Exploring avenues for agricultural intensification in the United States

by

Ignacio Massigoge

B.S., National University of Mar del Plata, 2019

M.S., National University of Mar del Plata, 2022

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the
requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agronomy
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2024

Abstract

Crop intensification is a key aspect for achieving global food security and exploring options for optimizing the use of land and environmental resources. Alternatives to increase production without increasing land area (herein termed as crop intensification) are limited to i) increasing the yield of a single crop per year per unit of land area, and/ or ii) increasing the number of crops harvested per year.

This dissertation is organized into six chapters (Chapter 1, General Introduction, and Chapter 6, Final Remarks) that present different case studies of crop intensification in major field crop production regions of the United States (US). Chapter 1 provides a general context for global food demand and the resulting need to intensify cropping systems. Chapter 2 explores different crop management strategies represented as combinations of planting dates by hybrid maturity to optimize rainfed maize grain yield in the central Great Plains region of the US, while Chapter 3 investigates alternative crop rotations, including summer field crops, relative to continuous winter wheat cropping systems within the same region. Chapter 4 offers a new perspective on crop rotations via exploring the feasibility of cultivating maize-soybean double cropping system in the US Southern region, integrating field data with the APSIM crop growth model. The analyses developed in Chapter 5 revealed patterns of soybean yield deceleration and stagnation relative to maize for Kansas and the most relevant crop production region, the US Corn Belt. Lastly, Chapter 6 provides a summary of key findings and directions to guide future research linked to crop intensification in the United States and globally.

Exploring avenues for agricultural intensification in the United States

by

Ignacio Massigoge

B.S., National University of Mar del Plata, 2019

M.S., National University of Mar del Plata, 2022

A DISSERTATION

submitted in partial fulfillment of the
requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agronomy
College of Agriculture

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2024

Approved by:

Major Professor
Dr. Ignacio A. Ciampitti

Copyright

Abstract

Crop intensification is a key aspect for achieving global food security and exploring options for optimizing the use of land and environmental resources. Alternatives to increase production without increasing land area (herein termed as crop intensification) are limited to i) increasing the yield of a single crop per year per unit of land area, and/ or ii) increasing the number of crops harvested per year.

This dissertation is organized into six chapters (Chapter 1, General Introduction, and Chapter 6, Final Remarks) that present different case studies of crop intensification in major field crop production regions of the United States (US). Chapter 1 provides a general context for global food demand and the resulting need to intensify cropping systems. Chapter 2 explores different crop management strategies represented as combinations of planting dates by hybrid maturity to optimize rainfed maize grain yield in the central Great Plains region of the US, while Chapter 3 investigates alternative crop rotations, including summer field crops, relative to continuous winter wheat cropping systems within the same region. Chapter 4 offers a new perspective on crop rotations via exploring the feasibility of cultivating maize-soybean double cropping system in the US Southern region, integrating field data with the APSIM crop growth model. The analyses developed in Chapter 5 revealed patterns of soybean yield deceleration and stagnation relative to maize for Kansas and the most relevant crop production region, the US Corn Belt. Lastly, Chapter 6 provides a summary of key findings and directions to guide future research linked to crop intensification in the United States and globally.

Table of Contents

List of Figures

List of Tables

Acknowledgments

First, I would like to express my deepest gratitude to my advisor, Dr. *Ignacio A. Ciampitti*, for his invaluable trust, guidance, and support throughout my years at Kansas State University, which has greatly contributed to my personal and professional growth.

In addition, I would like to thank my committee, Drs. *Sara Lira*, *Trevor Hefley*, and *P.V. Vara Prasad*, for their extraordinary contributions to my research and interesting discussions, but especially for their selfless dedication to my personal and professional growth.

A big thank you to all the members of the Ciampitti Lab during the years 2021, 2022, 2023, and 2024, for all their tremendous help, support, and friendship, and to all of the students, faculty, and staff of the Department of Agronomy at Kansas State University.

I would also like to acknowledge the financial support provided by Corteva Agriscience and the United States Department of Agriculture (USDA) through the Rainfed Agriculture Innovation Network (RAIN).

Finally, I would like to thank my family and friends for their invaluable support and guidance, which has had a profound impact on who I am today.

Dedication

To *Coni* for her endless love, guidance, and support throughout this incredible experience together, and for helping me to make my dreams come true.

To my wonderful family, especially to my dad -*José*-, my mom -*Ana*-, and my brother and sister, -*Nicolás* and *Belén*-, for their love and always being there by my side.

A *Coni* por su infinito amor, por ser guía y apoyo a lo largo de esta increíble experiencia juntos, y por ayudarme a hacer realidad mis sueños.

A mi maravillosa familia, en especial a mi papá -*José*-, mi mamá -*Ana*-, y mis hermanos, -*Nicolás* y *Belén*-, por su amor y estar siempre a mi lado.

Chapter 1

General Introduction

The global population has grown exponentially over the past century and is expected to reach 10.9 billion by 2050 (Gu et al., 2021), which will be accompanied by an increase in global food demand. Some of the key factors in understanding this phenomenon are related to improvements in diet quality (i.e., animal protein) due to increases in per capita income, particularly in South Asia (Robinson & Pozzi, 2011), and rises in the demand for biofuels with the goal of reducing the dependence on fossil fuels (Y. Liu et al., 2021). Therefore, although global crop demand is projected to increase by 100-110% in the first half of the century (Tilman et al., 2011), meeting the challenging global food demand for human development is still a daunting task.

Alternatives to increase crop production include: i) expanding the cultivated area (Potapov et al., 2022), ii) increasing the yield of a single crop per year per unit of cultivated area (Ray et al., 2013; Tilman et al., 2002), and/or iii) increasing the number of crops harvested per year (F. H. Andrade, 2011; Gaba et al., 2015; Waha et al., 2020). However, the limited amount of land available for agricultural expansion, and the associated negative impacts such as biodiversity loss (Lark et al., 2020) or soil erosion (Hu et al., 2021) impose a limitation on this first option.

In this context, the focus of future production increases should be on rising the production per unit of area in a sustainable way. The United States Agency for International

Development (USAID) and the United Nations (UN) have defined the concept of "sustainable crop intensification" as "a means of using land to increase food supply while protecting biodiversity and ecosystem processes" (Petersen & Snapp, 2015). This is a key aspect for increasing land (Xiang et al., 2022; Y. Yu et al., 2015) and resource (J. F. Andrade et al., 2017; Caviglia & Andrade, 2010) use efficiency, apart from providing benefits to the ecosystem (Gaba et al., 2015). The present dissertation focuses on exploring different case studies for sustainable crop intensification in major producing regions in the United States.

The general objectives of this dissertation, as outlined in the following chapters, are to: investigate combinations of different crop management strategies such as planting date and hybrid maturity to optimize maize grain yield in the US central Great Plains region (Chapter 2); explore alternative crop rotations to continuous winter wheat to increase resource use capture and efficiency, overall crop productivity, and profitability in the US central Great Plains (Chapter 3); assess the feasibility and associated risks of cultivating maize-soybean double crop in the southern US (Chapter 4); and analyze and compare maize and soybean yields grown in similar environments in Kansas and the US Corn Belt region (Chapter 5).

Chapter 1 of this dissertation introduces the importance of intensifying cropping systems in a sustainable way to face future challenging scenarios for increasing global food production and presents the general objectives to be addressed in each chapter. In Chapter 2, a crop modeling approach provides an opportunity to evaluate maize management practices (planting date and hybrid maturity) aimed at optimizing rainfed maize grain yield in the US central Great Plains region. This information could assist agronomists and direct future research efforts on implementing effective management practices to intensify the current less diversified rotations, especially with options for early and late planting windows. Chapter 3 presents a data analysis from a three-year field experiment to evaluate the resource use efficiency of the dominant cropping system (continuous winter wheat) and to explore feasible alternative rotations (including grain and forage crops) in terms of resource use efficiency, productivity, and profitability. This information will be useful in developing more sustainable rainfed agricultural systems in the US central Great Plains region compared to traditional systems that typically raise concerns about soil erosion and water use. Chapter 4 combines a one-year field experiment data analysis and crop modeling to evaluate maize-soybean double cropping in terms of productivity and system performance (land equivalent ratio and risk assessment) for the Southern US. This knowledge could be useful to increase land use efficiency and diversify risk compared to the dominant monocropping systems in the region. In Chapter 5, data from maize and soybean trials evaluates a comparative crop yield performance for Kansas and then extended to the entire US Corn Belt region. This crop comparison provides an opportunity to identify the major factors driving yields between these crops and in better strategizing land allocation, future strategies for both crop intensification and diversification. Finally, Chapter 6 presents a summary with the main findings of the different case studies from this dissertation. This last chapter concludes with a discussion of where future research should focus as we move toward more intensive cropping systems.

Chapter 2

Maize planting date and maturity in the US central Great Plains: Exploring windows for maximizing yields

* Published in *European Journal of Agronomy*

Massigoge, I., Carcedo, A., Lingenfelser, J., Hefley, T., Prasad, P. V., Berning, D., ... & Ciampitti, I. (2023). Maize planting date and maturity in the US central Great Plains: Exploring windows for maximizing yields. *European Journal of Agronomy*, 149, 126905.

https://doi.org/10.1016/j.eja.2023.126905

2.1 Abstract

Region-specific guidelines for maize in the US Great Plains are needed to account for variability in farmer practices and inherent soil and climate differences. Therefore, it becomes critical to define environment tailored management strategies for maize crop to improve and sustain yields over time. The aims of this study were to: i) define homogenous maize yield environments classified as related to the maximum yield and its stability over time in the US central Great Plains region; ii) explore the combinations of planting date and hybrid maturity that lead to optimal yield for each of the previously defined homogenous maize yield environments; and iii) identify environments presenting different windows for maximizing yields (combinations of planting date by hybrid maturity). Hybrid maturity (growth cycle) by planting date combinations were explored at 70 sites within central and eastern Kansas and northern Oklahoma (herein defined as the US central Great Plains region) using 30 years of historical weather data. In addition to the analysis of an extensive maize field dataset, a crop growth model, Agricultural Production Systems Simulator (APSIM), was utilized to evaluate the crop yield and phenology of all hybrid maturity by planting date combinations to define environment tailored management strategies. The simulated yields were spatially clustered based on attainable yield and stability over time to delimit more homogeneous productivity environments. Overall, greater yields were attained with long-maturing hybrids (comparative relative maturity, CRM, 101 and 115). Delaying the planting date from April to mid-May decreased yield in eastern environments. Moreover, late planting maintained yields and increased stability in central environments. For central Kansas and Oklahoma, anticipation of physiological maturity date (3–16 days) with reduced yield penalties (<5%) were possible by using short-season hybrid maturities (CRM 85). Future scenarios for intensification could be explored in those environments presenting more windows for maximizing yields, either with early planting and harvest dates or via late planting providing time for a short crop before maize. Adoption of more region-specific guidelines for maize management could help to optimize yield and its stability over time and seek further opportunities to diversify risk and intensify our current maize-based farming systems in the US central Great Plains.

2.2 Introduction

Global crop production must increase by 60% by 2050 to satisfy an increasing demand for food due to population growth, rising per capita incomes, and biofuel use (T. Fischer et al., 2014). However, the incorporation of new land areas for agriculture is limited (Lark et al., 2020; Pretty & Bharucha, 2014) due to environmental concerns and legislation pertaining to environmentally sensitive areas (Bringezu et al., 2014; Heald & Spracklen, 2015; Rickson et al., 2015). Thus, it is critical to define management strategies to optimize yield by targeting environments and exploring potential intensification alternatives in time and space in the current agricultural land area. The US central Great Plains (Kansas-Oklahoma) region is a major producer of field crops, accounting for roughly 20 MT of maize production (United States Department of Agriculture (USDA), 2023). Despite the productivity of the region, most of the literature regarding optimizing management strategies has focused on the northern Corn Belt (Abendroth et al., 2021, 2017; Baum et al., 2019, 2020; Grassini et al., 2011; Lobell et al., 2020). Therefore, further research is needed to provide farmers with this critical knowledge within the US central Great Plains.

Undoubtedly, the selection of planting date and hybrid maturity are key when defining management strategies. A trend of shifting to earlier planting dates has been reported (Kucharik, 2008), mainly benefiting maize yields in shorter season environments towards northern latitudes (Long et al., 2017). Furthermore, the decision of planting date must be accompanied by a set of management practices to optimize crop yield (Grassini et al., 2011; Long et al., 2017). Thus, the selection of a late-maturity hybrid together with early planting dates aims to produce higher, more stable yields. These higher yields are explained by longer crop duration (longer accumulation of radiation), placing flowering just before the peak of extended heat stress, and decreasing the risk of killing frost before physiological maturity (Duvick, 1989). Abendroth et al. (2021) highlighted the relevance of region-based climate adaptation strategies with high specificity of local challenges to cope with the hybrid maturity heterogeneity across the US Midwest.

To explore the optimal scenarios of crop genotype, environment, and management (e.g., planting date), multiple field trials with several combinations are needed, which increases labor costs and time while limiting the testing capability of each unique scenario. In this context, crop modeling has been proposed as an efficient tool to simulate the development, growth, yield, and resource use efficiency of major crops at different spatial and temporal scales (S. Liu et al., 2013; Mohanty et al., 2012; Sun et al., 2016; Yang et al., 2020). Within the Corn Belt, application of crop models included exploration of different plant traits (Hammer et al., 2009; Messina et al., 2015), effect of management practices (Balboa et al., 2019; Basche et al., 2016; Baum et al., 2019), and evaluation of crop rotations (R. Gupta et al., 2022; Nicoloso et al., 2020; Ojeda et al., 2018; Puntel et al., 2016). Nevertheless, only a few studies performed calibration of cultivar parameters, despite the relevance of adjusting genotypes traits to local behavior (Archontoulis et al., 2014). Furthermore, accurate simulation of crop phenology should be a priority when calibrating crop growth models as it has an impact on many physiological processes (Wallach, 2011). Hence, the employed *in-silico* approach addressed these methodological concerns.

In this study, we explored planting date by hybrid maturity combinations via a crop growth model using the Agricultural Production Systems Simulator (APSIM) with phenology-calibrated hybrids to define environment-tailored management strategies. Exploring alternative planting dates and duration of crop growth cycle has not been extensively evaluated in this maize producing region and could assist agronomists implementing effective management to intensify the current less diversified rotations. Thus, the aims of this study were to: i) define homogenous maize yield environments classified as related to the maximum yield and its stability over time in the US central Great Plains region; ii) explore the combinations of planting date and hybrid maturity that leads to optimal yield for each of the previously defined homogenous maize yield environments; and iii) identify environments presenting different windows for maximizing yields (combinations of planting date by hybrid maturity), mainly with options for early or late planting windows.

2.3 Materials and Methods

The region for this study encompasses the eastern and part of the central region of Kansas and the northern east and central regions of Oklahoma. This region has a mean annual precipitation ranging from 700 to 1200 mm and annual temperature spanning from 12.6 to 14.4 °C. This area constitutes an important region for rainfed maize production, with yields ranging from 1.6 to 13 Mg ha^{-1} (United States Department of Agriculture (USDA), 2023). The study region is characterized for rainfed cropping systems, with only less than one third of the total irrigated fields of Kansas (Lanning-Rush, 2016). Towards the west of this region, the agricultural farming systems are characterized by irrigation (mainly dedicated to maize production) under the influence of the High Plains (Ogallala) aquifer (Graham et al., 2007; Y. Xie & Lark, 2021) and with a major influence in the last two decades for the ethanol production to support the US mandate for renewable energy (Rhodes et al., 2023; Searchinger & Heimlich, 2009). For the purpose of this study with the main focused on rainfed agriculture, the western areas of Kansas and Oklahoma were excluded of this evaluation.

In the present study, different cultivar parameters of the APSIM-Maize module (H. Brown et al., 2014) were calibrated and then validated with an independent phenology and grain yield dataset. Further analyses involved using simulations to perform geospatial clustering and evaluating management practices (planting date and hybrid maturity). Lastly, the management practices evaluations were corroborated with on-farm data. We used R software (R Core Team, 2022) for all the analyses, figure generation, and APSIM model simulations. A description of all the data sources for each step of the proposed workflow is given in Table 2.1. Hereafter, the methods for each step are explained in detail.

2.3.1 Model calibration and validation

A field experiment was conducted in Ashland Bottoms, KS, USA (39.141; -96.620) during the 2021 growing season to enable model calibration. Four commercial maize hybrids were explored: Pioneer® brand P7211AM, P8588AM, P0157AM, and P1548AM (Corteva Agriscience™ Johnston, IA, United States) with comparative relative maturities (CRM) 72, 85, 101, and 115, respectively. This rating is an indication of the time required to achieve physiological maturity (∼35% moisture content; Abendroth et al. 2011) for a specific hybrid, and it is based on the comparison with maturity checks for crop phenology (flowering and physiological maturity) and the harvest moisture level. Long-maturing hybrids (CRM 105-

115) are most commonly used in the study area. The experimental design was a randomized complete block design with three replicates. The size of the plots was eight rows, 0.762 m apart, and 15 m long. The planting date was May 8th, and the target plant densities used were 10.9; 9.4; 7.9, and 6.4 plants m^{-2} across all hybrids. Maize was fertilized with 200 kg N ha^{-1} two weeks after planting, and weeds were effectively controlled across the whole crop season. Crop phenology (silking and physiological maturity) (Ritchie et al., 1986) was recorded once a week tracking six plants per plot.

