


Figure 3.3: Pearson's correlation coefficients between detrended rainfed maize yields and anomalies of climatic variables: EDD, VPD, ET0, RD, DTA, and PP explained in Table 2. These climatic variables were computed during different crop stages (VEG, CP, and GF: see Table 2) for each region based on crop yield and climate data from 1993 to 2021. The regions are sorted by increasing yields. The color green shows low correlation values, while red represents high correlation values. Non-significant (NS; $p > 0.05$) correlations are denoted by grey color. Levels of significance between yield detrended and anomalies of climatic variables: *** p value < 0.001 ; ** p value < 0.01 ; * p value < 0.05 .

3.4.3 Detrended yields vs anomalies of climatic variables

Extreme degree days and vapor deficit pressure presented the highest negative correlations with grain yields and showed a positive correlation with each other. Thus, EDD during the critical period negatively impacted grain yield across most regions, but this response statistically varied among them (Figure 3.4). In five of the eight regions where EDD during the critical period was the highest correlated variable, a negative linear trend response with grain yield was found. However, for the West-Central, South-West, and Central regions grain yields response to EDD during the critical period exhibited a plateau followed by a linear decline response, with the breakpoint around 24 and 9.4 °Cd in the Central and Western regions; respectively. Besides, considering the linear response in these eight regions, a 1 °Cd increase in EDD during the critical period decreased grain yields in 46 kg ha⁻¹ (0.88%). The maximum penalty of EDD during the critical period on grain yield was around 90 kg ha⁻¹ (1.5%) in the South-East, and the minimum was approximately 29 kg ha⁻¹ (0.46%) in the East-Central.

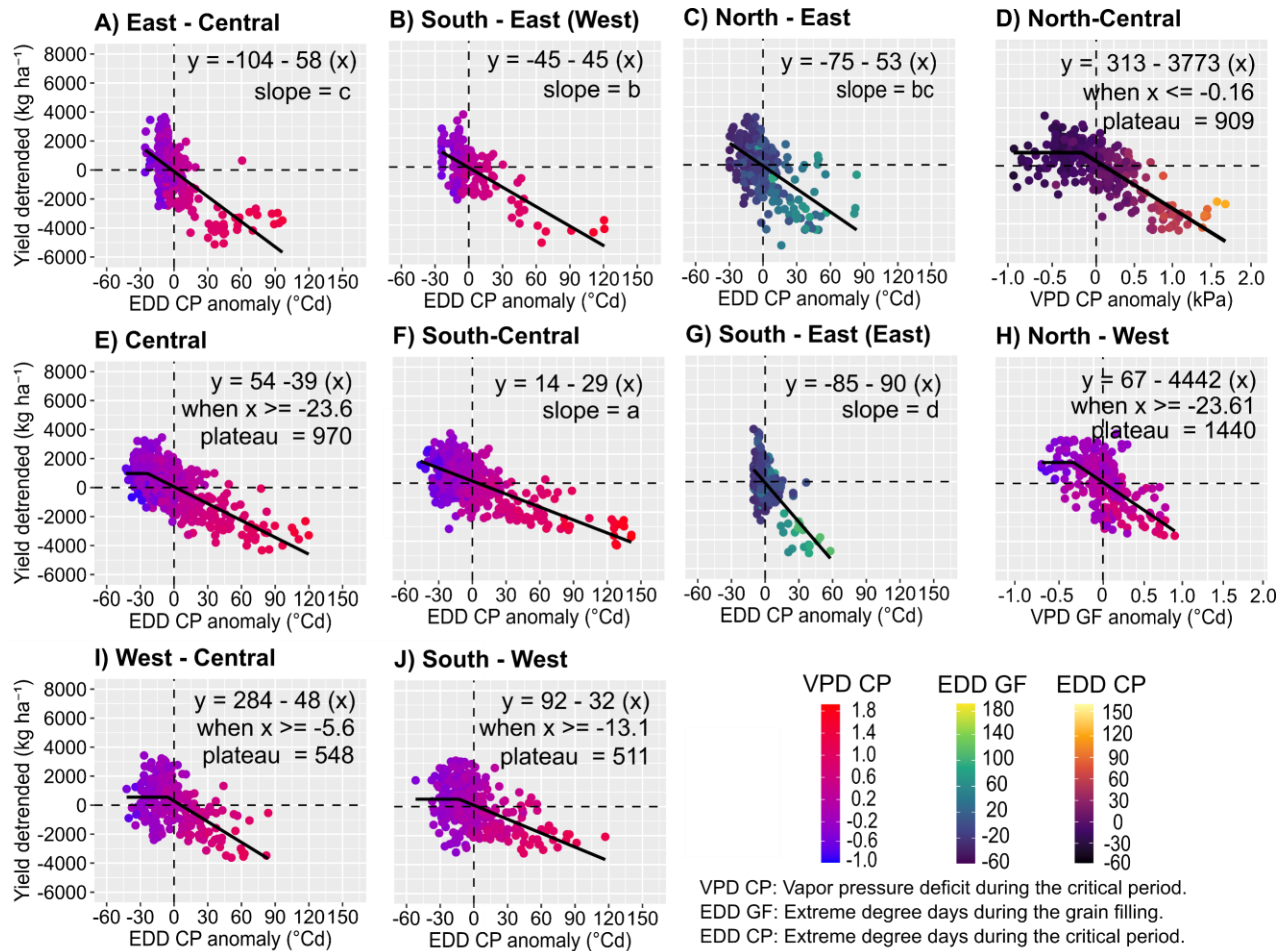


Figure 3.4: Relationship between grain yield and the most correlated climatic variables (A-J), shown as detrended yields (residual of observed minus predicted yield by the linear model) and anomalies (observed weather data adjusted to the historical mean of the variable). Each plot presents the primary climatic variable on the x-axis for a specific region, with point colors representing the second most influential variable. A regression line illustrates the variable relationship, and letters indicate significant differences between slope values, with no significant differences found for intercepts. VPD = vapor pressure deficit; EDD = extreme degree days; CP = critical period; GF = grain filling period.

3.4.4 Spatial variability of extreme degree days and vapor pressure deficit

The historical trends of climatic variables during the critical period of maize crops across Kansas confirmed the positive correlation between EDD and VPD (Figure 3.5). The second decade of the study period (2003-2012) exhibited the highest EDD and VPD values across all regions, especially in 2011 and 2012. In contrast, during the latter seven years of this period, six out of seven years had values falling below the historical mean.