The APSIM-Maize module (H. Brown et al., 2014), included in the APSIM Next Generation software platform (Holzworth et al., 2018) was calibrated using the observed days to silking (i.e., R_1; Ritchie et al. 1986) and physiological maturity (i.e., R_6; Ritchie et al. 1986) for each hybrid maturity. The model was calibrated for the following parameters: Juvenile.Target.Fixed.Value, GrainFilling.Target.FixedValue, and the respective values for each hybrid maturity are detailed in Table A.1. The parameters that were not changed during calibration were the base cultivar 'PioneerP93M11_MG31' in the APSIM systems. The aim of keeping the rest of the parameters the same as the base cultivar was to highlight the phenological differences in our analysis. The `apsimx` package (Miguez, 2022) was used for the optimization, employing Nelder—Mead (Nelder & Mead, 1965) algorithm. The `apsimx` package (Miguez, 2022) was employed to download and format the weather data from Mesonet (`https://mesonet.k-state.edu/weather/historical`, last accessed in June 2022) using the closest weather station to each site. Furthermore, soil data was gathered from USDA-SSURGO (`https://www.nrcs.usda.gov/`, last accessed in June 2022) to a depth of 200 cm. The `apsimx` package (Miguez, 2022) was used to calculate soil parameters.

Model validation was performed using two independent data sources : i) the Kansas Maize Hybrid Performance Trials collected from 2014 to 2020 (`https://www.agronomy.k-state.edu/outreach-and-services/crop-performance-tests/`, last accessed in June 2022), and ii) field experiments carried out in Manhattan during 2021 and 2022. For both data sources information about crop management (planting date, nitrogen fertilizer applied, and seeding rate) was included in the simulations. This information is detailed in Table A.3. Yield and silking date were available for these trials. The weather (Mesonet) and soil (SSURGO) data sources detailed in the calibration description were employed to perform the validation simulations.

`Metrica` package (Correndo et al., 2022) was employed to assess model performance. The following metrics were calculated to measure model calibration: root mean square error (RMSE), relative RMSE (RRMSE), Kling-Gupta efficiency (KGE; H. V. Gupta et al. 2009; Kling et al. 2012) and percentage bias error (PBE; H. V. Gupta et al. 1999).

2.3.2 *In-Silico* analysis

Simulations setup

The APSIM model was set to plant dryland maize crops from 1992 to 2021 in the coordinates of the selected NOAA weather stations, resulting in a total of 70 sites (12 in Oklahoma and 58 in Kansas). Precipitation and temperature data were obtained from NOAA (National Oceanic and Atmospheric) weather stations (`www.noaa.gov`, last accessed in June 2022). One weather station per county was selected considering the nearest weather station to the centroid of each county. Solar radiation was gathered from the NASA-POWER project (`https://power.larc.nasa.gov/`, last accessed in June 2022). Furthermore, soil data were gathered from USDA-SSURGO (`https://www.nrcs.usda.gov/`, last accessed in June 2022) to a depth of 200 cm. The `apsimx` package (Miguez, 2022) was used to calculate soil parameters.

The simulations at each site were set from the combination of seven planting dates: April 1, April 15, May 1, May 15, June 1, June 15, and July 1, and four hybrid maturities: CRM 72, 85, 101, and 115. Moreover, the plant density was set at 7.5 plants m^{-2}, seed depth at 30 mm, row spacing at 0.762 m, and 300 kg N ha^{-1} (100 kg N ha^{-1} more than the field experiment used for model calibration) were applied at sowing as fertilizer (non-limiting N supply). This set of fixed management practices is standard for the region, except for N rate, which was included to avoid any nutrient limitation and potential interactions with our key management factors (planting date x hybrid maturity) under investigation in this study. The predictions retrieved from the model were: grain yield (kg ha^{-1}), days after sowing, and physiological maturity (days after sowing).

Spatial clustering

The number of clusters was determined considering the Xie-beni index (X. L. Xie & Beni, 1991) (Figure A.1). All sites were grouped into six environments with similar maize productivity using the spatial Fuzzy c-Means (FCM) clustering algorithm (Bezdek et al., 1984) with the `Geocmeans` package (Gelb & Apparicio, 2021). The variables included in environmental clustering were the mean and standard deviation of the yield for the optimal combination of planting date and hybrid maturity at each site for each year (30 years) (Table A.4). These two variables were selected with the purpose of assessing not only the potential yield but also its stability.

Planting date x hybrid maturity effect

To analyze the effect of environment, planting date, hybrid maturity, and their interactions on grain yield, a linear mixed effects model was fit using the `mgcv` package (Wood, 2017) and then analyzed with ANOVA. For this linear mixed effect model, environment, planting date, and hybrid maturity and their interactions were set as fixed effect factors, while latitude and longitude were included as a site-level random effect. The contribution of the variables to the observed variance was calculated as the partitioning of the sums of squares for each one, excluding the contribution of the residuals, as proposed by de La Vega & Hall (2002). Pairwise comparisons were conducted using the `emmeans` package (Lenth et al., 2023), with a Tukey-Kramer method using a significance level of $\alpha = 0.05$.

The percentage of yield reduction, from the optimal combination of planting date (PD) and hybrid maturity (HM), at each environment, was calculated as:

$$\frac{\textit{Yield optimal combination}\ \mathrm{PDxHM} - \textit{Yield specific combination}\ \mathrm{PDxHM}}{\textit{Yield optimal combination}\ \mathrm{PDxHM}} \times 100. \tag{2.1}$$

On-farm planting date validation

A validation of the effect of planting date over grain yield was conducted using data from the Kansas Corn Yield Contests (https://kscorn.com/yieldcontest/) and the Kansas entries from the National Corn Yield Contest (www.ncga.com). This dataset included four growing seasons (2013, 2014, 2015, and 2021) of farmer maize rainfed fields (Table A.3). The observations included in the analysis corresponded to the yield ranges presented in the simulations. No restrictions regarding CRM were implemented. Each individual observation was grouped in the correspondent environment defined in section 3.2.2. according to its geographical location. Due to the self-reported nature of this dataset, on-farm yield data was available from selected counties, representing only three out of the six environments. A linear regression was fit to represent the change in yield as a function of the delay on planting date for the observed and simulated dataset independently. To match the planting dates included in the observed dataset, a restriction was imposed on the simulated data (April 15^{th} to June 1^{st}). A comparison between predicted and observed slopes for this relationship was executed. The observed data from each cluster, and their respective fitted functions, are shown in Figure A.2.

2.4 Results

2.4.1 Model calibration and validation

The overall performance of the model was adequate, as the model efficiency (KGE) ranged between 0.5 and 0.8 (Table A.2). From all data points, 93% of the phenology (days to silking) and 54% of the grain yield observations were within the 20% deviation from the 1:1 line (Figure 2.1). These represented a RMSE of 10 days for days to silking, and 2388 kg ha^{-1} for grain yield, (Table A.2), a RRMSE of 14 and 25%, and a PBE of -11 and 0.06, respectively (Table A.2).

2.4.2 Spatial clustering

Six maize yield environments were obtained by using the spatial c-means clustering analysis technique (Figure 2.2), accounting for 71% of explained inertia in the spatial scale. The environment classification was linked to the east-west precipitation gradient in the region. Yield decreased (12458 to 7469 kg ha^{-1}), and standard deviation increased (1766 to 3106 kg ha^{-1}) in the direction southeast to northcentral. From a weather-soil standpoint, these environments were mainly described by i) mean annual cumulative precipitation (432 mm of difference between SE and NC environments) and ii) soil texture (from 11% in NE to 48% sand content in the SC environments) (Table A.4), and without a clear air temperature pattern across environments (Figure A.3 and Table A.4).

2.4.3 Planting date x hybrid maturity effect

The analysis of the long-term yield simulation exploring 28 combinations of hybrid maturity by planting date in each site showed that the environment classification accounted for 77% of the observed yield variability. Hybrid maturity and planting date attributed to 15% and 8%, respectively. Furthermore, the three-way interaction (environment $\times$ planting date $\times$ hybrid maturity) was significant ($p < 0.001$) (Table A.5). Hereafter, a brief description of the interactions is done. In general, higher yields were attained with long-maturing hybrids (CRM 101 and 115; Figure 2.3). However, in some cases, as for central environments (C, NC, and SC) in early to intermediate planting dates, the CRM 85 achieved similar yields compared to these long-maturing hybrids, CRM 101 and 115 (Table A.5). Delaying planting date from April to mid-May significantly decreased yield (15% on average) for long-maturing hybrids in eastern environments (E, SE). However, in both SC and NC environments, the effect of planting date was less accentuated (< 5% on average). The shorter season CRM 72 hybrid was the most stable across planting dates but with the lowest yield. Finally, the SE environment was the most stable regarding yield variability. In this environment, changes in yield stability when delaying planting date were highly dependent on hybrid maturity (1414 and 1973 kg ha^{-1} yield standard deviation for CRM 72 and 115, respectively).

In general, the maximum yield was obtained with the combination of April 1st planting date and hybrid maturities CRM 101 or CRM 115 for the SE environment (Figure 2.4). Only in NC environment, maximum yields were attained with the combination of June 1st planting date and hybrid maturity CRM 115. Although this date $\times$ maturity combination attained the maximum yield, utilization of a shorter cycle such as CRM 101 can reduce the potential risk of early freeze damage before physiological maturity. In the NE and SC environments, it was possible to anticipate the physiological maturity date (to reduce the growth cycle by 3-to-16 days) with a low ($<$ 5% average) yield penalty when planting a hybrid maturity CRM 85 on April 15th relative to a longer maturity, (CRM 101) planted on April 1st. In the case of SE, this was feasible by using a hybrid maturity CRM 101 planted on April 1st or 15th (7-19 days). However, employing a shorter hybrid (CRM 72) reduced yield above 10% in all environments. Finally, delays in planting date until June 1st or 15th did not penalize yield in central environments (NE, SC, and NC).

2.4.4 On-farm planting date validation

Finally, the validation of the effect of planting date and maize grain yield was adequate, with a distribution of the yield penalty with planting date close to the 1:1 line (Figure 2.5). Likewise, as with the simulated crop data (Figure 2.4), greater yield penalties were observed when delaying planting dates from the farmer dataset for SE relative to both E and NE environments (Figure 2.5).

2.5 Discussion

Our study presents new insights for selecting maize hybrid maturity and planting date combinations to maximize yield (and for potential crop intensification) within a target environment of the US central Great Plains. This study offers new opportunities for future scenarios exploring best management to increase i) production per unit of land (Ray et al., 2013; Tilman et al., 2002) and/or ii) number of crops harvested per unit of time (F. H. Andrade, 2011;

Gaba et al., 2015; Waha et al., 2020).

Maize yield was maximized when using long-maturing hybrids in early planting dates, confirming previous research in the US central Great Plains (Assefa et al., 2016; Norwood, 2001; Trooien et al., 1999). Longer hybrids benefit by fully exploring the potential length of the growing season (Capristo et al., 2007), resulting in an increased use efficiency of available resources. However, a reduction in CRM was beneficial when planting after mid-June. This was also reported by Jiang et al. (2020), which highlighted the role of shorter hybrids in reducing water consumption (conservation strategy) while maintaining yields. Even though this pattern was evident for eastern environments, where delays after mid-May caused significant yield penalties, when moving towards the central environments, the effect of planting date was less evident, and in some cases, maximum yields were attained on delayed planting dates. In these environments with more irregular precipitations, exploring late planting dates for maize might represent a strategy to attain more stability over time (T. Li et al., 2022; Mercau & Otegui, 2014). Maize production in Argentina is a proof of concept of this experience, where late sowing has become a preferable choice for producers to reduce risk, especially in sub-humid and semi-arid regions (Rotili et al., 2019), leading to cropland area expansion (Otegui et al., 2021). Furthermore, there is an implicit benefit of employing diverse planting dates to diminish risk and distribute labor during the season (Cutforth et al., 2001; Krupinsky et al., 2002; Wan et al., 2016).

Furthermore, crop intensification in the US Great Plains is a practice with an increasing rate of adoption, which could potentially lead to a 26% of income increase (Rosenzweig & Schipanski, 2019). In this context, our results show these maize-based systems can provide an opportunity for crop intensification in environments with less yield potential (C, NC, SC) under rainfed conditions. In these environments, delays in planting date without significant yield penalties present a potential scenario for winter/service crop-maize rotations. J. Andrade & Satorre (2015) and J. Andrade et al. (2022) explored the combination of winter/summer crops sequences, highlighting field pea-maize double-cropped as the most productive system. Furthermore, wheat-maize combinations had been previously explored in the North China Plain, showing potential N application savings of more than 30% (Fang et al., 2008). However, attention should be taken regarding the risks associated with late harvest, including frost and unfavorable weather conditions for grain dry-down. Further, the double crop system must match the water availability in the target environments, and considerations must be made for the economic returns from a double crop. When maturity groups and planting density were optimized, winter wheat-soybean systems were profitable in Kentucky (Rod et al., 2021). On the other hand, a double-cropping system economic return analysis done in North Carolina showed fewer promising results (Hare et al., 2020). However, this last study did not test changes in variety or hybrid maturity relative to planting dates, highlighting the importance of adjusting crop management when exploring different crop sequences.

Another potential for intensification would be early planting dates of short-maturing maize genotypes (CRM 85) followed by a cash-crop after anticipated maize harvest. Even though this option has been less explored, promising results in different parts of the globe support this practice (Garbelini et al., 2022; Meza et al., 2008; Monzon et al., 2014; Widstrom & Young, 1980), and novel crop combinations are yet to be tested. Shorter season crops with less water and nutrient demand could be an option to intensify and diversify our current production systems (Howell et al., 1998; S. C. Rao & Northup, 2009). Towards the west of the state of Kansas, the use of resources (mainly limited by water supply) is a limitation towards intensification. In the higher yield potential environments (E, SE, NE), different options for intensification, such as intercropping, or relay-cropping should be explored. In general, increased cropping intensity has been proven to raise annual land productivity due to a larger resource capture and resource use efficiency (Caviglia & Andrade, 2010; Gaba et al., 2015; Jat et al., 2020; Jensen et al., 2020; Rodriguez et al., 2020).

One of the limitations of our study is linked to the restricted availability of data for calibration and validation (Wallach, 2011), especially on short-season genotypes and late planting dates. Furthermore, limitations related to the overestimation of the phenology should be acknowledged. The correct prediction of the flowering moment has great implications on the model outcomes as it relates to heat and water stress simulation. This point has been previously addressed in the literature (Messina et al., 2019; Peng et al., 2018).

Moreover, the use of crop models does not capture all the relevant aspects of a cropping system, especially the ones related to nutrient limitations (other than nitrogen) or to pests and diseases (Silva & Giller, 2020). In addition, improving our current knowledge of new crops and other farming systems (new management such as late planting time) is critical not only for the main sustainability goal but for a farming perspective and crop insurance purposes. Finally, future studies considering crop sequences should address not only physiological maturity date but the effect of dry-down that is not currently included in the crop model.

2.6 Conclusions

Maize planting date and hybrid maturity management allow opportunities to increase i) production per unit of land and/or ii) number of crops harvested per unit of time. Greater yields were attained with long-maturing hybrids (CRM 101 and 115), while delays in planting date from April-mid May decreased yield for eastern environments. Furthermore, late planting maintained yields and increased stability in central environments. Moreover, the anticipation of physiological maturity date (ranging from 3-to-16 days) with reduced yield penalties (<5%) was possible by using short-season hybrid maturities (CRM 85) in central environments. Future studies should explore the potential of early or late planting dates as intensification alternatives either before (e.g., service crops) or after maize crop (e.g., cash crops), as well as their long-term impacts on water-nutrient dynamics in farming systems.

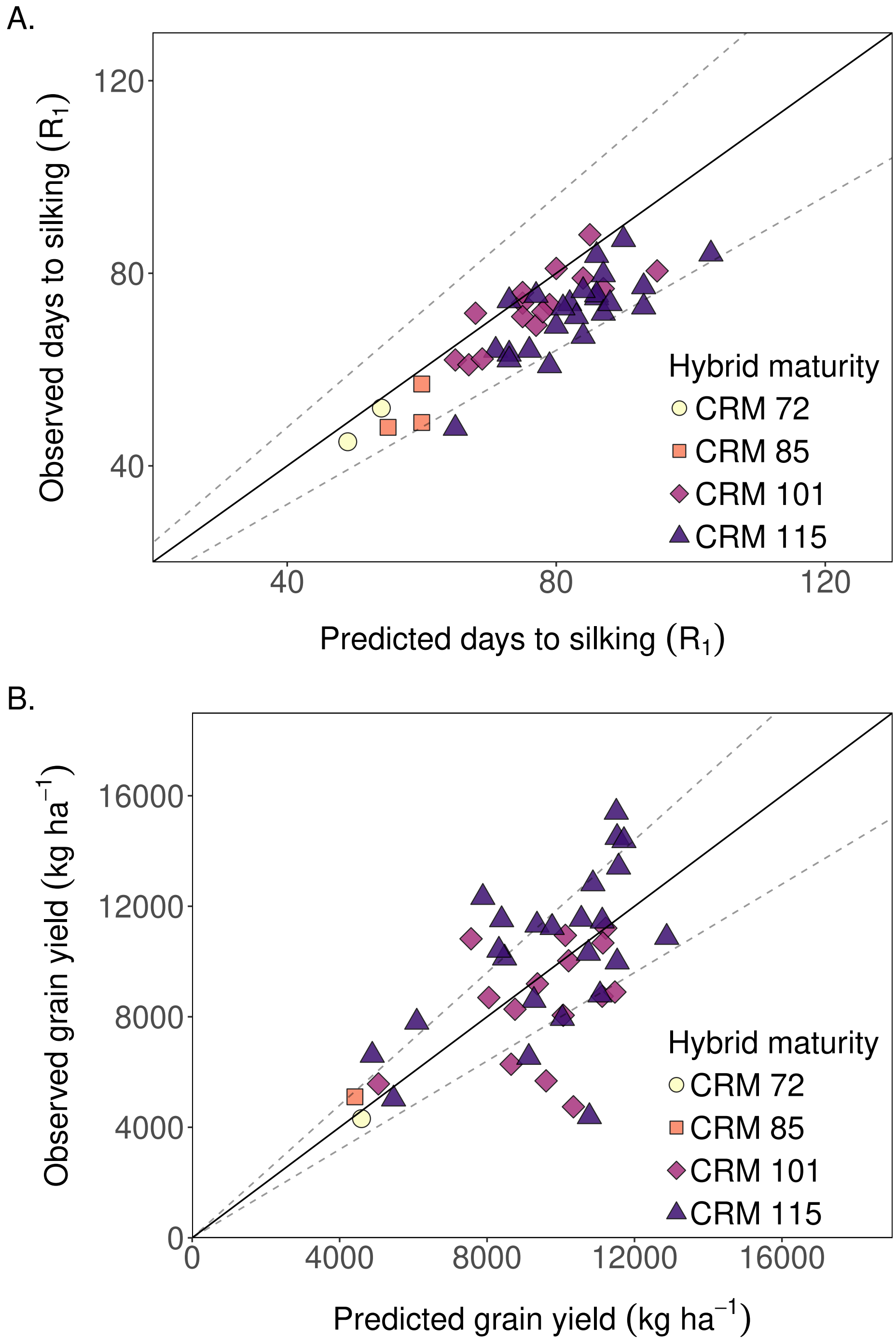

Figure 2.1: Observed versus predicted relationships for (**A**) days to silking (from planting to R1), and (**B**) grain yield (kg ha^{-1}) for four maize hybrid maturities (CRM 72, 85, 101, and 115). In each panel, diagonal solid line: 1:1 ratio; dotted lines: ±20% deviation from 1:1 line.

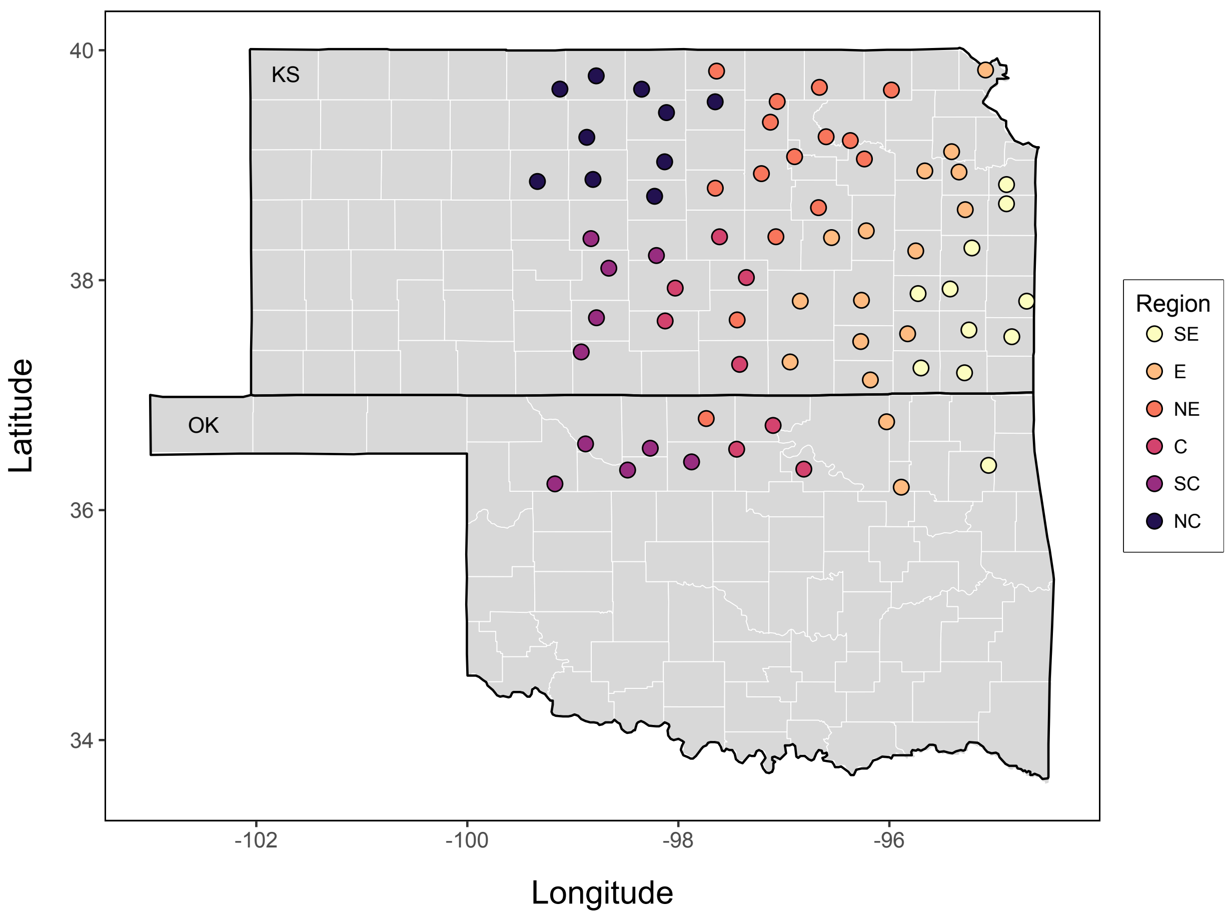

Figure 2.2: Maize productivity environments (Southeastern: SE; Eastern: E; Northeastern: NE; Central: C; Southcentral: SC; Northcentral: NC) using the spatial Fuzzy c-means (SFC) clustering technique based on mean grain yield and its corresponding standard deviation (30 years) for the optimal combination of planting date (April 1st, April 15th, May 1st, May 15th, June 1st, June 15th, and July 1st) and hybrid maturity (CRM 72, 85, 101, and 115) at each site.

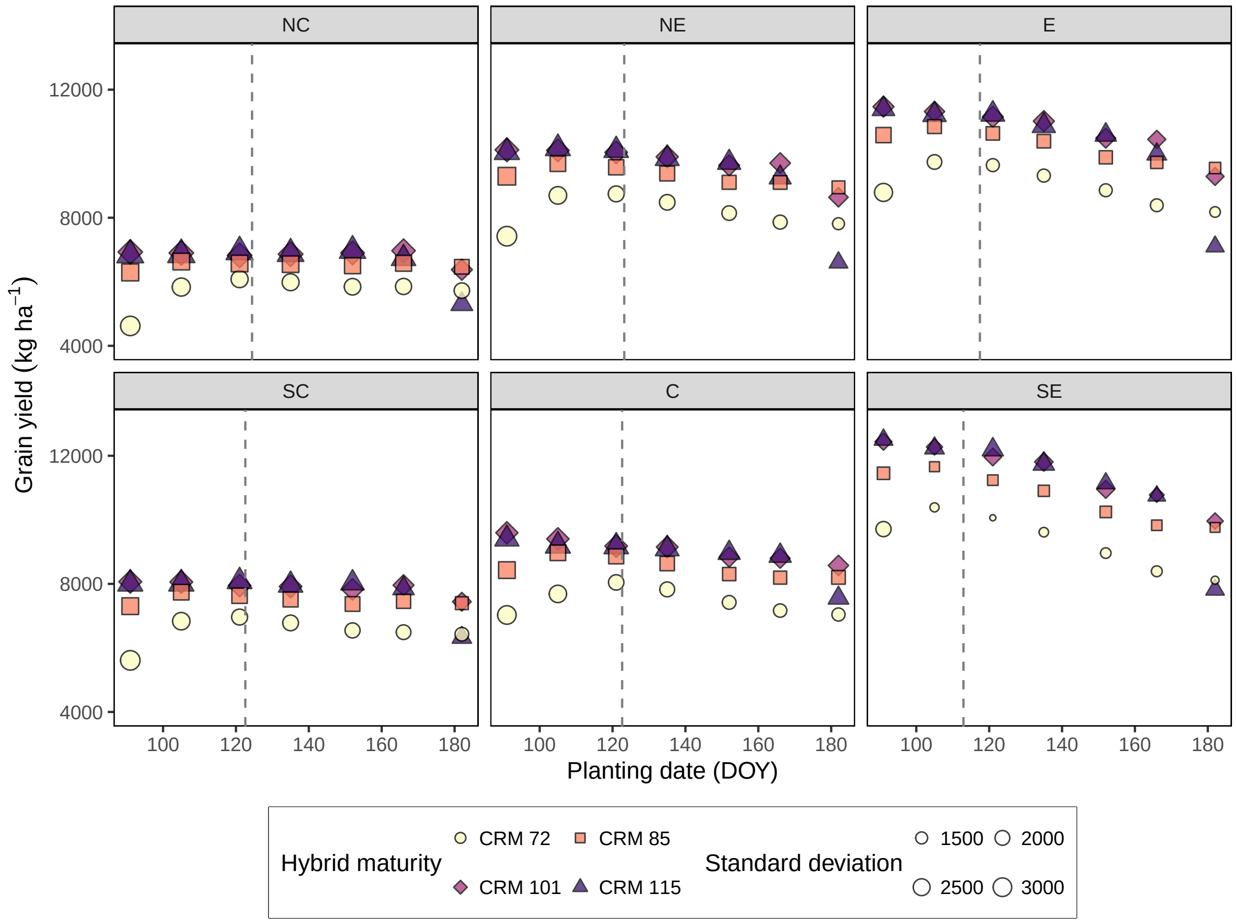

Figure 2.3: Grain yield (kg ha^{-1}) as a function of planting date (day of the year; April 1st, April 15th, May 1st, May 15th, June 1st, June 15th, and July 1st) for four maize hybrid maturities (CRM 72, 85, 101, and 115) at six maize productivity environments (Southeastern: SE; Eastern: E; Northeastern: NE; Central: C; Southcentral: SC; Northcentral: NC). The size of the points indicates the standard deviation of the mean (kg ha^{-1}) as a measure of yield stability. The vertical gray dashed line indicates the average planting date (50% planting progress) reported to the United States Department of Agriculture (United States Department of Agriculture (USDA), 2023) for the counties belonging to each environment.

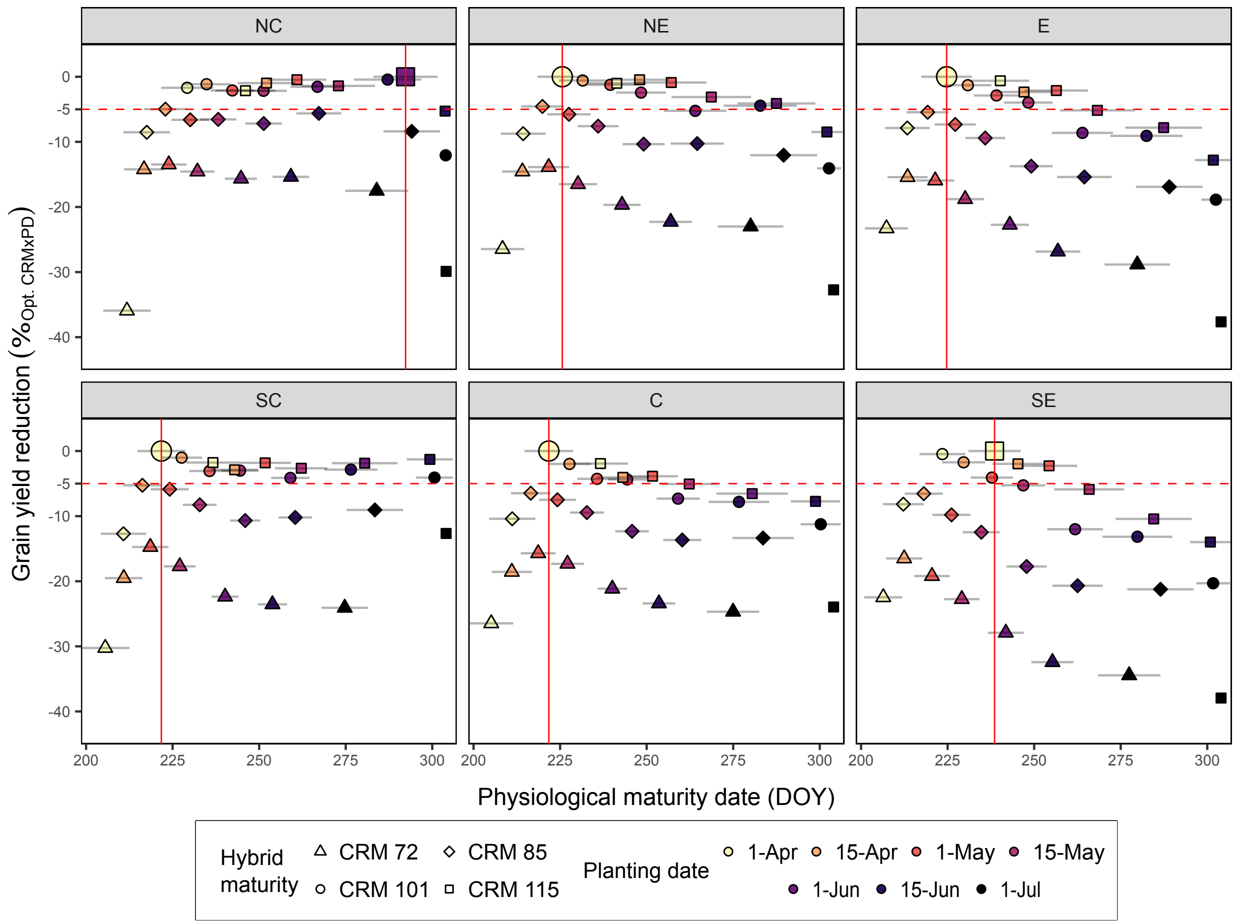

Figure 2.4: Grain yield reduction (as a percentage of the yield from the optimal combination of hybrid maturity and planting date at each environment) as a function of physiological maturity date (day of the year) for the combination of four maize hybrid maturities (CRM 72, 85, 101, and 115) and seven planting dates (April 1st, April 15th, May 1st, May 15th, June 1st, June 15th, and July 1st) at six productivity environments (Southeastern: SE; Eastern: E; Northeastern: NE; Central: C; Southcentral: SC; Northcentral: NC). For each plot, the solid red line represents the physiological maturity date for the optimum combination of hybrid maturity and planting date, and the dashed red line represents a 5% grain yield reduction (621, 574, 495, 479, 380, and 369 kg ha^{-1} for the SE, E, NE, C, SC, and NC environment, respectively). The larger point represents the optimal combination of hybrid maturity and planting date. Horizontal lines in each point represent the standard deviation of the simulated physiological maturity date.

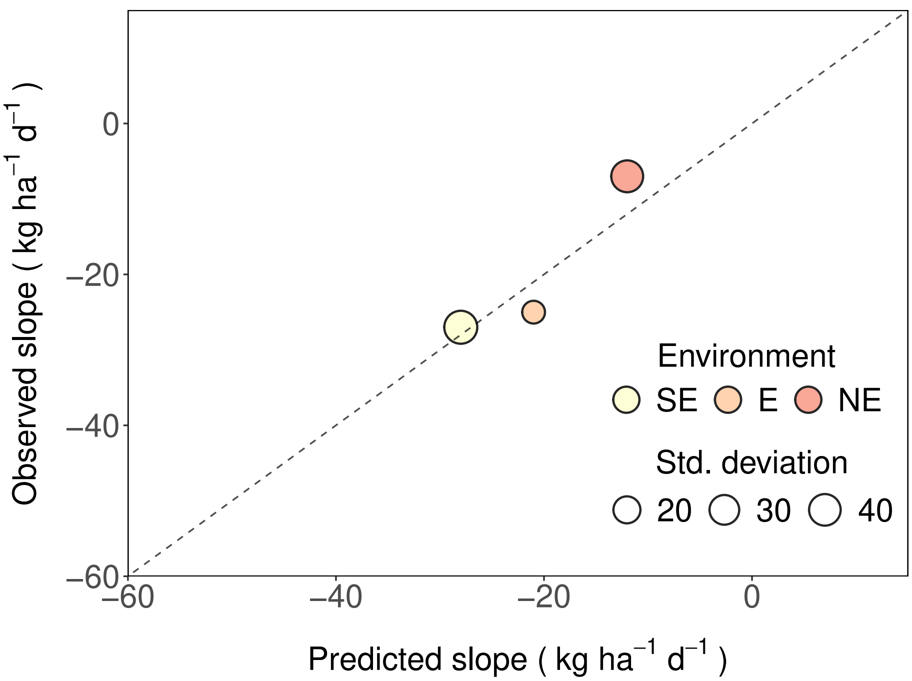

Figure 2.5: Observed versus predicted slope (kg ha^{-1} d^{-1}) for the relationship between planting date and grain yield. Due to data limitations (self-reported on-farm data) only three productivity environments (Southeastern: SE; Eastern: E; Northeastern: NE) are shown in the figure. These slopes were calculated in the regressions shown in Figure A.2. The dashed line represents the 1:1 ratio. The size of the points indicates the standard deviation for the estimation of the observed slope (kg ha^{-1} d^{-1}).

Table 2.1: Description of the field, weather and soil data sources for the different steps of the proposed workflow.