There was a distinct and regional gradient in the EDD and VPD during the critical period in the studied time. For EDD this gradient spanned along the state of Kansas, displaying variations from 6.4 to 42 °Cd with a mean value of 25°Cd (Figure 3.5). Notably, the gradient exhibited a consistent pattern, increasing ~ 30 °Cd when moving from the North-Eastern to the South-Western regions. In the case of VPD the average was 1.3 kPa, with the highest value (1.8 kPa) in the South-West region, and the lowest (0.86 kPa) in the South-East (East) region.

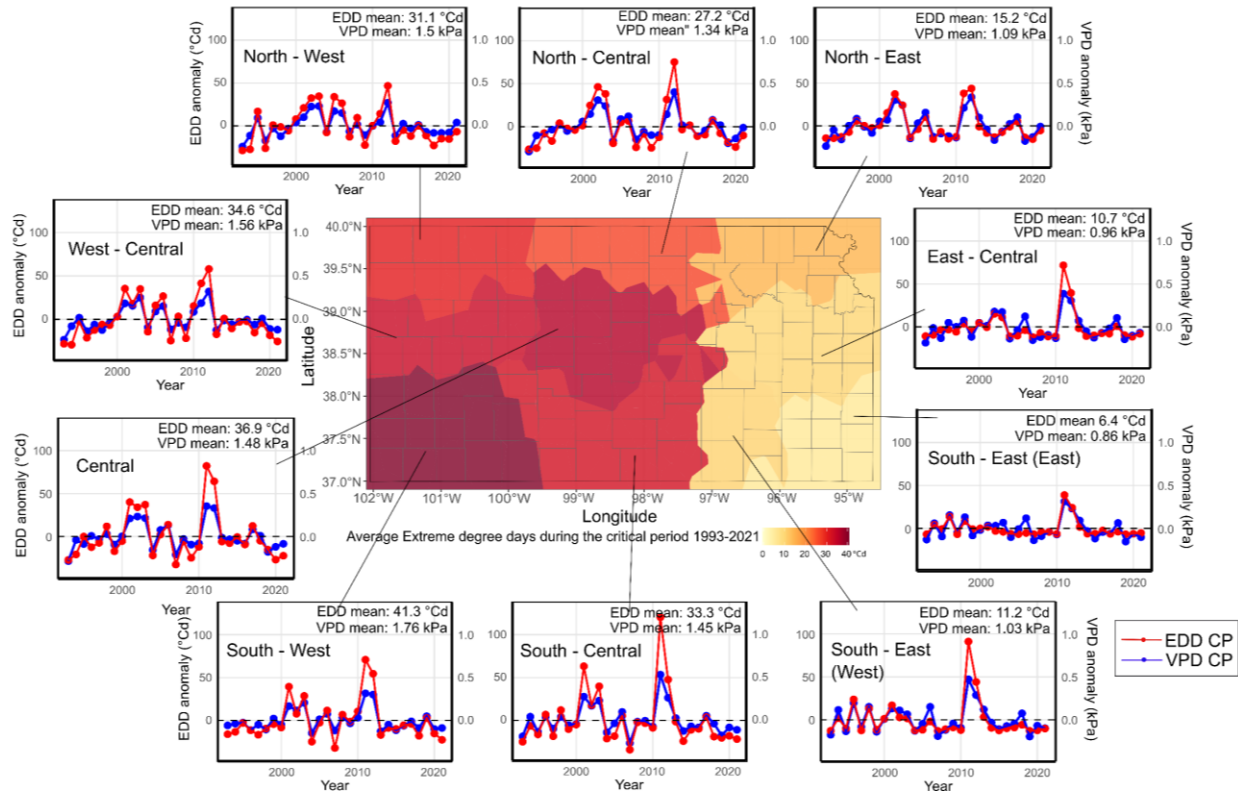


Figure 3.5: Extreme degree days accumulated over 35 °C during the critical period (EDD CP), and the historical trend of EDD CP and vapor pressure deficit during the critical period (VPD CP) for maize crop environmental regions in Kansas State. The central map illustrates the spatial distribution of EDD CP for the regions. Ten plots surrounding the central map provide a detailed insight into the Historical Trends of anomaly values of EDD CP and VPD CP from 1993 to 2021.

3.5 Discussion

This study provides an environmental characterization for rainfed summer cereal crop production, limited by precipitation, using maize in Kansas State as a case study. This

characterization offers the potential basis for i) breeding programs to select sites for testing pre-commercial genotypes and for product characterization, ii) selection of the most suitable climate adaptative management strategies, and iii) stakeholders in developing policies for regions with similar yield environments.

Previous research in this area has explored different approaches for performing environmental characterization (Lobell et al., 2013, 2014; Löffler et al., 2005; Mourtzinis et al., 2020; Seifert et al., 2017). Likewise, past environmental characterizations considered stress factors during critical periods of different crops along major US regions (Couëdel et al., 2021; Löffler et al., 2005; Van Wart et al., 2013). However, these studies employed crop growth models to perform simulations to account for crop phenology. Instead, our study stands out for using reported crop phenology data to define distinct crop growth stages. This approach enhances our understanding of the intricate relationship between yield and climatic variables at different timings while avoiding the bias of model predictions and reflecting the reality of the farmer's choices (Maddonni, 2012b; Porter & Semenov, 2005). Fewer efforts have been made for the Central Great Plains region. For example, Assefa et al., (2012) divided Kansas into eight productive zones based only on annual rainfall. This last regionalization resembles the one obtained in this study, yet this approach ignores many factors from the crop perspective. Another division is the Agricultural Statistics Districts (ASD), defined by the US Department of Agriculture (USDA). This classification groups counties based on geography, climate, and cropping practices (USDA-NASS, 2018a), dating the first ASD Kansas reports to 1929 (USDA-NASS, 2022). As a result of this regionalization, it is critical to identify key climatic variables associated with crop yield by region and during specific stages of the crop growth cycle.