Step	Field data source	Weather data	Soil data
Model Calibration	Field experiment (1 site-year)	Mesonet	SSURGO
Model Validation	i) Kansas Maize Performance Trials, and ii) field experiments (29 site-years in total; Table A.3)	Mesonet	SSURGO
In-Silico analysis	-	NOAA and NASA-POWER	SSURGO
On-farm planting date validation	Kansas Corn Yield Contests and Kansas entries from the National Corn Yield Contest (26 site-years in total; Table A.3)	-	-

Chapter 3

Exploring alternative crop rotations to continuous winter wheat for agricultural intensification in the US central Great Plains

* Published in *Agricultural Systems*

Massigoge, I., Baral, R., Cominelli, S., Denson, E., Helguera, P. G., Guareschi, C., ... & Ciampitti, I. A. (2024). Exploring alternative crop rotations to continuous winter wheat for agricultural intensification in the US central Great Plains. *Agricultural Systems*, 216, 103879.

https://doi.org/10.1016/j.agsy.2024.103879

3.1 Abstract

Low productivity, yield stagnation, and reduction of water use, altogether with increased susceptibility to climate variability represent a challenge for agricultural producers in the United States (US) central Great Plains. In this context, a more holistic assessment of the cropping systems should be considered as a critical aspect for developing more sustainable rainfed agricultural systems in this region. The objectives of this study were to: i) quantify the fallow precipitation storage efficiency for a continuous winter wheat rotation (traditional rotation), ii) analyze and compare glucose-equivalent yields and economic results for different cropping sequences, and iii) determine efficiency components of the rotation for components such as precipitation use efficiency (PUE) and nitrogen (N) partial factor productivity (PFP_N) for different cropping sequences and N management. A three-year field experiment (2019-2022) was conducted near Manhattan, Kansas (US), under rainfed conditions. Treatments included eleven crop rotations, combining forage and grain purpose crops, and two N management, standard and progressive. An economic analysis based on the yield data combined with historical budgets was developed to compare income, expenses, and economic margins of different cropping systems. No-till summer fallow represented low (<20%) precipitation storage efficiency in the continuous winter wheat cropping system. In terms of cumulative dry matter and glucose-equivalent yields, greater overall productivity was feasible for more intensified systems and when forage crops were included in the crop sequence (e.g., 15 vs. 30 Mg glucose equivalent (GE) ha^{-1}, for wheat monoculture and forage purpose only rotations, respectively). However, cropping sequences with high frequency of forages had negative economic margins (US$ -1113 to US$ -626 ha^{-1}), while winter wheat combined with grain double crop rotation attained the highest positive economic returns (US$ 571 ha^{-1}). Finally, progressive N-management increased PFP_N relative to the standard management (63.5 vs. 54.2 kg GE kg N^{-1}, respectively) while maintaining PUE for several intensified crop rotations. Expanding the adoption of more intensified and diversified cropping systems could increase resource capture and use efficiency and productivity in the dominant continuous winter wheat systems in the US Central Great Plains.

3.2 Introduction

The central Great Plains region in the United States (US) is a vast area characterized by high evaporative demand (700-1500 mm historical mean reference evapotranspiration between

May and September; (Dewes et al., 2017) and limited annual precipitation (300 - >800 mm historical mean annual precipitation; Deines et al. 2019) that typically results in temporary soil water deficits. Rainfed agricultural systems are critical to meeting global food demand (Russelle et al., 2007). Moreover, the US Central Great Plains is the largest growing region of monoculture winter wheat (*Triticum aestivum* L.) in the world (T. Fischer et al., 2014), as the crop is adapted to the temperate climate, annual precipitation distribution, and frequent soil water deficits.

Winter wheat growing season in this region typically ranges from October to June ($\sim$ 9 months), and the timing between harvest and next crop planting is defined as fallow period. Following winter wheat harvest, fallow period can be as short as c.a. 4 months in the eastern part of the region (>600 mm), or as long (but currently less frequent) as c.a. 14 months (Peterson et al., 1996) in the western part of the region (<600 mm) in an attempt to replenish the soil profile with moisture. However, fallow periods typically have low (<40%) precipitation storage efficiency (PSE) (Nielsen et al., 2005; Nielsen & Vigil, 2010; Patrignani et al., 2019), which is defined by the amount of precipitation stored in the soil during the fallow. In addition, the yield stagnation of winter wheat (Patrignani et al., 2014) and the extensive soil degradation (Mikha et al., 2013) in this region have resulted in consistently low total factor productivity levels making the region susceptible and more vulnerable to climate variability (Ko et al., 2012; Lollato et al., 2020).

In this context, a more holistic assessment of the cropping systems should be considered as a critical aspect for developing more sustainable rainfed agricultural systems in this region. Potential solutions to increase the resilience of wheat-based cropping systems rely on the adoption of more intensified (herein defined as the number of crops in a crop rotation) and diversified (herein defined as the number of crop species per unit of time) cropping systems that can better use the available precipitation and improve system productivity. In water-limited environments, crop intensification and diversification can lead to a more efficient use of precipitation water for each crop in the rotation (Holman et al., 2020; Kelly et al., 2021; Simão et al., 2023). Several studies have shown promising results of more intensified and diversified rotations in the region via increasing total crop productivity (Holman et al., 2020; Peterson & Westfall, 2004; Rosenzweig et al., 2018) or decreasing year-to-year variability (Anderson et al., 1999). These phenomena could arise from an overall increase in resource capture and/or use (e.g., water, nitrogen; J. F. Andrade et al. 2017; Schlegel et al. 2019). Additionally, more diversified crop rotations present multiple benefits for the system, such as improved soil health (Acosta-Martinez et al., 2007; Poeplau & Don, 2015), and soil physical properties (Blanco-Canqui et al., 2013; S. Wright & Anderson, 2000), improved weed control (Bushong et al., 2012; Kumar et al., 2020; Mirsky et al., 2011), and a decrease in crop diseases (Anderson, 2008; Krupinsky et al., 2002; Vukicevich et al., 2016) or soil erosion (Blanco-Canqui et al., 2015). Meanwhile, some evidence also suggests that replacing the fallow period with a crop could reduce winter wheat productivity due to less water available at sowing (Aiken et al., 2013; Holman et al., 2018; Horn et al., 2020; Singh et al., 2023). However, it is unclear whether this reduction in wheat productivity is outweighed by an increase of the overall productivity of the agricultural system.

Beyond crop rotation, a few previous efforts evaluated tactical in-season management strategies to improve winter wheat grain yield in this region to alleviate yield stagnation (e.g., Jaenisch et al., 2021; Lollato et al., 2021). Overwhelmingly, studies suggested that N management was among the most important drivers of wheat yield. This aligns with other more holistic studies looking at historical timescales for crop yield limitation which also pointed back to N (Sinclair & Rufty, 2012). However, excessive N input can lead to increased losses to the environment (Tamagno et al., 2022) and challenge system's sustainability (Sutton et al., 2021; Zhang et al., 2015). Thus, the question here is whether improved strategic management practices (intensified and diversified crop rotations) could increase overall regional productivity when combined with improved tactical management practices (N-management).

To the extent of our knowledge, only a few studies have attempted to quantify changes in resource use efficiency of crop rotations under varied degree of intensification and diversification in the US Central Great Plains, and they were typically comparing cropping systems based on economic performance or total biomass production (Holman et al., 2020; Lyon et al., 2007; Nielsen et al., 2005, 2011, 2016). However, these approaches are subjected to commodity price fluctuations and do not consider differences in biomass composition and grain quality (e.g., carbohydrate, protein, oil components). Thus, we propose to compare different crop rotations by unifying biomass production using the glucose-equivalent concept (Angus et al., 1983; Loomis & Amthor, 1999), which allows for comparisons among crops by calculating the amount of glucose required to produce the different plant components (i.e., carbohydrates, proteins, and oil components) of their harvestable organs of forage and grain crops (Caviglia et al., 2011; Novelli et al., 2017).

Therefore, the goal of this study was to evaluate the effects of eleven crop rotations, including annual and perennial forages, cover crops, and grain crops, during a 3-year field experiment. Our working hypothesis was that diversified and intensified crop rotations will result in higher total rotation productivity, gross revenue and resource use efficiency compared to continuous winter wheat. The objectives of this study were to: i) quantify the fallow PSE for continuous winter wheat, ii) analyze and compare glucose-equivalent yields and economic results for different rotations, and iii) determine efficiencies such as precipitation use efficiency (PUE) and N partial factor productivity (PFP_N) for different cropping sequences and N management.

3.3 Materials and Methods

3.3.1 Description of experimental site

A field experiment was conducted at the Kansas State University Ashland Bottoms Experiment Field (39°07'29.8" N, 96°38'06.4" W, altitude 325 m) located near Manhattan, KS, USA from 1st October 2019 to 31st October 2022. The soil was classified as silty clay loam (Wymore series, fine mesic Aquertic Argiudoll; United States Department of Agriculture (USDA), 2014). The experimental site was managed with winter wheat before the beginning of the study, following a sorghum (*Sorghum bicolor* L. Moench)-soybean (*Glycine max* L. Merr.)-wheat conventional tillage rotation (chisel plow, tandem disk, and field cultivator). Initial soil analyses at the beginning of the study (October 2019) showed total C contents of

1.47% (± 0.15), total N 0.17% (± 0.02) bulk density 1.11 g cm-3 (± 0.15) (0-5 cm depth), pH 6.66 (± 0.54) and Mehlich 3 extractable P 14.3 ppm (± 5.68) (0-15 cm depth). Daily precipitation and temperature data were obtained from the Mesonet weather station in Manhattan, Kansas (Patrignani et al., 2020), located less than 10 km from the experimental site. Based on historical records (33 years), the average annual rainfall was 876 mm while the average annual temperature was 12.4 °C and the frost-free period was 179 days. Monthly summaries during the experimental period and absolute deviation from historical data are presented in Table 3.1.

3.3.2 Experiment description

The treatments consisted of eleven cropping sequences that varied in crop type and intensity and included cover crops, forage crops, and grain crops (Figure 3.1). The continuous wheat treatment was based on a continuous winter wheat rotation, while the remaining treatments, beginning with the abbreviations Gr, GF, or For, consisted of a combination of winter and summer crops for grain only, grain and forage, or forage purpose, respectively. Within each of the latter, the cropping systems were subdivided according to the number of crops per year by adding the following abbreviations: Ba (base), Sem (semi-intensive) and Int (intensive), A number (1 or 2) was added to differentiate cropping systems with the same abbreviations but different crop species. Specifically, the species included were alfalfa (*Medicago sativa* L.), cowpea bean (*Vigna unguiculate* L.), maize (*Zea mays* L.), moth bean (*Vigna aconitifolia*), grain sorghum, soybean, tepary bean (*Phaseolus acutifolius*), triticale (× *Triticosecale* Wittmack) and winter wheat. Treatments consisting of continuous wheat (ContW), grain purpose only (Gr – Ba, Gr – Sem 1, Gr- Sem 2, Gr – Int,) and grain-forage purpose, base and semi-intensive 2 (GF – Ba, GF – Sem2), were managed under a standard N-management strategy (traditional farming practices), while the grain-forage purpose intensive treatments (GF – Int 1 and GF – Int 2) were managed under a green N-management (no nitrogen fertilizer applications) (Table 3.2). Additionally, a progressive N-management that differed in application timing, placement, rate and source compared to the standard management was applied to treatments for grain purpose only (Gr – Ba, Gr – Sem 1, Gr- Sem 2, Gr – Int,), grain-forage purpose, base and semi-intensive (GF – Ba, GF – Sem1, GF – Sem2), and forage purpose only (For). The N fertilizer rate was applied according to an in-season N recommendation, based on crop modeling that uses cropland observation through monitoring crop conditions and water balance (Table 3.2). Nitrogen was broadcasted at Feekes 4 for standard management, while for progressive management it was applied with streamer bars split at Feekes 4 and 7 for winter crops and coulter banded split at planting and V_6 for summer crops. The source was UAN (Urea Ammonium Nitrate; 32-0-0 of N–P_2O_5–K_2O) for standard management and UAN plus a urease + nitrification inhibitor (11 liters per ton of fertilizer) with a nitrification inhibitor (18 liters per ton of fertilizer) for progressive management. Treatments were established in a randomized complete block design with four replicates arranged in plots 12.19 m wide and 15.24 m long.

3.3.3 Crop management

Winter crops (i.e., winter wheat and triticale) for forage purpose were sown 2-3 weeks prior to the optimum sowing date for the region (i.e., second half of September to early October); winter wheat sown for grain-purpose after summer-fallow, after forage soybean, or after full season soybean was sown at the optimum sowing date (i.e., mid-October); and winter wheat sown for grain-purpose after double-crop soybean or maize, and triticale sown as cover crop, were sown considerably later (i.e., November) than the optimum window. Regarding summer crops, those following winter fallow, hay-triticale, or cover crops were planted early in the season (i.e., mid-May). Summer crops following a winter wheat crop harvested for grain were planted later (i.e., early July), immediately after harvest. Cowpea, moth bean, tepary bean, grain sorghum, and maize were only cropped at late planting dates. The alfalfa crop (treatment 17) was sown after winter wheat harvest in 2021 and grown until the end of the study (October 2022). A full description of the specific management practices for each cropping sequence is presented in Table B.1.

Winter wheat and triticale were sown in rows spaced 0.19 m apart and seeded using a

9-row Great Plains 606® no-till drill (Great Plains Manufacturing, Salina, KS, USA). Forage soybean, maize, sorghum, cowpea, and soybean were 0.76 m row-spaced, while moth, tepary, and alfalfa were 0.38 m, and were planted using a 2-row John Deere 7000® planter (John Deere, Moline, IA, USA).

The forage crops alfalfa, triticale and winter wheat and forage soybean were mowed at late bud (Fick & Mueller, 1989), late boot (Zadoks et al., 1974), and R_3 (beginning pod) phenological stages (Fehr & Caviness, 1977), respectively. For moth bean and tepary bean crops their mowing time corresponded to 68 days after planting. Alfalfa crop was mowed once during the seeding year (2021), and four times during growing season in 2022. In all forage plots mowed, shoot biomass was removed to avoid confounding effect of crop residue returning to the soil. Lastly, triticale for cover crop purpose was chemically terminated at booting stage using glyphosate two weeks before summer crop planting.

Diammonium phosphate (DAP; 18-46-0 of N–P_2O_5–K_2O) fertilizer was applied in furrow with the seed at the planting of winter crops at a rate of 55 kg ha^{-1}, while no phosphorus fertilizer was applied on summer crops. Weeds were controlled by a combination of pre-emergence and post-emergence herbicides, and hand weeded as necessary to control escaped weeds. For winter crops, spring herbicide applications consisted of mixtures of thifensuifuron-methyl, MCPA, and nonionic surfactant. Regarding summer crops, flumioxazin, pyroxasulfone, S-metolachlor, atrazine, mesotrione, imazamox, and glyphosate were applied at pre-emergence on selective crops, while glufosinate-ammonium, flumioxazin, pyroxasulfone and glyphosate were applied at post-emergence when needed. Herbicides mixtures were applied during fallow periods to suppress weeds when needed. Neither insecticides nor fungicides were applied to the plots. The experiment was managed under rainfed conditions (no irrigation) and a no-tillage system during the period under study.

3.3.4 Soil moisture measurements

Soil water content was measured periodically (i.e., 7-15 days) in the top meter of the soil profile using a portable capacitance probe (model Diviner 2000, Sentek, Inc., Stepney, SA, Australia) in the continuous wheat treatment (ContW). In the center of each plot, PVC access tubes were installed to facilitate measurements along the soil profile at 10 cm depth intervals and to accurately represent the plot.

The sensor was calibrated using the thermo-gravimetric method, which involves collecting soil samples at different depths and drying them at 105°C for 48 hours to determine soil's water content and collecting soil scaled frequency (SF) readings in extra access tubes installed near the experiment plots. Based on field observations, the following equation from the manufacturer's manual was adopted to convert SF readings into volumetric soil water content (θ):

$$\theta = a + b \times \mathrm{SF}^c, \tag{3.1}$$

where a is equal to 0.08, b is equal to 0.4, and c is equal to 5.2 (Evett et al., 2006).

3.3.5 Plant measurements

Physiological maturity date for grain-crops was recorded using specific phenological scales for different crops (Feekes, 1941; Fehr & Caviness, 1977; Fernandez de C. et al., 1986; Ritchie et al., 1986; Vanderlip & Reeves, 1972). Winter wheat grain yield and moisture content were determined by harvesting the center of each plot (18.5 m^2 area) using a Massey Ferguson XP8 small-plot self-propelled combine (Massey Ferguson Corp, Duluth, GA). Soybean and cowpea, and maize and sorghum grain yields were determined by hand-harvesting the center of the plot (1 and 7 m^2, respectively) and threshing the pods or shelling the ears using a stationary machine. Grain yield for all crops was calculated based on harvested area and adjusted to a 0 g kg^{-1} moisture basis to keep consistency with the usual results of resource use efficiencies (Caviglia et al., 2019).

For forage dry biomass determination, above-ground plant samples were collected at the respective mowing times for each crop (0.14 m^2 area) (Table B.1). The freshly harvested forage sub-samples were weighed and then dried in a custom built forced-air dryer at a constant temperature of 60°C for 72 hours to determine forage dry matter yield. The dried samples were then ground in a Willey mill and passed through a 1 mm sieve to analyze forage nutritive value parameters such as water-soluble carbohydrates (WSC), crude protein (CP), and fat and lignin contents using near-infrared spectroscopy (NIRS). A more detailed explanation of the use of the NIRS technique for the analysis of forage quality can be found in Marten et al. (1985) and Shenk & Westerhaus (1994).

3.3.6 Calculations

Cropping intensity was calculated for each cropping sequence as the ratio of the number of days with actively growing crops to the total duration of the rotation (e.g., Novelli et al., 2017). Similarly, precipitation allocation (PA) was defined as the percentage of the total precipitation during the 3-year study received during the growing season for each cropping sequence (e.g., Patrignani et al., 2019). Species richness was defined as the number of crop species in the cropping sequence. The values of each cropping system for these metrics are depicted in Table 3.3.

The PSE was determined for the summer fallow period in the baseline rotation (continuous winter wheat; treatment 1) for the years 2021 and 2022 by the following equation:

$$PSE(\%) = \frac{WS_F - WS_I}{P_F}, \tag{3.2}$$

where WS_F (mm) is the soil water storage in the top 1 meter at the end of the fallow period, WS_I (mm) is the storage at the beginning of the fallow period, and P_F (mm) is the total precipitation during the fallow period. We assumed the precipitation not stored in the soil profile during the fallow period was lost due to drainage, runoff, or evaporation.

To account for the contribution in energy equivalent terms of the different crops to accumulated forage or grain yield, these variables were expressed as glucose-equivalent yield. For grain crops, a specific conversion factor from grain into glucose (g glucose g grain-1) was found in the literature for each crop. These were 1.39 for wheat (Novelli et al., 2017), 1.93 for soybean (F. H. Andrade, 1995), 1.39 for maize (F. H. Andrade, 1995), and 1.35 g glucose (g grain)$^{-1}$) for cowpea (Morris et al., 1990). For forage crops, the conversion factor yield to glucose-equivalent was calculated considering forage quality as proposed by Wall et al. (1994). Thus, the following equation was used to obtain the glucose required for growth during biosynthesis (CRG; g glucose g tissue^{-1}):

$$CRG = 1.211F_c + 1.793F_P + 3.03F_F + 2.119F_L + 0.906F_O, \tag{3.3}$$

where F_c, F_P, F_F, F_L, and F_O are the carbohydrate, protein, fat, lignin, and organic acids fractions, respectively.

The PUE at the crop rotation level was computed as the ratio between the total glucose equivalent of all crops in each rotation and the total precipitation received during the experimental period. In this study we favored the use of growing season precipitation to compute PUE over soil moisture-based indicators because rootzone soil moisture observations were not available for the entire study period and for all rotations. Nitrogen partial factor productivity ($\mathrm{PFP_N}$) was calculated as the ratio between total glucose yield and total applied N for the cropping sequence.

3.3.7 Economic analysis

Observed grain and forage yields from the field experiment were used to calculate gross income per unit area. To better represent realist farmer operations, we assumed losses related to harvest and storage of 2.5% for grain (Paulsen et al., 2013) and 40% for forage (Rotz, 2005; Rotz & Muck, 1994). Prices received for Kansas at the time of harvest were used for grain crops (URL in Table B.2), except for cowpea, where the soybean price was used in replacement for the lack of data on this crop. Prices for forage crops were based on alfalfa hay prices received for Kansas at the time of mowing, due to the limited market for these crops (Miceli-Garcia, 2010). Thus, prices for triticale, forage soybeans, moth, and tepary beans were discounted by one-third of the alfalfa hay price, while the full price was used for alfalfa (URL in Table B.2). Variable and fixed costs were obtained from the historical (URL in Table B.2) budgets developed by the Department of Agricultural Economics at Kansas State University. All prices and costs were indexed to October 2022 US$ using the Consumer

Price Index inflation calculator (URL in Table B.2) elaborated by the US Bureau of Labor Statistics. Finally, gross margin per hectare was calculated as the difference between total income and total costs.

3.3.8 Statistical analyses

In order to analyze the effect of cropping sequence on harvestable dry matter, glucose-equivalent yield, and cumulative winter wheat yield, generalized linear models (GLM) were fitted using the `glm` function from the `stats` R package (R Core Team, 2023) with cropping sequence and block as predictor variables (Equation B.1). A similar procedure was used to analyze the effect of cropping sequence and N management on PUE and PFP_N, with cropping sequence and N management factors (and their two-way interaction) and block as predictor variables (Equation B.2). All GLMs models assumed a gamma distribution with a log link-function which matches the support of the response variables (positive and continuous). The fitted models were subjected to analyses of variance (ANOVA) using the `car` R package (Fox & Weisberg, 2019). Finally, pairwise comparisons of least-square means were conducted using the `emmeans` R package (Searle et al., 2021) by applying the Tukey–Kramer method. The R programming software (R Core Team, 2023) was used for all the analyses and figure generation.

3.4 Results

3.4.1 Precipitation storage efficiency during summer fallow

The summer fallow in 2021 had a precipitation of 196 mm over 136 days, which resulted in a PSE of 12.23 % (Table 3.4; Figure 3.2). Similarly, the summer fallow in 2022 received 380 mm of precipitation for 128 days, which resulted in a PSE of 16.11 %.

3.4.2 Dry matter and glucose-equivalent cumulative yields

Cumulative yields ranged from 10.8 to 49.88 Mg ha^{-1} for harvestable dry matter and from 15.02 to 29.57 Mg ha^{-1} for glucose-equivalent (Table 3.5). Continuous wheat (ContW) was among the least productive cropping systems (i.e., lowest yields), while forage purpose only (For) and grain-forage purpose intensive (GF – Int 1, GF – Int 2) attained the greatest yields. This scenario was explained by a greater contribution of forage crops either expressed as dry matter ($p < 0.001$) or glucose-equivalent ($p < 0.01$). There was a positive association between cumulative glucose-equivalent yield and precipitation allocation ($p < 0.05$), but not for the number of crops per year or cropping intensity. Finally, all rotations with more winter crops (e.g., three crops: ContW, Gr-Ba, Gr-Sem 1, and GF - Sem1) presented higher cumulative wheat production compared to the other cropping sequences (e.g., with two winter wheat crops) (Table 3.5). The cropping sequences with more winter wheat crops were not those with more total dry matter and glucose equivalent, but those that included forage crops.

3.4.3 Economic analysis

Regarding the economic analysis, the total income ranged from US$ 2,620 to US$ 4,282 (Figure 3.3a), while the total costs ranged from US$ 2,189 to US$ 4,908 US$ ha^{-1} (Figure 3.3b), corresponding to the continuous wheat (ContW) and grain-forage purpose intensive 2 (GF – Int 2) treatments, respectively. Total cost was related to the increase in cropping intensity ($p < 0.001$). The grain purpose only base (Gr – Ba) and continuous wheat (ContW) treatments attained the greatest gross margin (US$ 571 and 430 ha^{-1}, respectively) (Figure 3.3c). However, treatments with high frequency of forage crops (For, GF – Int 1, GF – Int 2) resulted in negative gross margins due to the increased costs such as custom operations (i.e., baling, side raking, and swathing and conditioning). Overall, the cropping sequences with positive gross margins were those with presenting three wheat crops in the rotation, except for Gr-Sem 1, which included one more fallow period compared to Gr-Sem 2. This emphasizes the importance of intensifying the rotation by adding more crops and diversifying by including different options after winter wheat.

3.4.4 Nitrogen management effect on PUE and PFP_N

When exploring the effect of N, the progressive management did not affect the precipitation use (PUE) efficiency in any of the tested cropping system ($p = 0.61$) (Table 3.6). However, PFP_N for progressive management (63.51 kg GE kg N^{-1}) was greater relative to the standard management (54.2 kg GE kg N^{-1}) ($p < 0.0001$). Finally, there was no clear relationship between increasing the number of wheat crops in the rotation with greater PUE and PFP_N (Table 3.6).

3.5 Discussion

Increasing cropping intensity is critical for meeting future food demand (F. H. Andrade, 2011; Waha et al., 2020). Beyond the positive impact on food production, crop intensification has the potential to improve agroecosystems and reduce the environmental impact of agriculture (Gaba et al., 2015). Examples of transition to intensified systems in water-limited environments include regions in Africa (Ali et al., 2017; Tsubo et al., 2004), Australia (Garba & Williams, 2023; Sadras & Roget, 2004), and the US Northern Great Plains (Berti et al., 2015; E. G. Smith et al., 2000). However, this trend has been adopted more slowly in the central region of the US Great Plains, primarily due to its drier climate (Hansen et al., 2012; Rosenzweig & Schipanski, 2019). Our study highlights the viability of implementing more intensive cropping systems in the US Central Great Plains to increase resource use efficiency and productivity on the dominant continuous winter wheat systems.

3.5.1 Precipitation storage efficiency during summer fallow

Fallow has been a traditional strategy in water-limited environments to store water to stabilize yields and minimize crop failure risks. Even in sub-humid regions such as central Kansas, continuous wheat still reflects about 50% of the wheat area grown in the region (Jaenisch et al., 2021). However, our findings indicate that less than 20% of the total captured precipitation has been effectively stored at the end of the no-till summer fallow in the continuous winter wheat system, consistent with values reported by previous studies (Farahani et al., 1998; Nielsen et al., 2005; Patrignani et al., 2019). This low storage efficiency is mainly attributed to evaporative losses due to the high atmospheric demand during the summer months (i.e., June-September) (Nielsen & Vigil, 2010). In addition, fallow periods increase herbicide costs due to the emergence of resistant weeds (Rosenzweig et al., 2018; Young, 2006) and increase soil degradation as well as nutrient erosion (Bowman & Halvorson, 1997; Hansen et al., 2012; Nielsen & Aiken, 1998). In this context, replacing the summer fallow period with the cultivation of crops is an interesting perspective for crop intensification when the entire rotation is considered.

3.5.2 Productivity and economic return of cropping systems

We have demonstrated that greater crop rotation productivity, in terms of cumulative dry matter and glucose-equivalent yields, is feasible for more intensified systems and when forage crops are included in the crop sequence, all relative to the continuous winter wheat scenario. This increase in cumulative productivity for the cropping sequence was achieved at the expense of decreased annually based winter wheat productivity. Moving away from continuous wheat systems or less diversified corn-soybean rotations by including other crops, intensifying, and diversifying cropping sequences can not only increase productivity but gross margin in a more sustainable manner (e.g., Congreves et al., 2015; Dhuyvetter et al., 1996; Gaudin et al., 2015; Halvorson et al., 2002; Nielsen & Vigil, 2018; Williams et al., 2012; Yang et al., 2024; Zuber et al., 2015). Previous studies have demonstrated greater annualized biomass productivities for intensified rotations integrating forages, with responses linked to increased precipitation (Anderson et al., 2003; Carr et al., 2021; Holman et al., 2020). Forage crops have greater precipitation use efficiency (Deng et al., 2020; Nielsen et al., 2005, 2006; Unger, 2001) and are less dependent on timely precipitation events than grain crops. However, sequences with high frequency of forages crops had negative economic margins, while winter wheat combined with grain double crop rotation attained the highest positive economic returns. These findings underscore the importance of the availability of crop markets and end-use processors, and the improvement of commercialization avenues, as crucial factors to consider when implementing more intensive cropping systems.

3.5.3 Nitrogen management for intensified cropping systems

From a key input to the system, N is the second most limiting factor in the US Great Plains (Campbell et al., 2007; Kröbel et al., 2012). Reduced rates of N fertilization under more intensive management can increase PFP_N while maintaining precipitation use efficiency for several intensified crop rotations. Likewise, previous studies found that N fertilizer use efficiency decreases as the application rates increase (R. Lin & Chen, 2014; Sindelar et al., 2016). Furthermore, including legumes in the rotation increases grain and protein yields, while reducing the amount of fertilizer applied compared to continuous cereal monoculture (St. Luce et al., 2020). Recently, Ciampitti & Lemaire (2022) highlighted the dependence of cereals on N fertilization to attain high productivity levels. These findings emphasize the importance of the synchrony between N supply and crop demand, as the impact of N on the productivity of cropping systems is driven by soil water content (Gan et al., 2015). For this purpose, in-season N management decision tools are crucial for increasing nutrient use efficiency while reducing the ecological footprint (e.g., nitrate leaching or GHG emissions).

A few limitations of this study are i) limited number and combination crops within each crop rotation due to the exponential combination of crop choices in relation to funding and labor. Crop modeling is a viable option to study a larger number of crop rotations in a wider range of environments and longer periods to circumvent some of the limitations of this study; ii) lack of repeatability of crop phases within each growing season, limiting the implications of weather impact on each rotation, iii) different number of complete phases repeated for each crop rotation mainly due to challenges in selecting crop combinations relevant to farmers in the region, iv) uncomplete testing of the N management effect among all crop rotations, and v) we did not observe root zone soil moisture in all the rotations which prevented us from computing the water use efficiency. However, because in this region, evapotranspiration is the dominant component of the soil water balance, precipitation use efficiency was used as a proxy of water use efficiency. Future studies should test the transition of these promising intensification alternatives to an on-farm scale. Fruitful collaborations and integrations between researchers and agricultural stakeholders will be critical in responding to the challenges facing agriculture today (Lacoste et al., 2022). In addition, other key points to explore are related to social constraints for establishing intensified systems, such as changes in land tenure and risk aversion of farmers. Finally, crop insurance policies can sometimes be a barrier to crop intensification (Rosenzweig et al., 2020). For instance, in some counties in the US Central Great Plain, farmers are not allowed to purchase subsidized crop insurance for wheat unless it is preceded by a year-long summer fallow. In this context, policies based on current scientific findings should be designed to promote the adoption of more intensified cropping systems. At a global level there are many successful examples of sustainable agricultural intensification practices (Pretty et al., 2018). Greater emphasis on social innovation and participatory approaches will be useful for large scale adoption (Middendorf et al., 2020; Pretty et al., 2020), as well as more integrated frameworks that include ecological impact (Moraine et al., 2017; Reckling et al., 2016) and human systems assessment (Ban et al., 2013; M. E. Brown et al., 2023) for designing more sustainable cropping systems.

3.6 Conclusions

This study demonstrates that more intensified cropping sequences are viable options for replacing less water use efficient summer fallow in continuous winter wheat systems in the US Central Great Plains. Thus, greater total productivity, in terms of both dry matter and glucose-equivalent, was attainable when forage crops were included in the rotation scheme. However, crop selection must be considered not only from productivity but also from an economic perspective in which rotations involving forage crops were at a disadvantage. Lastly, intensive N management is a key component of crop intensification that leads to increased partial factor productivity.

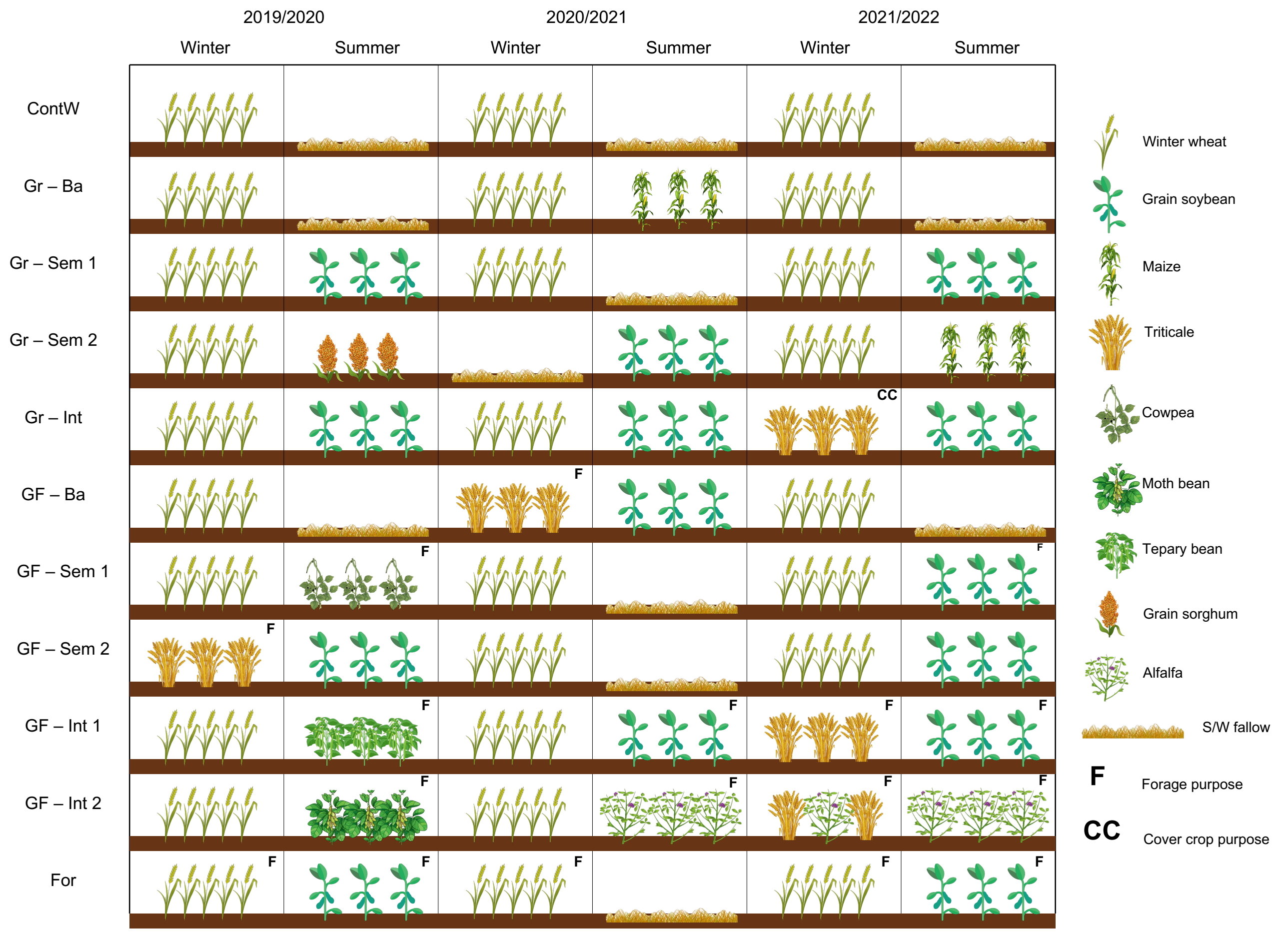

Figure 3.1: Schematic diagram of the cropping rotations used in this study from October 2019 to October 2022. S/W Fallow: summer or winter fallow; F: forage crop; CC: cover crop. ContW: continuous wheat; Gr: grain purpose; GF: grain-forage purpose; Ba: base; Sem: semi-intensive; Int: intensive.