Overall for Kansas, the eastern region tends to have more precipitation while the western region has become drier over time (Lin et al., 2017). For these regions, the maize critical period occurs from late June in the East to the first week of August in the West (Figure B.7) coinciding with the peak of the summer heat and atmospheric water demand. During flowering, extremely high temperature negatively affects maize kernel set through the process that involves plant development and growth (Neiff et al., 2016; Rattalino Edreira et al., 2011; Rattalino Edreira & Otegui, 2012). Thus, floret and silk development are negatively affected by extreme high temperatures during the critical period (Rattalino Edreira et al., 2011). In addition, temperatures above 33 °C during the critical period reduce grain number due to a reduction in crop growth

rate, associated with lower radiation use efficiency and biomass partitioning to kernels (Neiff et al., 2016; Rattalino Edreira & Otegui, 2012). Furthermore, elevated temperatures during the grain-filling period play a critical role in yield outcomes in the central US (Lobell et al., 2014). Elevated temperatures during this stage reduce grain yield due to a reduction in grain weight associated with lower potential grain weight (Shim et al., 2017) and lower grain-filling duration (Mayer et al., 2014; Rattalino Edreira & Otegui, 2012). Additionally, high VPD with low precipitation negatively affects plant growth (Li et al., 2019; Sadras & Milroy, 1996; Shrestha et al., 2021). Consequently, plants prevent water loss by closing their stomata, thus limiting CO₂ fixation and plant growth. Some reports suggest that VPD may affect yield independently of other factors despite its positive correlation with higher temperatures (L Hoffman et al., 2020; Lobell et al., 2014). However, in the present study, we found that EDD and VPD were strongly correlated, showing that conditions of extremely high temperature with high VPD are common in Kansas maize production systems. Moreover, a spatial variability of EDD during the critical period is evident across the state. Each Cd° above the historical mean in the east leads to a more significant yield decline compared to the west, where limiting environmental conditions, marked by lower precipitation, result in a plateau effect at lower EDD during the critical period values.

Plausible management strategies to mitigate the impact of the main climatic constraints are linked to the use of irrigation, adjustment on planting dates, and length of the crop growth cycle. Irrigation partially alleviates the effects of EDD (i.e. mitigation), especially during the post-silking period, without eliminating them (Hawkins et al., 2013; Luo, 2011). Planting dates and the use of different hybrid maturities are other options to avoid high EDD values during the most sensitive reproductive stages (i.e. scape), as was recently demonstrated by (Massigoge et al., 2023). The findings from (Massigoge et al., 2023) reveal that the choice of longer crop growth cycles and earlier planting dates leads to greater yields in the eastern part of the state, while later planting dates and shorter cycles can provide greater yield stability in the rainfed western regions, which have a dryland yield gap of ~30% (Sun et al., 2022). Late sowing dates have been widely adopted by farmers in other sub-humid and semi-arid regions where the critical period of early sowing matches with high water stressful conditions (Otegui et al., 2021; Rotili et al., 2019). Progress in this direction has been observed over the last 20 years in the South-East region of Kansas, where farmers have moved their planting and silking dates earlier (Figure B.7), decreasing EDD during the critical period compared to the South-West. These points highlight

the importance of exploring region-specific management strategies to cope with the main climatic limitations in future research.

In contrast to this, government management policies and practices, such as those seen in USDA's Agricultural Statistic Districts and crop insurance policies that restrict planting dates, often rely on administrative boundaries (Boyer & Aaron Smith, 2019). This limitation could be effectively addressed by our regional delineation methodology, which could also be used in research and breeding programs. Our study, which is primarily based on publicly available climate and yield data, can be readily extrapolated to other crops and regions in the United States and even to other countries. Furthermore, this regionalization approach becomes even more relevant in future scenarios where climate conditions may become more extreme, particularly impacting rainfed cropping systems (Zhou et al., 2021) making the establishment of such environmental delineations crucial.

We identified a few limitations to our study i) soil data were not considered for regionalization, a variable that could be used to incorporate information for water balance but high-resolution soil data may be more critical for future crop characterization, ii) the extrapolation of this approach to other sites/crops is limited to the existence of crop phenology data in public records, and iii) location-specific management history and genotype used for planting was not available and crop phenology reporting is only available at district scale, limiting the downscaling of this approach closer to a farmer field-scale. However, the approach presented in this study can serve as a framework to guide future research efforts to translate these results into actionable recommendations.

3.6 Conclusion

In this study, we have developed a novel methodology for environmental characterization focused on maize grown under rainfed conditions for the state of Kansas (as a case study) within the US Great Plains region. The utilization of a Fuzzy c-means spatial clustering algorithm, along with comprehensive datasets spanning a 29-year time series, allowed for the identification of ten distinct regions based on maize productivity and climatic variables. In turn, the division of the growing season into different maize periods allowed us to identify the most important climatic variable and its timing for influencing grain yield. According to a correlation analysis, the extreme high temperatures (accumulating maximum air temperature above 35 °C) and atmospheric water demand around flowering (± 15 days centered in female flowering) are the

major factors limiting rainfed maize yields in Kansas. Although their behavior varies among years and regions, we can confirm that the average yield penalty is 0.88% for each °Cd increase in extreme high temperatures around flowering. These findings provide valuable insights for a wide range of stakeholders, from researchers to policy makers, to develop regionally tailored strategies for optimizing rainfed maize production.

Chapter 4 - Final Remarks

Crop management strategies based on long-term studies that capture spatial and temporal variability help ensure sustainable crop production in rainfed agricultural systems. This study aimed to improve management decisions in the US Central Great Plains, using Kansas as a case study, by integrating long-term simulations and agro-environmental characterization. This dissertation comprises two approaches: (i) assessing the feasibility of crop intensification in rainfed wheat-based systems through an in-silico approach (Chapter 2), and (ii) developing a methodology to delineate cropping environments based on productivity and climate-related constraints for summer crops under rainfed conditions (Chapter 3).

Firstly, in Chapter 2, crop modeling analysis using APSIM Classic provided insights into the viability of intensification strategies in wheat-based cropping systems through the inclusion of summer crops. The study demonstrated that the intensifying wheat-based cropping systems can enhance productivity per unit of land area; however, its success is highly dependent on the choice of summer crop species and summer crop planting dates. Water stress was identified as the primary abiotic stress for early planting dates of summer intercrops, with maize being more sensitive than soybean. Conversely, delaying planting dates shifts the primary constraint to frost, which can prematurely interrupt the grain filling period and reduce yield potential. As a result, soybean proved to be a more reliable summer crop than maize under early planting conditions, while shorter crop cycles in both maize and soybean performed better when planting was delayed.

In Chapter 3, the environmental characterization revealed that rainfed maize productivity is largely influenced by extreme temperature and vapor pressure deficits during the critical period, i.e. 15 days after and before maize flowering. The analysis identified ten distinct production regions within Kansas, allowing for a more targeted approach to crop management based on climate-related constraints. These results highlight the importance of spatial characterization in optimizing agricultural decision making, particularly in regions with high environmental variability such as the state of Kansas.

Despite the contributions of this study, several limitations should be acknowledged. In Chapter 2, the simulation framework relied on the assumptions and parameterization of the APSIM crop model, which inherently introduce prediction errors. Therefore, field trials are

essential to validate and refine these initial in silico results to ensure their accuracy and applicability to real-world management decisions. While the regional delineation based on productivity and climatic constraints in Chapter 3 provides a strong basis for decision making, on-farm validation is needed to improve its applicability in field-scale systems. In addition, the integration of soil databases would further improve the accuracy and reliability of the classification results.

Future research should focus on expanding environmental characterization to other crops and regions within the Central Great Plains, as well as conducting simulations for additional sites across Kansas and the broader region. Furthermore, incorporating on-farm validation of model predictions and environmental regionalization will be essential for bridging the gap between theoretical assessments and practical applications in agricultural decision-making.

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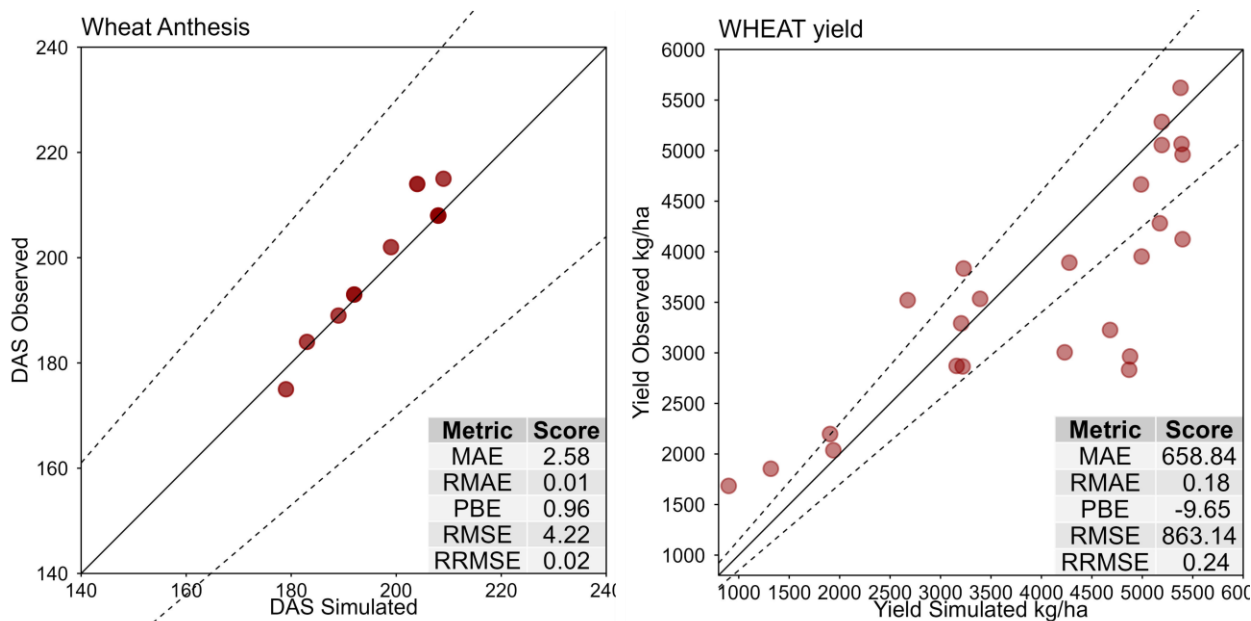
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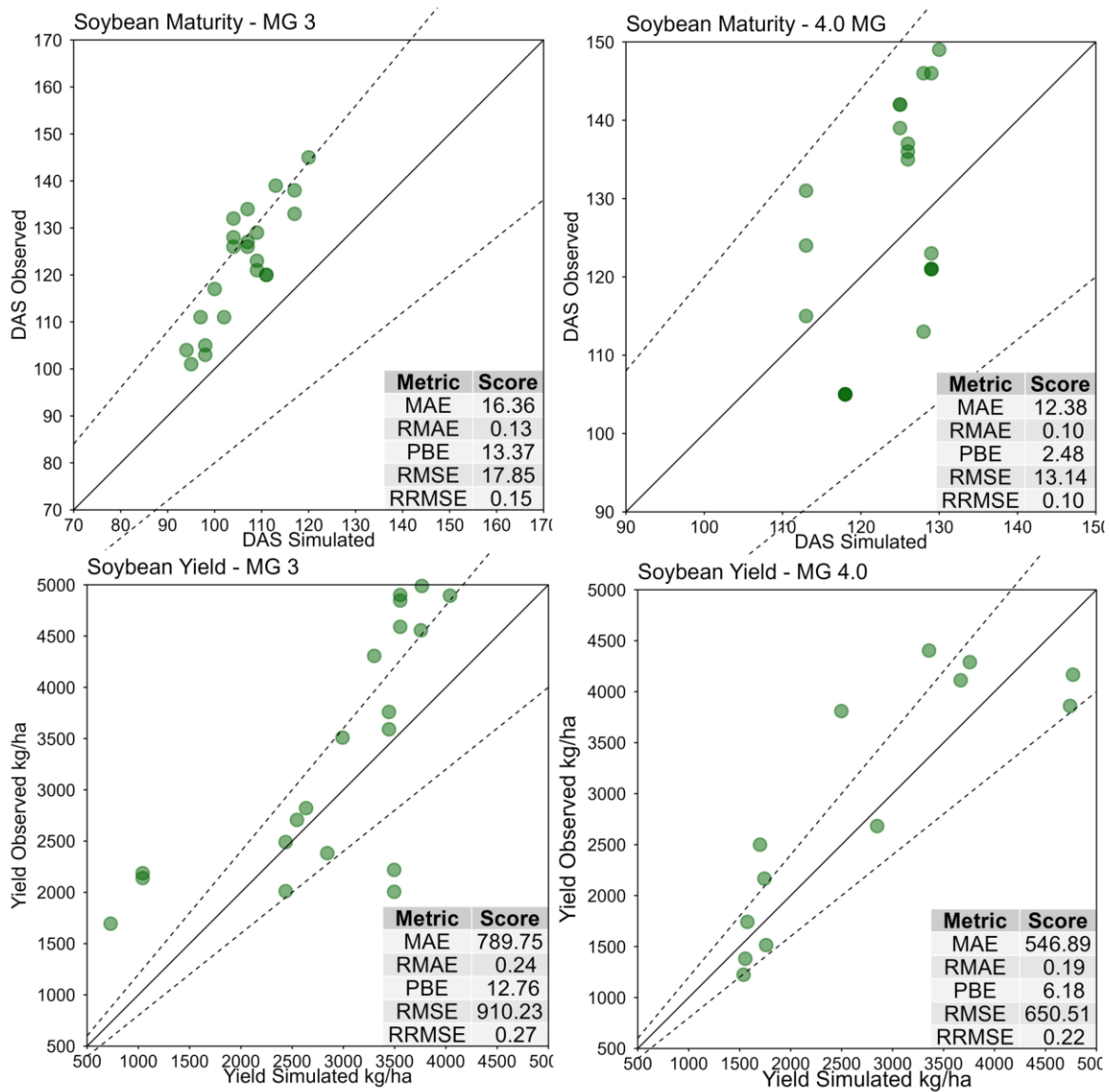
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Appendix A - Chapter 2