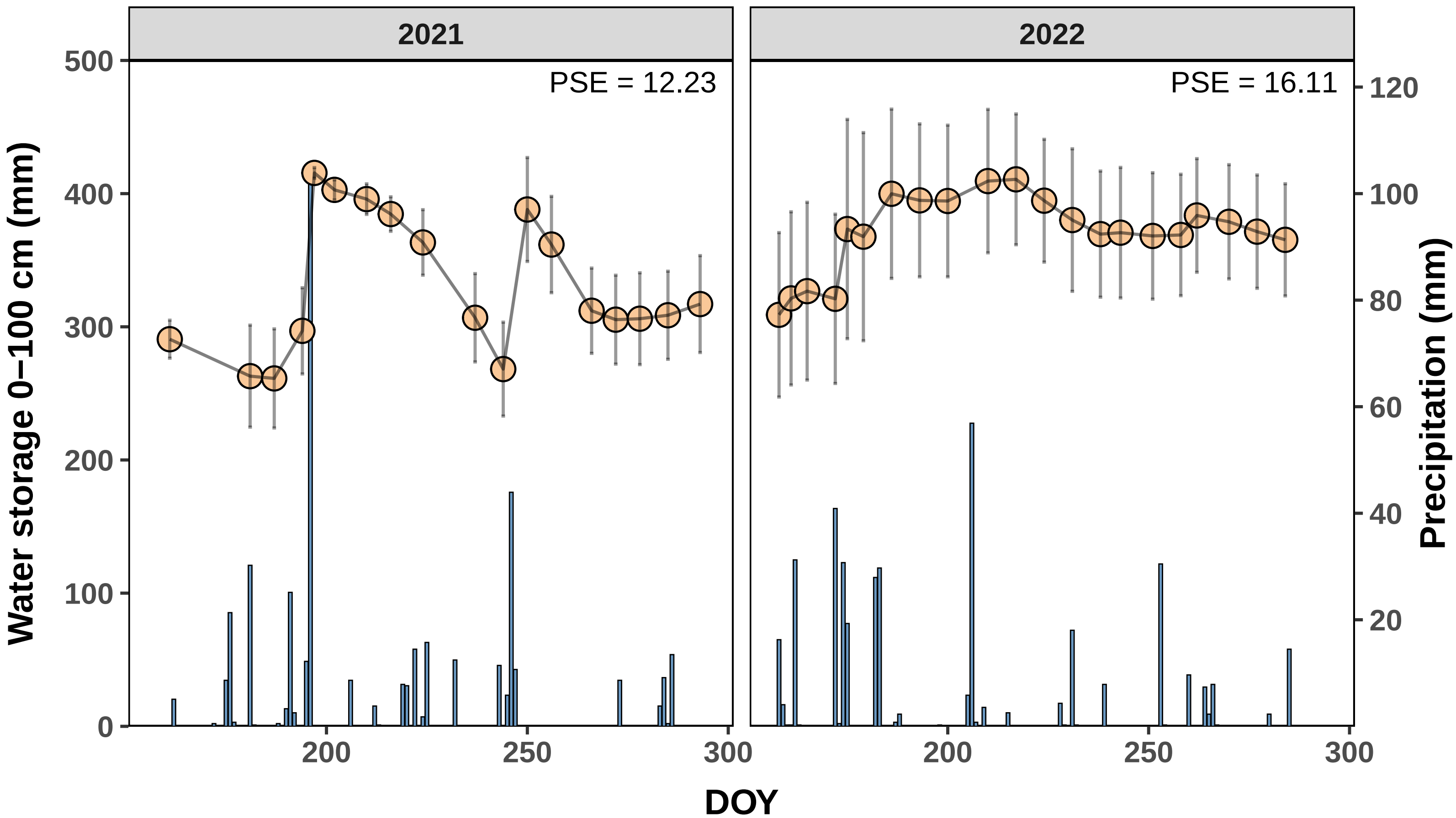

Figure 3.2: Soil water storage (mm; 0-100 cm; orange points) and precipitation (mm; blue bars) as a function of the day of the year (DOY) for the fallow period on a continuous wheat cropping system (ContW) during 2021 and 2022. Vertical error bars represent the standard deviation of the mean water storage value for each date. PSE: Fallow precipitation storage efficiency (%).

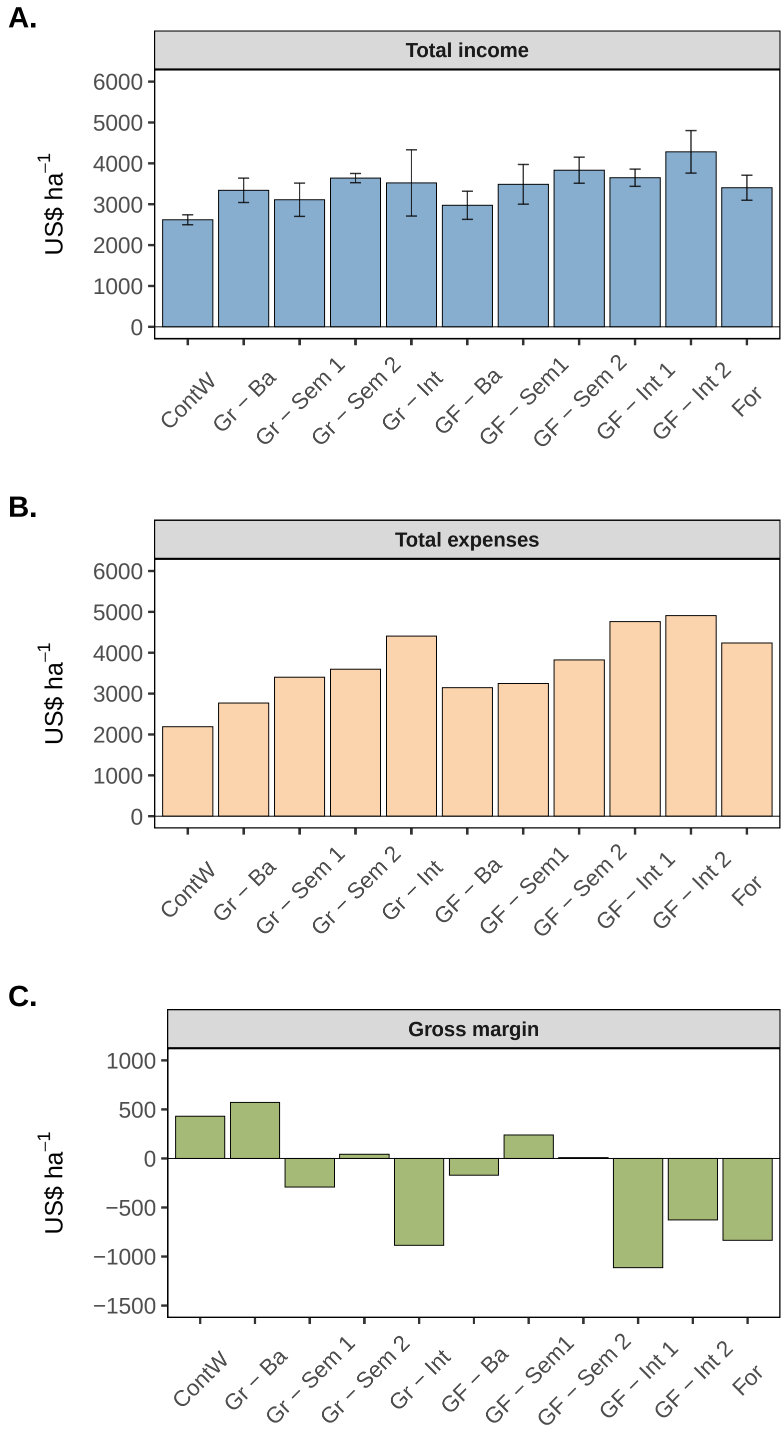

Figure 3.3: Total income (**A**), total expenses (**B**) and gross margin (**C**) (US$ ha^{-1} indexed to October 2022 US$) for eleven cropping sequences in experiments conducted from October 2019 to October 2022. ContW: continuous wheat; Gr: grain purpose; GF: grain-forage purpose; For: forage purpose; Ba: base-intensive; Sem: semi-intensive; Int: intensive.

Table 3.1: Monthly mean solar radiation (Rad; MJ m^{-2}), mean air temperature (T; °C), and accumulated precipitation (P; mm) recorded from October 2019 to October 2022. Values within brackets represent the absolute deviation from the historical value (33 years). Source: NASA Power Data Access Viewer (2023) and Kansas Mesonet station in Manhattan (2023).

Month		**2019**			**2020**	
	Rad (MJ m^{-2})	**T° (°C)**	**P (mm)**	**Rad (MJ m^{-2})**	**T° (°C)**	**P (mm)**
January	-	-	-	7.3 (-1.1)	-0.1 (+1.2)	17 (+6)
February	-	-	-	12 (+0.9)	1.2 (+0.3)	20 (+1)
March	-	-	-	13.6 (-1.2)	8.6 (+1.3)	64 (+18)
April	-	-	-	19.4 (+1.1)	11.7 (-1.3)	49 (-27)
May	-	-	-	18.7 (-2.2)	16.5 (-2.2)	141 (+34)
June	-	-	-	26 (+2.6)	25.9 (+1.9)	89 (-33)
July	-	-	-	22.8 (-0.7)	26 (-0.2)	168 (+72)
August	-	-	-	23.1 (+2.4)	24.6 (-0.4)	45 (-66)
September	-	-	-	16.3 (-0.7)	19.1 (-1.2)	55 (-27)
October	12.6 (0.0)	10.3 (-3.3)	61 (+2)	12.8 (+0.2)	11.5 (-2.1)	17 (-42)
November	9.5 (+0.6)	4.6 (-1.6)	7 (-23)	10.2 (+1.3)	8.8 (+2.5)	60 (+30)
December	7.5 (+0.3)	2.3 (+2.2)	18 (-3)	8.2 (+1.0)	1.6 (+1.5)	24 (+4)
Month		**2021**			**2022**	
	Rad (MJ m^{-2})	**T° (°C)**	**P (mm)**	**Rad (MJ m^{-2})**	**T° (°C)**	**P (mm)**
January	7.4 (-0.9)	0.8 (+2.2)	23 (+12)	9.3 (+0.9)	-1.6 (-0.3)	7 (-4)
February	11.3 (+0.2)	-5.3 (-6.2)	3 (-16)	13.8 (+2.7)	0.2 (-0.8)	2 (-17)
March	14.9 (+0.1)	9.5 (+2.2)	92 (+45)	14.9 (+0.1)	6.3 (-1.0)	57 (+10)
April	19.4 (+1.0)	12 (-1.0)	52 (-24)	18.7 (+0.3)	12.5 (-0.5)	26 (-50)
May	18.1 (-2.9)	16.7 (-2.0)	134 (+27)	19.7 (-1.2)	19 (+0.3)	231 (+124)
June	24.7 (+1.2)	25.1 (+1.2)	67 (-55)	23.9 (+0.5)	24.8 (+0.8)	154 (+33)
July	23.2 (-0.2)	25.5 (-0.7)	162 (+65)	21.8 (-1.7)	26.2 (0.0)	128 (+32)
August	21.8 (+1.0)	26.4 (+1.4)	72 (-40)	22 (+1.3)	25.6 (+0.7)	33 (-78)
September	17.6 (+0.6)	23 (+2.7)	69 (-12)	18.3 (+1.3)	21.7 (+1.5)	58 (-23)
October	12.8 (+0.2)	15.2 (+1.5)	83 (+24)	13.7 (+1.1)	-	-
November	9.4 (+0.5)	8.4 (+2.2)	29 (-1)	-	-	-
December	8.3 (+1.0)	5.1 (+5.1)	8 (-12)	-	-	-

Table 3.2: Nitrogen rates (kg N ha^{-1}) and application timing for standard and progressive N managements in each season in experiments conducted from October 2019 to October 2022. ContW: continuous wheat; Gr: grain purpose; GF: grain-forage purpose; Ba: base; Sem: semi-intensive; Int: intensive; PL: planting.

Season	**Treatments**	**Nitrogen management**	**Nitrogen rate (kg N ha^{-1})**	**Timing**
Winter 2019/20	ContW, Gr – Ba, Gr – Sem 1, Gr- Sem 2, Gr – Int, GF – Ba, GF - Sem1, GF – Sem 2, GF – Int 1, GF – Int 2, For	Standard	90	Feekes 4.0
		Progressive	45 + 45	Feekes 4.0. + 7.0
Summer 2020	Gr- Sem 2	Standard	107	Planting
		Progressive	53.5 + 53.5	Planting + V6
Winter 2020/21	ContW, Gr – Ba, Gr – Sem 1, Gr – Int, GF – Ba, GF - Sem1, GF – Sem 2, GF – Int 1, GF – Int 2, For	Standard	90	Feekes 4.0
		Progressive	45 + 24	Feekes 4.0. + 7.0
Summer 2021	Gr – Ba	Standard	107	Planting
		Progressive	53.5	Planting
Winter 2021/22	ContW, Gr – Ba, Gr – Sem 1, Gr- Sem 2, Gr – Int*, GF – Ba, GF - Sem1, GF – Sem 2, GF – Int 1, GF – Int 2, For	Standard	90	Feekes 4.0
		Progressive	45 + 24	Feekes 4.0. + 7.0
Summer 2022	Gr- Sem 2	Standard	107	Planting
		Progressive	53.5	Planting

For all winter crops and regardless of N management, an additional 10 kg N ha^{-1} was applied at planting with diammonium phosphate (DAP; 18-46-0 of N–P_2O_5–K_2O) fertilizer in furrow with the seed. * 45 + 45 kg N ha^{-1} applied with progressive nitrogen management in winter 2021/22.

Table 3.3: Number of crops per year, cropping intensity (d d^{-1}), precipitation allocation (%), and species richness for the eleven cropping sequences used in this study from October 2019 to October 2022. ContW: continuous wheat; Gr: grain purpose; GF: grain-forage purpose; For: forage purpose; Ba: base-intensive; Sem: semi-intensive; Int: intensive.

Treatment	**Number of crops per year (d d^{-1})**	**Cropping intensity (d d^{-1})**	**Precipitation allocation (%)**	**Species richness**
ContW	1.00	0.62	0.51	1
Gr – Ba	1.33	0.68	0.62	2
Gr- Sem 1	1.67	0.78	0.68	2
Gr- Sem 2	1.67	0.70	0.70	4
Gr – Int	2.00	0.84	0.85	3
GF – Ba	1.33	0.72	0.66	3
GF - Sem1	1.67	0.75	0.65	3
GF – Sem 2	1.67	0.81	0.73	3
GF – Int 1	2.00	0.89	0.89	4
GF – Int 2	2.00	0.89	0.88	4
For	1.67	0.75	0.65	2

Table 3.4: Wheat harvest and planting dates and total precipitation (mm), initial storage (mm; 0-100 cm), final storage (mm; 0-100 cm), and fallow storage efficiency (%) for the fallow period on continuous winter wheat cropping system (ContW) during 2021 and 2022. Values within brackets represent the standard deviation of the mean.

Variable	**2021**	**2022**
Wheat harvest date	06/08/2021	06/07/2022
Wheat planting date	10/22/2021	10/13/2022
Total precipitation (mm)	396.0	379.9
Initial storage (mm)	291 (14.3)	309 (61.7)
Final storage (mm)	317 (36.4)	365 (42.1)
Fallow storage efficiency (%)	12.23 (4.69)	16.11 (11.52)

Table 3.5: Contribution of grain-only and forage crops from field data, cumulative crop dry matter and glucose-equivalent yields (Mg ha^{-1}) and cumulative winter wheat yields (Mg ha^{-1}) for eleven cropping sequences in experiments conducted from October 2019 to October 2022. Values followed by different letters indicate significant differences in mean cumulative yield among cropping sequences according to Tukey test ($p < 0.05$). ContW: continuous wheat; Gr: grain purpose; GF: grain-forage purpose; For: forage purpose; Ba: base-intensive; Sem: semi-intensive; Int: intensive.

Treatment	**Dry matter yield (Mg ha^{-1})**			**Glucose-equivalent yield (Mg ha^{-1})**			**Cumulative winter wheat yield (Mg ha^{-1})**
ContW	10.8	-	10.8 j	15.0	-	15.0 i	10.8 a
Gr – Ba	14.0	-	14.0 g	19.5	-	19.5 e	10.2 b
Gr- Sem 1	10.8	-	10.8 j	15.8	-	15.8 h	9.26 d
Gr- Sem 2	12.2	-	12.2 h	18.4	-	18.4 f	7.40 e
Gr – Int	11.6	-	11.6 i	18.5	-	18.5 f	7.39 e
GF – Ba	8.44	7.08	15.5 f	12.7	3.56	16.3 g	6.62 f
GF - Sem1	10.1	9.2	19.3 d	14.0	6.09	20.1 d	9.69 c
GF – Sem 2	9.63	6.76	16.4 e	15.8	3.48	19.3 e	5.13 h
GF – Int 1	5.76	33.4	39.2 b	8.02	21.0	29.0 b	5.77 g
GF – Int 2	6.03	28.2	34.3 c	8.38	19.7	28.1 c	6.03 g
For	-	49.9	49.9 a	-	29.6	29.6 a	-

Table 3.6: Nitrogen rate (kg ha^{-1}), precipitation use efficiency (kg glucose-equivalent (GE) mm^{-1}), and N partial factor productivity (PFP_N; kg GE kg N^{-1}) for standard and progressive N managements on six cropping sequences in experiments conducted from October 2019 to October 2022 and respective analysis of variance (ANOVA). Gr: grain purpose; GF: grain-forage purpose; Ba: base; Sem: semi-intensive; Int: intensive.

Treatment	**Nitrogen management**	**Nitrogen rate (kg N ha^{-1})**	**PUE (kg GE mm^{-1})**	**PFP_N (kg GE kg N^{-1})**
Gr - Ba	Standard	407	13.55	47.87
	Progressive	312	12.06	55.59
Gr – Sem 1	Standard	300	9.89	52.5
	Progressive	258	10.21	63.03
Gr – Sem 2	Standard	414	11.23	44.47
	Progressive	340	10.25	49.25
Gr - Int	Standard	300	9.20	61.65
	Progressive	279	9.17	66.11
GF - Ba	Standard	300	10.55	54.32
	Progressive	258	10.41	62.3
GF – Sem 2	Standard	300	11.32	64.38
	Progressive	258	12.79	84.57
Source of variation				
Treatment (T)			***	***
Nitrogen management (NM)			NS	*
T x NM			NS	NS

*** and *, indicate statistically significant effect on the response variable by ANOVA at $p < 0.001$ and $p < 0.05$, respectively.