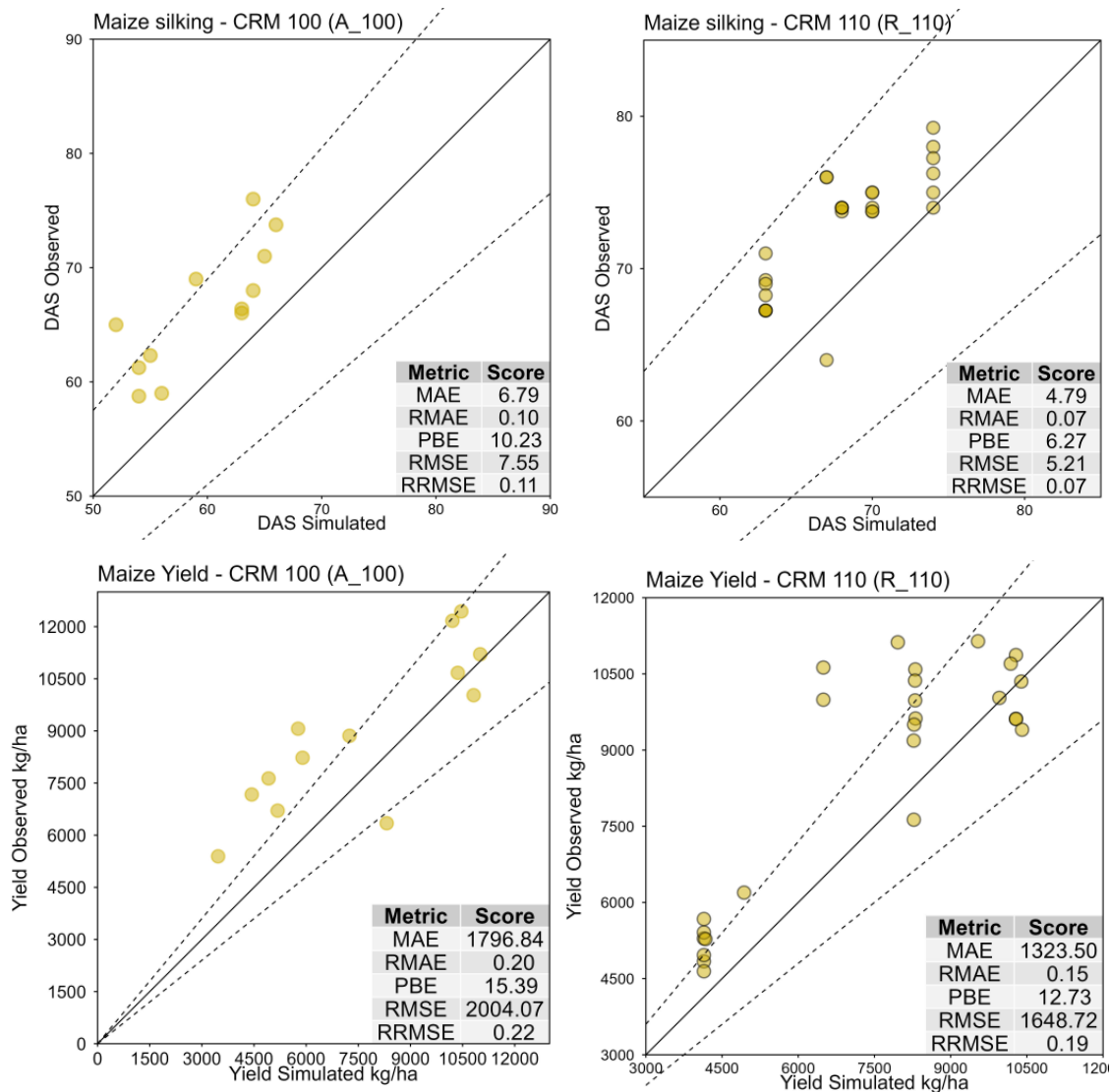
Supplementary figures



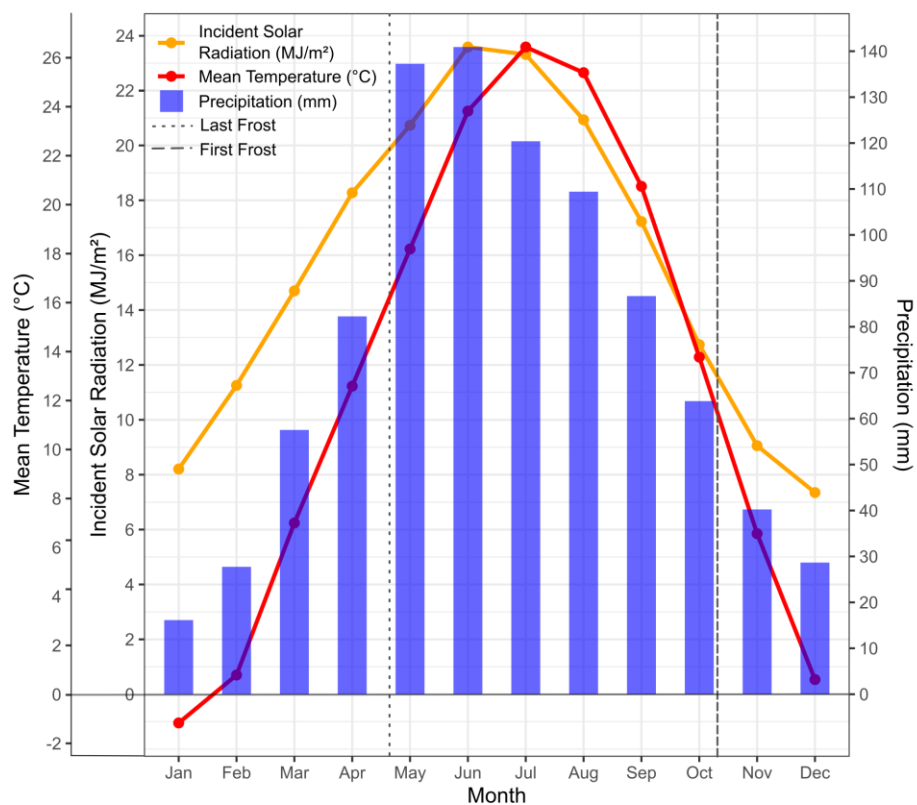
Appendix Figure A.1: Metrics describing the agreement between predicted and simulated days to anthesis from sowing (Wheat Anthesis) and grain yield in kg/ha (Wheat yield) by APSIM Classic v7.10 using independent dataset in Northeast Kansas for the last 10 years.



Appendix Figure A.2: Metrics describing the agreement between predicted and simulated days to maturity from sowing (Soybean Maturity – MG 3 and Soybean Maturity – MG 4) and grain yield in kg/ha (Soybean Yield – MG 3 and Yield Maturity – MG 4) by APSIM Classic v7.10 for soybean maturity groups (MG) 3 and 4 using independent dataset in Northeast Kansas for the last 10 years.

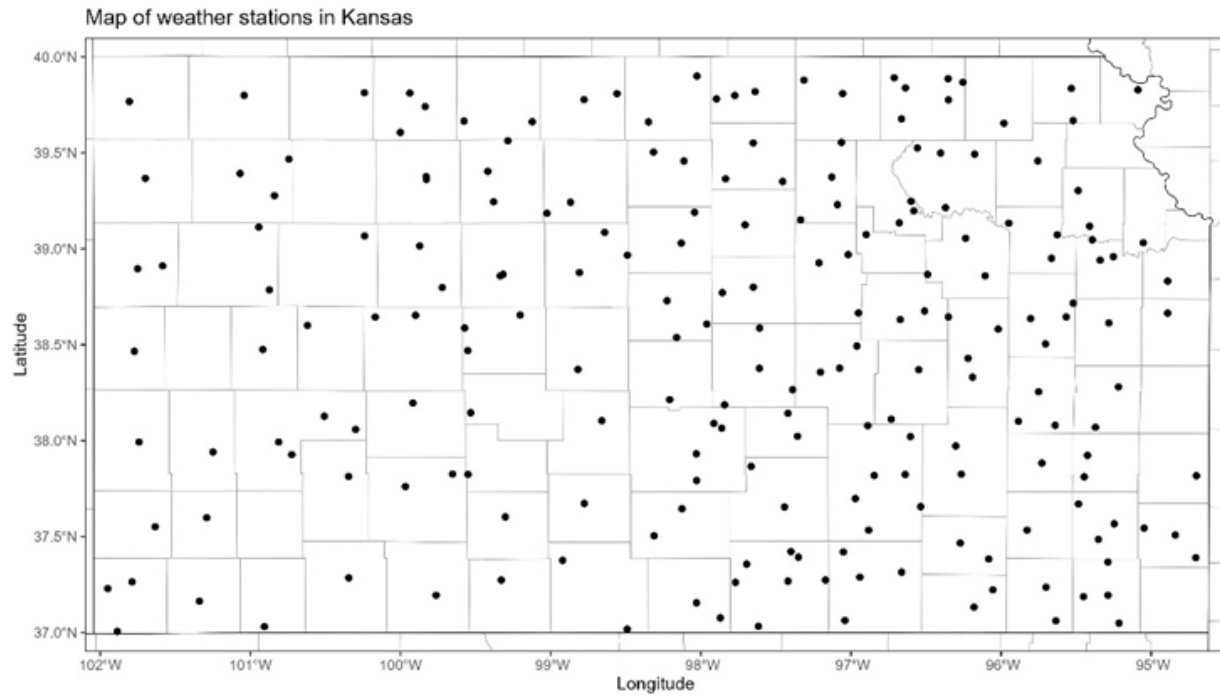


Appendix Figure A.3: Metrics describing the agreement between predicted and simulated days to silking from sowing (Maize silking – CRM 100 and Maize silking – CRM 110) and grain yield in kg/ha (Maize Yield – CRM 100 and Maize Yield – CRM 110) by APSIM Classic v7.10 for maize crop cycles corn relative maturity (CRM) 100 and 110 using independent dataset in Northeast Kansas for the last 10 years.

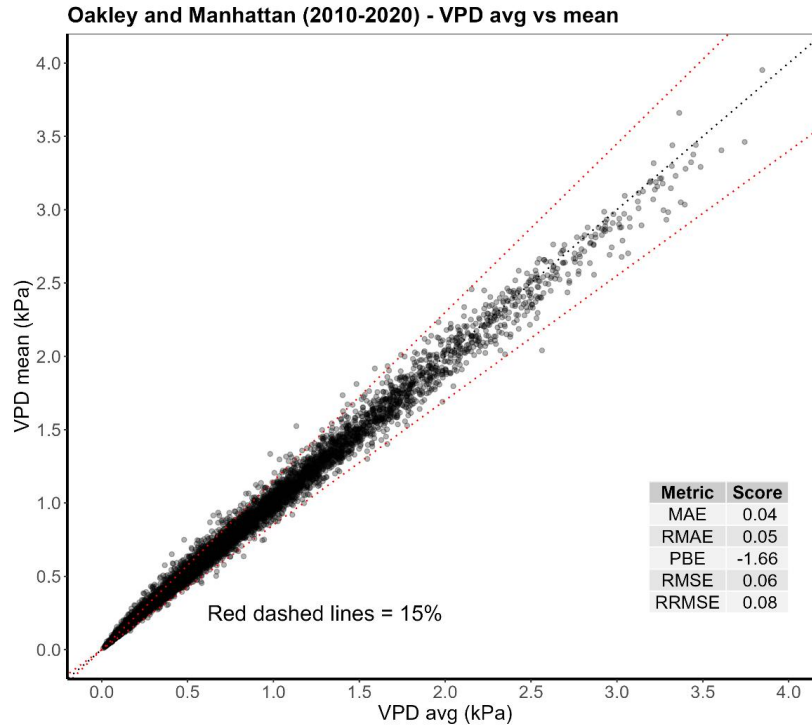


Appendix Figure A.4: Climate summary for Eastern Kansas (Manhattan, Kansas, U.S.) based on 30 years of data. Monthly mean temperature (°C, red line), mean incident solar radiation (MJ m⁻², yellow line), and monthly precipitation (mm, blue bars) are shown. Vertical dashed lines indicate the average dates of the last and first frost events.