Chapter 4

Exploring avenues for agricultural intensification: A case study for maize-soybean in the Southern US region

* Published in *Agricultural Systems*

Massigoge, I., Carcedo, A., de Borja Reis, A. F., Mitchell, C., Day, S., Oliverio, J., ... & Messina, C. D. (2023). Exploring avenues for agricultural intensification: a case study for maize-soybean in the Southern US region. *Agricultural Systems, 204*, 103539.

https://doi.org/10.1016/j.agsy.2022.103539

4.1 Abstract

Crop intensification is a key aspect for achieving global food security and exploring options for optimizing land use and environmental resources. Following this rationale, a maize (*Zea mays* L.) – soybean (*Glycine* max L.) double cropping was tested to intensify current agricultural systems in the Southern region of the United States (US). The aims of this study

were to i) assess the feasibility of cultivating maize-soybean double crop in the Southern US, ii) explore the best scenario of maize-soybean crops integrating field data with APSIM crop growth model via calculation of the land equivalent ratio (LER), and iii) evaluate the risk of crop failure for each crop combination. For this case study, one year field research and *in-silico* experiments using 30-years of weather data were analyzed to evaluate the different lengths of growth cycle for both crops for yield, LER, and percentage of success. The feasibility of the maize-soybean sequence was determined by increasing yield gain for the soybean crop while maintaining similar yield for maize crop. Simulated LER values ranged from 1.1 to 1.3 with the maize hybrid 110 comparative relative maturity followed by a soybean maturity group 3.0 as the best combination for maximum LER. Lastly, long-term simulations confirmed the low risk associated with maize-soybean double crop sequences across sowing dates. Expanding the implementation of this farming system could produce additional benefits not only on productivity and land use efficiency but in overall economic return for farmers in the Southern US region.

4.2 Introduction

Global food security faces a growing imbalance between cropland supply and demand (Barrett, 2010; Keeney, 1982; Lambin & Meyfroidt, 2011; Lotze-Campen et al., 2010; Pinstrup-Andersen, 2009). Production must increase 70% by 2050 (Hunter et al., 2017) with limited prospects for incorporating new areas to agricultural (Garnett, 2013; Lark et al., 2020) . Alternatives to increase production without land expansion are limited to increasing yield of a single crop per year per unit of land area (Ray et al., 2013; Tilman et al., 2002), or increasing the number of crops harvested per year via crop intensification (F. H. Andrade, 2011; Gaba et al., 2015; Waha et al., 2020). Yield increase remains a successful strategy to secure global production, but this task is becoming more challenging due to slower gains compared to the past (Duvick et al., 2004; T. Fischer et al., 2014). In this scenario, crop intensification emerges as a valuable tactic for meeting an increased food demand.

Increasing the number of crops per year is a potential avenue to increase production, resource utilization, and land use efficiency (J. F. Andrade et al., 2015; Brooker et al., 2015; L. Li et al., 2007; Van Opstal et al., 2011). However, most of the 63 M ha cropland area available for multiple cropping in North America is under cereal or legume production on a single crop per year rotation (Siebert et al., 2010; Spiertz & Ewert, 2009; Waha et al., 2020). The expansion of crop intensification is limited by several factors including the length of the growing season (Cohn et al., 2016; L. Liu et al., 2013; Monzon et al., 2014; Y. Yu et al., 2015) and the availability of water (Arvor et al., 2014; Cohn et al., 2016; L. Liu et al., 2013). Current experience with temporal intensified cropping systems in North America was associated with summer legumes and winter cereal rotational schemes. Our working hypothesis is that cereal – legume double summer crop system provides untapped potential to increase land productivity of farming systems in North America.

Double crop summer systems became a notoriously successful and established system in the western production regions of Brazil (Abrahão & Costa, 2018). Combing the right climate, including the length of the growing season and adequate water availability, with proper management, including the selection of appropriate genotypes and sowing dates, are key to maximize the probability of success of these systems (Cohn et al., 2016; L. Liu et al., 2013; Widstrom et al., 1984; Yang et al., 2015). The Southeastern US is a relevant farming region accounting for 37 M ha of crop land (United States Department of Agriculture (USDA), 2017) with long growing season and water availability (A. Brown & Perkins, 1979). These features make this region ideal to test the feasibility of temporal crop intensification. Indeed, past studies reported the viability of maize (*Zea mays* L.)-legumes (C. R. Smith, 1981) and maize-soybean (*Glycine* max L.) (Tsai et al., 1987) double cropping. However, despite environmental and economic opportunities, the long-term feasibility of a double crop maize-soybean system has not been widely explored.

The land equivalent ratio (LER) is a useful index for assessing land use efficiency of double versus monoculture cropping systems (Martin-Guay et al., 2018; Xu et al., 2020; Y. Yu et al., 2015). It describes the relative land area required for the monoculture to produce the same yield as the double crop. Even though the economic return is the most critical index for farmers, the LER is a reliable proxy of economic feasibility (Caviglia et al., 2011; Jacques et al., 1997; Sandler et al., 2015; Yamane et al., 2016). Testing the feasibility of a novel cropping system where this system has never been adopted requires extensive field experimentation to assess environmental and management constraints. Crop growth models can be integrated as a complementary evaluation of feasibility when the elevated costs and required scale for environmental sampling and risk assessments are extensive. We propose to augment empirical study of double cropping with crop growth models to explore genotype x environment x management (GxExM) interactions (L. Liu et al., 2013; Mohanty et al., 2012; Sun et al., 2016; Yang et al., 2020) for the assessment of LER under alternative intensification strategies (Paut et al., 2020; Van Oort et al., 2020).

The aims of this study were to i) assess the feasibility of cultivating maize-soybean double crop in the Southern US, ii) explore the best scenario of maize-soybean crops integrating field data with APSIM crop growth model via calculation of the land equivalent ratio (LER), and iii) evaluate the risk of crop failure for each crop combination.

4.3 Materials and Methods

4.3.1 Field studies

Site and crop management

Maize-soybean double crop and their respective full season crops were grown at Stoneville, Mississippi, United States (latitude 33.418644, longitude -90.882882), during the 2018 growing season. The soil characterization of the experimental site can be found on Table 4.1. Maize was fertilized with 190 kg N ha^1 three weeks after planting. Plant densities were 9.1 plants m^2 for maize and 39.5 plants m^2 for soybean. Weeds and insects were effectively controlled. Gravity irrigation was applied during the growing season as required to supplement precipitation on 06/09/2018 and 07/15/2018.

Plant material and experimental design

Treatments included maize-soybean double crop and their respective full-season crops sown with different genotypes combinations varying cycle length. Maize genotypes were P0157AM (comparative relative maturity, CRM, 101 days), P0574AM (CRM, 105 days), P0805AM (CRM, 108 days), and P1197AM (CRM, 111 days). Maize hybrid comparative relative maturity (CRM) ratings were obtained from Corteva Agriscience™ . Soybean genotypes were P15A63X (maturity group, MG, 1.5), P16A13X (MG 1.6), P28A94X (MG 2.8), P37A78X (MG 3.7), and P46A57BX (MG 4.6). Soybean genotypes' maturity group (MG) ratings were obtained from Corteva Agriscience™ . The treatments were arranged in a split-plot design in two complete blocks (replications). The whole plot consisted of the maize CRM entries, and the subplots were the soybean MG entries. Within each whole plot, there were three subplots for each double-cropped soybean. Maize as the first crop was sown on March 22nd, and soybean as a full-season crop was sown on April 11th. Double-cropped soybean was planted according to maize harvest, resulting in the following planting dates: August 1st (predecessor P0157AM), August 7th (predecessors P0574AM and P0805AM), and August 15th (predecessor P1197AM). Crops were sown on beds with plots having twelve rows arranged in 38-inch twin rows. The overall plot length was 10 m.

Measurements and LER calculation

Grain yields (kg ha^{-1}) were expressed at 14.0% grain moisture for maize crop and 13.5% for soybean. Crop phenology for maize (Ritchie et al., 1986) and soybean (Fehr & Caviness, 1977) were recorded. Eight central rows per plot were harvested with a self-propelled combine. Analysis of variance and Tukey Test were used to test the effect of genotype on yield for each crop in the sequence, and the effect of genotype combination on LER.

Double cropping systems versus full-season crop comparisons were made via yield and the land equivalent ratio (LER) (Giménez et al., 2018; Monzon et al., 2014). The LER was estimated as the sum of the relative yields of component crops in the double crop system relative to the longest CRM or MG best-adapted full-season reference crop for the region, as follows:

$$LER = \frac{\text{Maize (A) short season}}{\text{Maize (B) full season maize sole}} + \frac{\text{Soybean (A) short season}}{\text{Soybean (B) full season soybean sole}} \quad , \quad (4.1)$$

where Maize (B) and Soybean (B) are the full season reference crop of adapted germplasm for the region. It is assumed these crops express the maximum attainable yield for that location and optimal planting date. Maize (A) and Soybean (B) have shorter CRM or MG compared to their full season counterparts. Maize (A) and (B) are full season crops planted on the same date while Soybean (B) is planted later than (A) in the double crop sequence. For the field experiment, representing the full season of hybrid performance of reference maize (A) was P1197AM (15.5 Mg ha^{-1}) and the reference soybean (B) was P46A57BX planted on April 11$^{\text{th}}$ (5.5 Mg ha^{-1}). A value greater than 1 indicates advantages of the double crops over the full season crops.

4.3.2 *In-silico* experiment

Modeling approximation and inputs

The Agricultural Production Systems Simulator software platform (APSIM; Holzworth et al. 2014) is a crop growth model that combines biophysical and management modules to simulate crop growth for a given genotype, environment, and management combination, without considering pests nor diseases. In this study the Soybean (Robertson et al., 2002) and Maize (Keating et al., 2003) modules included in APSIM (version 7.10) were used to perform simulations to quantify variations on yield due to different planting dates and maturity cycles within the double crop maize-soybean system. For this study, standard CRM genotypes were built as a modification of the standard cultivar coefficients described in Balboa et al. (2019). In addition, coefficients defining the leaf size distribution were also derived for the Balboa et al. (2019) maize hybrid CRM 111. Thermal time from emergence to floral initiation was set at 250-degree days. Leaf initiation rate, leaf appearance rates, and cardinal temperatures were not changed from those used in the base version of the model. The difference among the CRM was simulated through changes on the thermal time period from anthesis to physiological maturity derived from (Table 4.2). Following the same rationale, the soybean cultivars were built using Balboa et al. (2019) soybean genotype as a template, and the maturity groups differences were derived from Archontoulis et al. (2014) (Table 4.2).

Long-term simulation over 30 years of weather data (starting from January 1st, 1990, to January 1st, 2020) from Stoneville, MS, were performed combining all the maize cultivar CRM as the first crop in 4 planting dates (5-Mar, 15-Mar, 25-Mar, 5-Apr), and the soybean MG as double cropped, planted after the maize harvest. Earlier planting dates were not included in the analysis due to the effect of low temperatures extending the sowing-emergence phase for a period longer than 2 weeks (data not shown). From the earliest planting date, 5-Mar, planting dates were separated at intervals of 10 days until the last date, 5-Apr. The estimated range of planting date is in accordance with the recommended dates for maize, from Mar-5, in the central region of Mississippi (Larson, 2013) and with the 50% planting date (Apr-5, week #14) at the state-level in the last 5 years (USDA-NASS). This window of time also agrees with the period that maximizes soybean yields in the region (Bateman et al., 2020).

The model initial conditions for soil water and N were set to start the simulation in January. Soil data was obtained from USDA-SURGO (Soil Survey Manual, 2017), and soil parameters were calculated following Archontoulis et al. (2014). Precipitation and temperature data was collected from NOAA (*National Oceanic and Atmospheric Administration*, 2021) considering the nearest weather station to the experimental site (less than 20km). Solar radiation was retrieved from NASA-POWER project (*NASA Prediction Of Worldwide Energy Resources*, 2021) (Table 4.1). Crop yield and growth stages (date and thermal time) were outputs retrieved from the model.

Experiment set up and LER calculation

The same approximation was used for the *in-silico* experiments, accounting LER values for each crop, season, and management (planting date × cultivar) combination. For maize and soybean, the reference crop was obtained via testing the planting date × cultivar combination that maximized yields in the simulations across all years of evaluation. In maize crop, this combination represented the 110 CRM hybrid sown on early planting dates (March 5th), while for soybean, it consisted of the MG4 variety sown on early April (April 10th). To define the reference crop for both maize and soybean crops, simulations were executed testing planting dates from early February to April for maize and February to early June for soybeans (data not shown).

Success rate of the double-cropped soybean was calculated as the percentage of simulations reaching full maturity in the *in-silico* experiment. The success rate was accounted as the percentage of the thermal time accumulated relative to the physiological maturity, representing this stage 100%. The APSIM crop growth model simulates crop failure when the leaf area of the crop is 0. Reduction of leaf area could be caused by several factors such as water deficit and low temperatures (Robertson et al., 2002). For the *in-silico* study, the major driver of leaf area reduction (i.e., the death of the crop) was mainly linked to low temperatures. This is the model approach to simulate frost damage, which is a major concern when implementing double crop systems. For this case, less than 100% of success rate conveys a reduction in the time to maturity; for example, 80% of success refers to 80% completion of the total crop phase.

4.4 Results

Maize grain yields from the field study ranged from 12.4 to 14.4 Mg ha^{-1} with a trend of increasing yields with the longer crop growth cycle (Figure 4.1a). The overall yields for the soybean crop following maize ranged from 0.9 to 2.2 Mg ha^{-1} (Figure 4.1b). For all planting dates after the maize crop, greater yields were achieved with intermediate to long

MG ranging from 2.8 to 4.6 MG. The highest soybean yield (1.94 Mg ha^{-1}) was achieved with the latest harvesting date for maize (P1197, 111 CRM), but with yields not differing for the late-planted soybeans when different MG were tested (Figure 4.1b).

The LER values from the field experiment ranged from 1.06 to 1.44 for all maize-soybean genotypes combinations (Figure 4.2). On average across soybean cultivars, the highest LER values were attained with the longest growth cycle for maize (Figure 4.2). The absolute highest LER was achieved with the combination of P1197 maize hybrid with the 3.7 soybean MG. Moreover, within each maize hybrid, a greater contribution from the soybean crop to LER was obtained with intermediate-to-long soybean genotypes (mainly with 3.7 to 4.6 MG) (Figure 4.2).

When the maize-soybean double sequence was simulated, higher LER values were attained using longer CRM maize hybrids (Figure 4.3). The overall reduction in LER values was mainly led by the decrease in maize contribution to this index that was not compensated for by the potential increase in the portion of share for soybean to this factor. Moreover, among all maize genotypes, the highest values for LER were obtained when using soybean MG 3.0. Additionally, when considering a fixed maize hybrid, a larger difference in LER between the shortest and longest soybean MG was obtained for the shorter maize hybrid, 90 CRM (Figure 4.3). Therefore, the highest value of LER (1.33) was observed with the maize-soybean combination CRM110-MG3, while the lowest LER (1.06) was recorded with the shortest materials, CRM90-MG1 maize-soybean combination.

Lastly, we assessed the probability of success of double cropping sequences using the maize hybrid with greatest yields (CRM 110; Figure 4.4). The outcome from the modeling reported an overall decrease in maize yield with the delay in sowing date and reduced success of the system with use of intermediate-to-long soybean maturity groups (3-4 MG). For maize crops, large changes in success occur when the crop is planted after March 15 for this southern US region, with this factor exerting a much greater effect relative to variations in growth cycle for soybean crop (Figure 4.4).

4.5 Discussion

This study presents a feasible implementation of maize-soybean double summer crop system for the US Southern region. Integration of field studies with in-silico assessments provides an opportunity to test scenarios for crop intensification as a promising and sustainable approach.

The feasibility of maize-soybean system was linked to the success of the maize phase. Longer growth cycles can use available resources more efficiently than shorter ones (Bruns & Abbas, 2006; Lafitte & Edmeades, 1997). Conversely, the soybean season was placed in a less favorable environmental condition (short-day duration, low temperatures and radiation) which did not enable expression of genotype yield potential. We observed that regardless of the selection for the soybean maturity group in the second season, crop yield did not compensate for the maize yield penalty. For Brazilian systems, soybean-maize safrinha have successfully reached a balance point, where soybean (first-crop) yield is not compromised (Battisti et al., 2020; Oligini et al., 2021). However, less is known for soybean-maize US systems (C. R. Smith, 1981; Tsai et al., 1987) with a need for further research.

From a crop intensification standpoint, field and simulated LER values are similar to those reported for different crop sequences by Monzon et al. (2014), but lower from Giménez et al. (2018) in Argentina (maize-soybean sequence) and adapted from Battisti et al. (2020) in Brazil (soybean-maize sequence). From our side, long-term benefits of double cropping are not explained in a one year-trial, and cumulative effects may increase attainable yield over the years. Lastly, although LER is not considered an economic evaluation, it is reasonable to expect a decrease in the impact of fixed costs and an increase in gross revenue due to the additional harvest (Burton Jr et al., 1996; VanWey et al., 2013). Therefore, farmers that adopt double cropping systems are diversifying economical risk since it allows compensation when one crop has lower prices (Arvor et al., 2014) or different yields (Graß et al., 2013). Giving a long-term outlook, the potential financial damage for years of crop failure could be off-set by the years of success and the economic revenue would still be positive (V. N. Rao et al., 2015; VanWey et al., 2013).

Potential bottlenecks for implementation of crop intensification systems range from production to policy constraints. From a production standpoint, a few relevant factors to be considered are: i) water availability restrictions to sustain more crops in the rotation (Arvor et al., 2014; Cohn et al., 2016; L. Liu et al., 2013), ii) level of input to maintain intensification level (e.g., fertilization, chemicals pest control) (Litsinger & Moody, 1976; M. V. Pires et al., 2015), iii) erratic incidence of late season freeze damage before maturity (Egli & Bruening, 1992; Monzon et al., 2014), and iv) onset of dry-down under less favorable environmental conditions (Martinez-Feria et al., 2019; Philbrook & Oplinger, 1989; G. F. Pires et al., 2016). From country policy standpoint, federal policies incentivizing crop intensification such as biofuel options and opportunities on less restrictive crop insurance policies (reducing initial risk and uncertainties) can help to provide support to farmers moving from less to more intensified cropping systems (O'Donoghue et al., 2009). Additional factors impacting the intensification process are linked to the availability of crop markets and end-use processors, improvement of commercialization avenues to capture more profit (Rosenzweig & Schipanski, 2019), changes in land tenure, and social behavior of farmers (with a perception of greater time investment and labor).