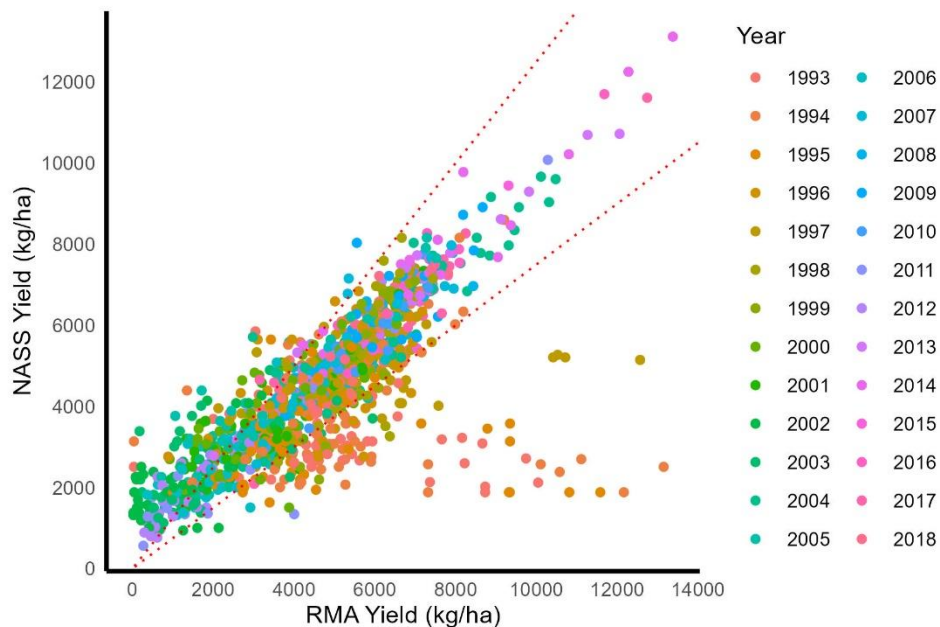
Appendix B - Chapter 3



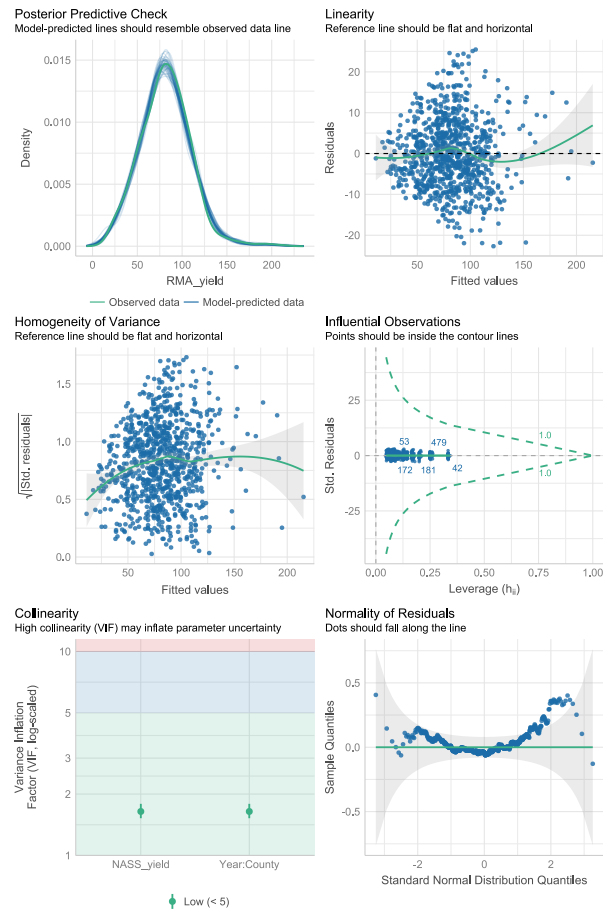
Appendix Figure B.1: Map of NOAA's weather stations with long-term period data in Kansas State.



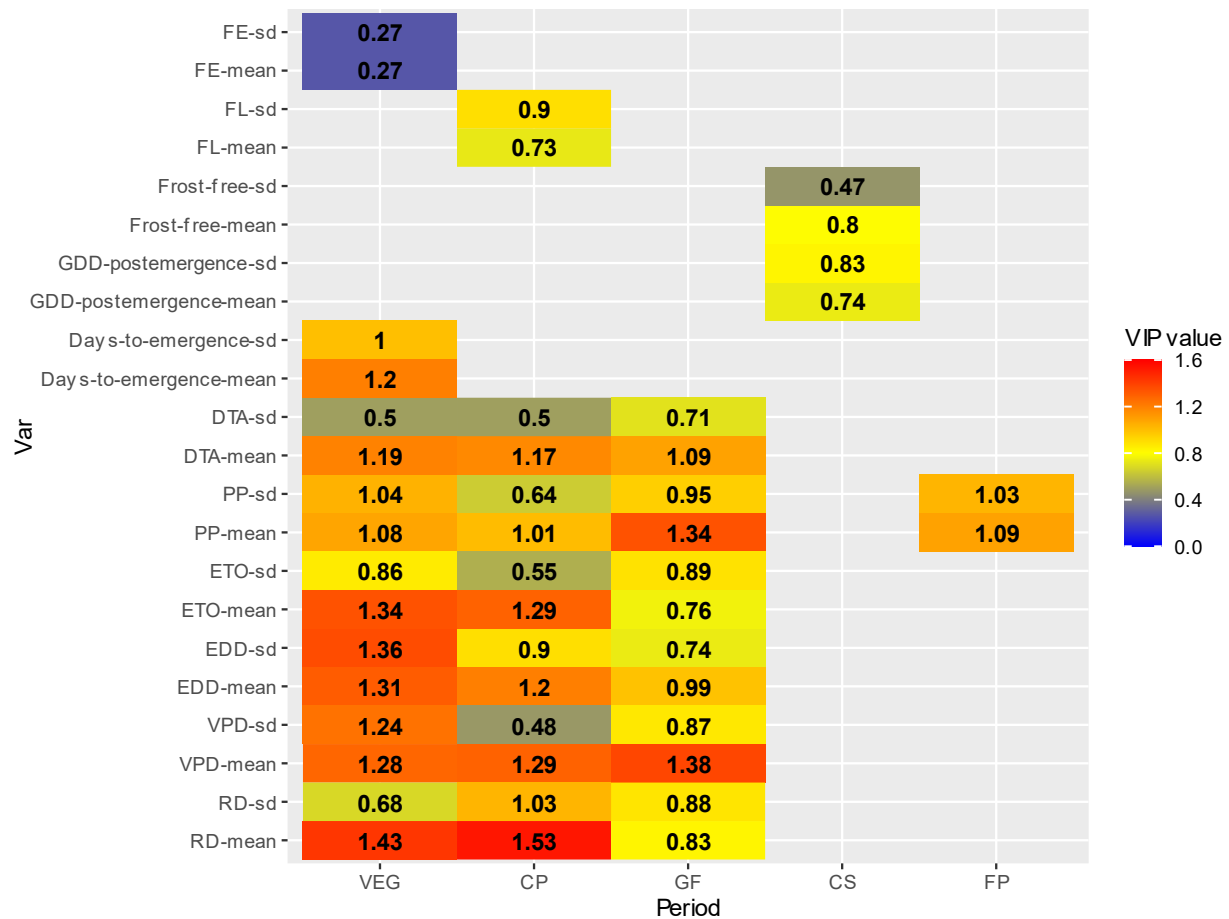
Appendix Figure B.2: Daily vapor pressure deficit (VPD) values are derived as averages of hourly VPD values calculated from hourly temperature and relative humidity data (VPD avg), and from mean daily temperature and relative humidity (VPD mean).



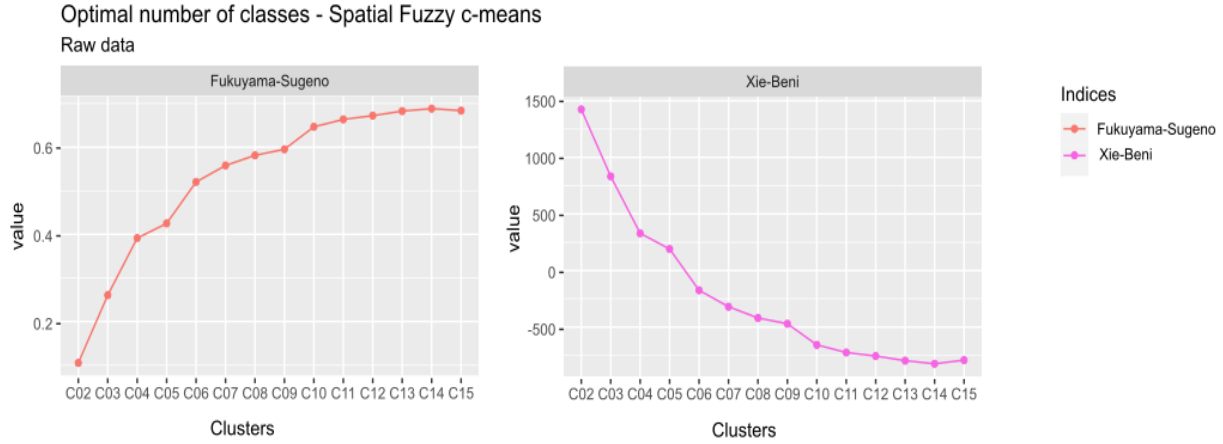
Appendix Figure B.3: Comparison between NASS and RMA datasets, displaying grain yield values reported by County and Year at each data point. The red dashed lines delineate the region where differences between the two data sources are less than 25%.



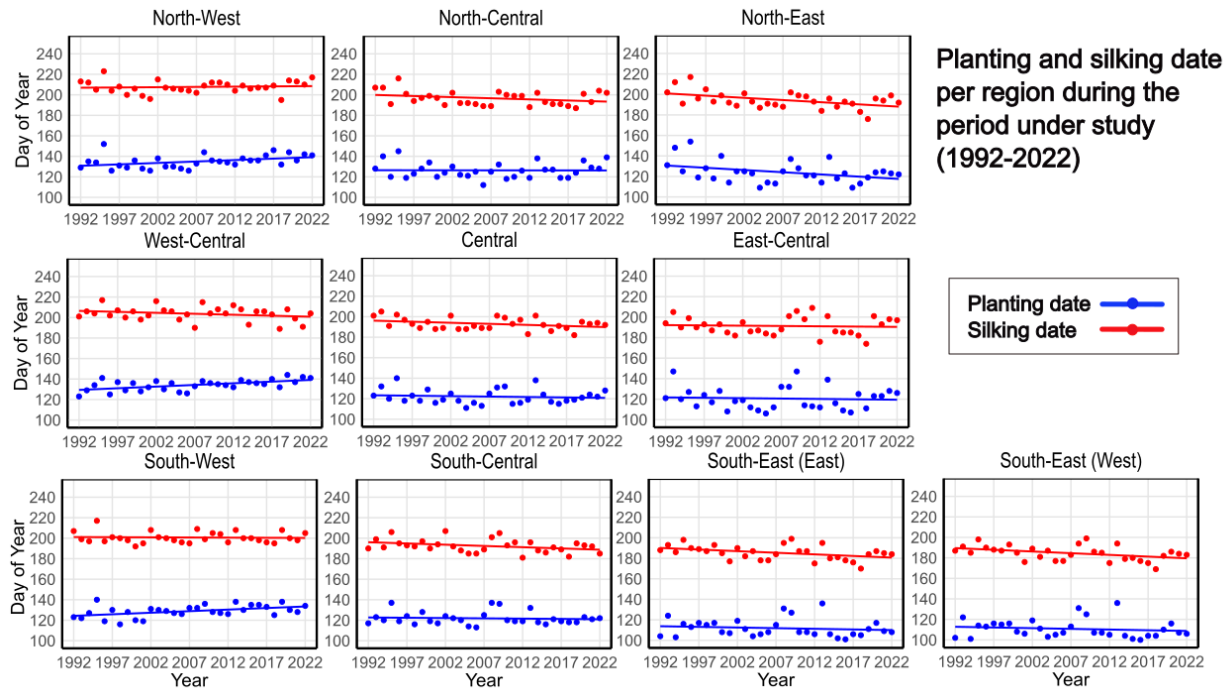
Appendix Figure B.4: Full display of the model assumptions used to recalculate county grain yields reported by the RMA with a 25% difference from grain yields of NASS database.



Appendix Figure B.5: Result of VIP scores, showing the relative weight (0.0 to 1.6) of the mean and standard deviation (sd) of each variable in the different maize periods VEG (Vegetative); CP (Critical Period); GF (Grain-filling); CS (Crop season, planting - maturity); FP (Fallow period) on maize grain yield.



Appendix Figure B.6: Fukuyama-Sugeno and Xie-Beni indices used as evaluation metrics to determine the most appropriate cluster structure. The number of clusters that minimize or stabilize these indices usually indicates the best group division.



Appendix Figure B.7: Distribution of planting (blue points) and silking (red points) dates across ten regions over the study period, with their respective trends illustrated by blue and red lines.