Further research should explore other intensification systems (e.g., canola-soybeans; soybean-sunflower, Castro & Leite 2018; Matsuura et al. 2017; or soybean-cotton, Arvor et al. 2012; Hampf et al. 2020), and management technologies such as optimal planting dates (Brumatti et al., 2020; Garcia et al., 2018; Nóia Júnior & Sentelhas, 2019; Oligini et al., 2021). In addition, another key point to explore is the expansion of these intensified systems to other cropland areas within the Southern U.S. and towards higher latitudes. Finally, under the current scenario of climate change (e.g., rising temperatures), double cropping production possibilities (and risks) need to be addressed (Brumatti et al., 2020; Hampf et al., 2020; G. F. Pires et al., 2016).

4.6 Conclusions

Maize-soybean was a feasible system for the southern US region, increasing productivity by including a soybean crop while maintaining similar yields for maize. Based on modeling and field observation, the maximum LER was achieved with longer maize growth cycle and relatively intermediate-to-late soybean maturity group. Lastly, long-term simulations permitted to confirm the low risk associated with maize-soybean sequences across changes in sowing dates. In overall, this double cropping system represents an advantage for farmers to improve their productivity and land use efficiency. Future studies should explore the potential to expand these intensification systems to more cropland areas within this region and higher latitudes in the US Midwest.

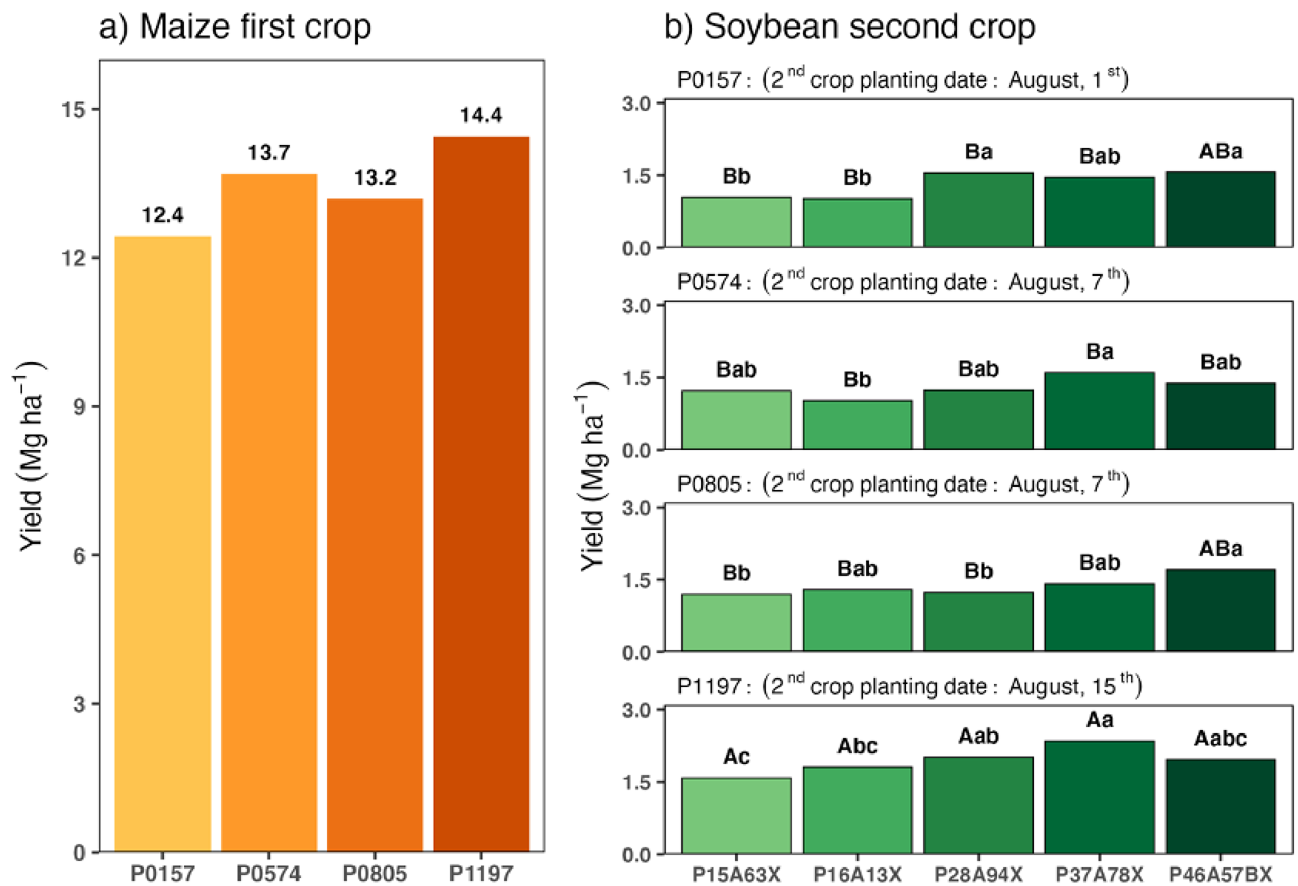

Figure 4.1: Mean grain yield (Mg ha^{-1}) of (**a**) four maize hybrids as first-crop and (**b**) five double-cropped soybean genotypes after their respective four maize hybrids (predecessor) from field experiments during the 2018 growing season. Different uppercase letters indicate significant differences (Tukey test at $p < 0.05$) among maize predecessors within individual soybean genotypes; different lowercase letters indicate significant differences (Tukey test at $p < 0.05$) among soybean cultivars within a single maize predecessor.

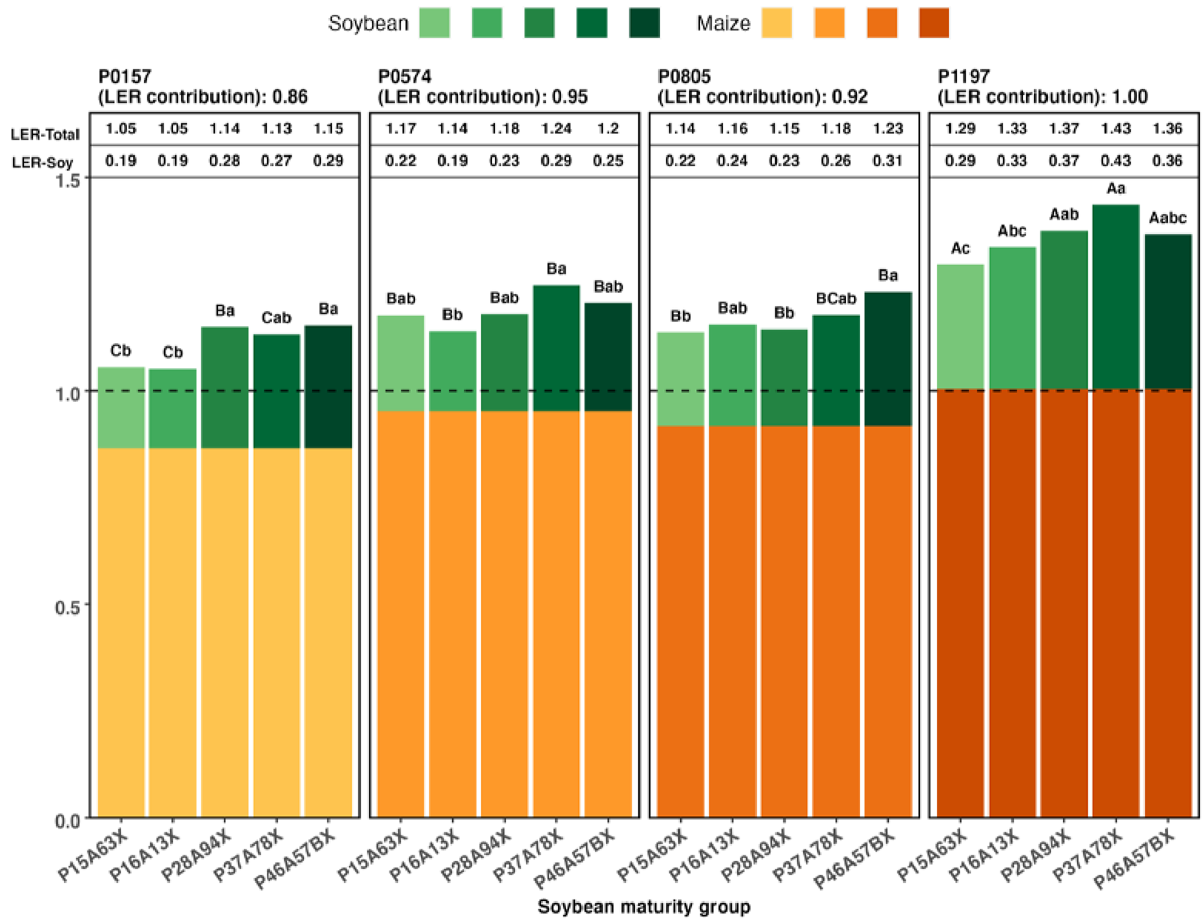

Figure 4.2: Land equivalent ratio (LER) for maize-soybean double cropping system and respective contribution of maize (orange bars) and soybean (green bars) crops, obtained by the combination of maize hybrid (upper axis x) and soybean genotype (lower axis x) in field experiments during the 2018 growing season. Different uppercase letters indicate significant differences (Tukey test at $p < 0.05$) among maize predecessors within individual soybean genotypes; different lowercase letters indicate significant differences (Tukey test at $p < 0.05$) among soybean cultivars within a single maize predecessor.

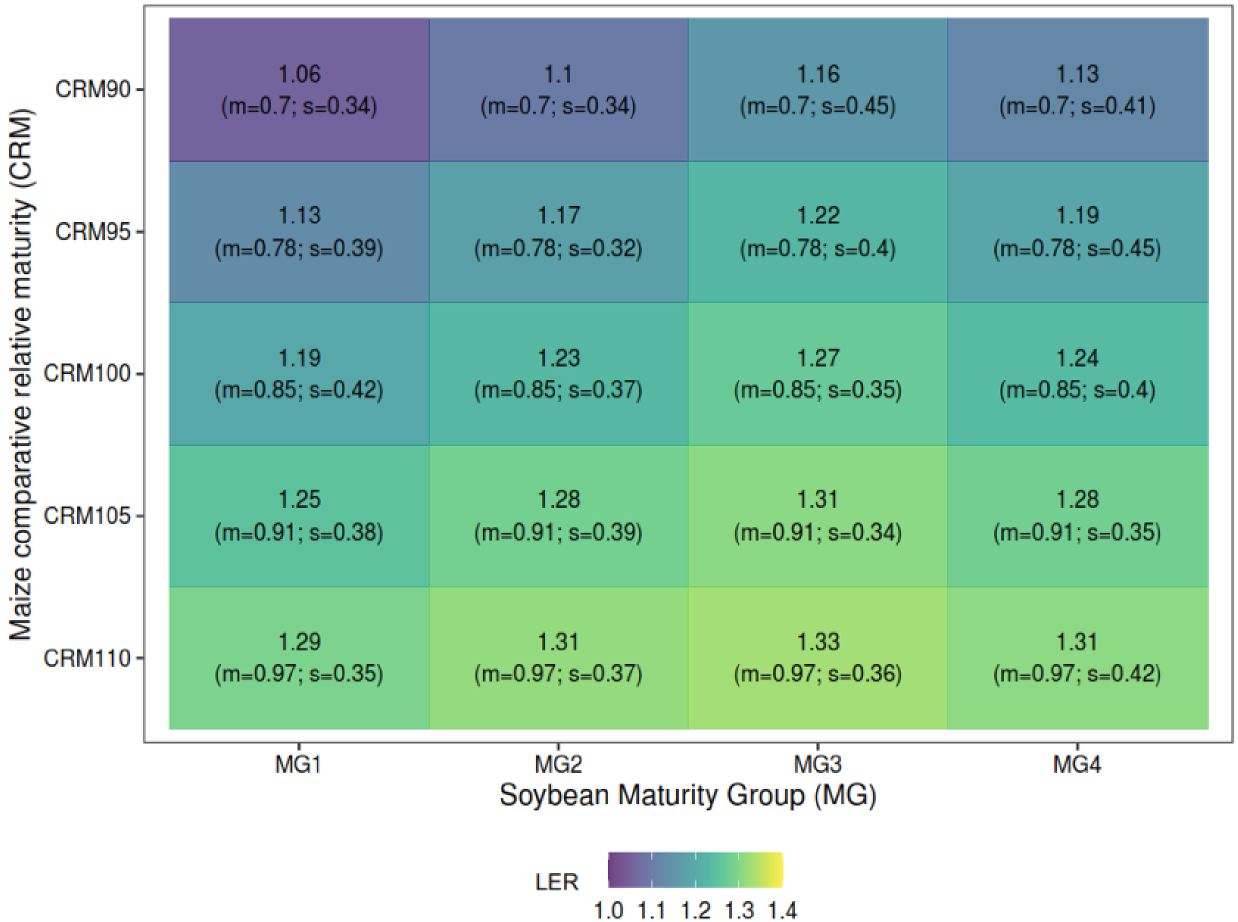

Figure 4.3: Land equivalent ratios (LER) for simulated maize-soybean double cropping system, obtained by the combination of maize comparative relative maturity (CRM; axis y) and soybean maturity group (MG; axis x) for 30-year data series. Data between brackets indicate the respective contribution of maize (m) and soybean (s) crops to the total LER. Lighter colors refer to high LER.

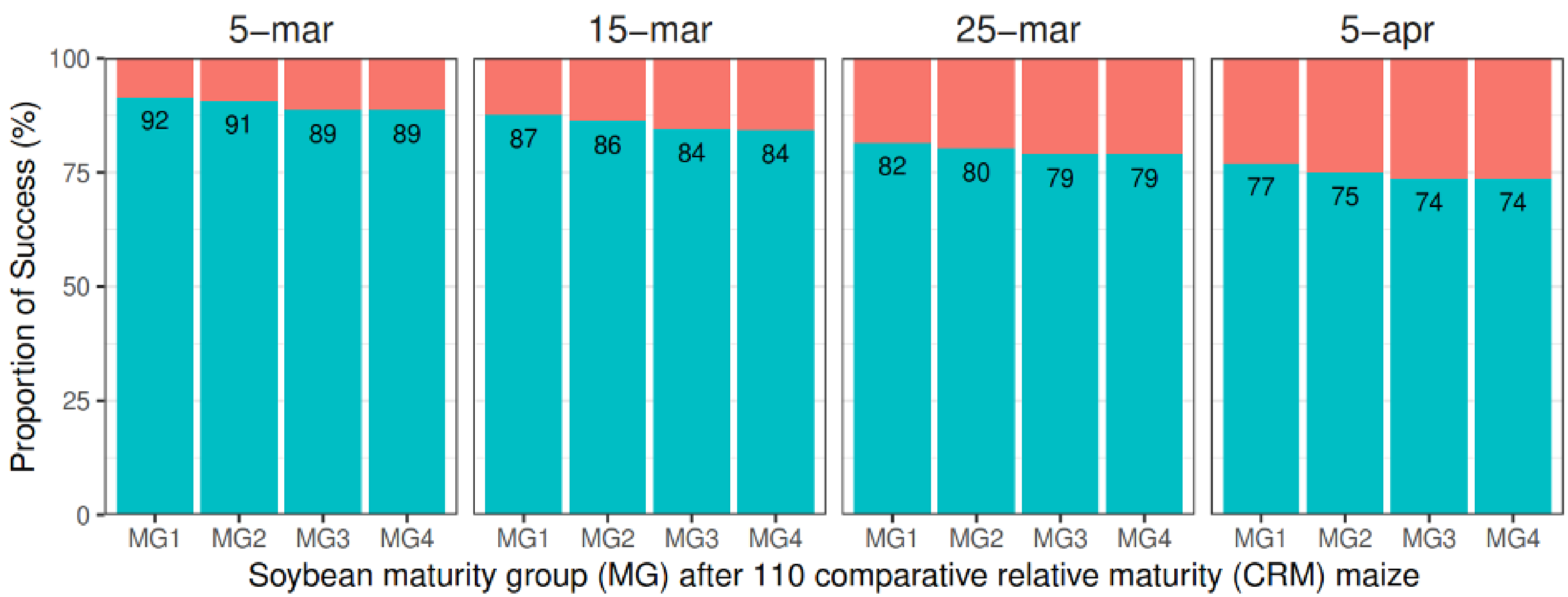

Figure 4.4: Simulated probability of success (in percentage) for the combination of the 110 CRM Maize and four soybean genotypes (MG 1, MG 2, MG 3, MG 4) under four sowing dates (5-Mar, 15-Mar, 25-Mar, and 5-Apr) for a 30-year data series.

Table 4.1: Weather and soil descriptors. Weather variables are described for the long-term dataset (30 years, from 1990 to 2020), and for the 2018 growing season (field experiment).

Weather variables				
Descriptive statistics	**Minimum Temperature (ºC)**	**Maximum Temperature (ºC)**	**Radiation (MJ m^{-2})**	**Precipitation (mm)**
Standard Deviation	8.8	9.5	7.2	292
Mean	12.0	23.4	16.0	1209
Median	12.8	25.0	16.7	1241
Minimum	-19.1	-12.8	0.4	238
Maximum	28.9	41.1	31.9	1648
Crop season 2018	12.9	23.5	19.5	923

Soil variables						
Depth (cm)	**Bulk density (g cc^{-1})**	**LL15 (mm mm^{-1})**	**DUL (mm mm^{-1})**	**Sand (%)**	**Silt (%)**	**Clay (%)**
0-5	1.35	0.29	0.40	1.8	33.2	65.0
5-20	1.35	0.29	0.40	1.8	33.2	65.0
20-50	1.35	0.33	0.41	1.8	29.5	68.7
50-80	1.35	0.40	0.44	1.8	23.2	75.0
80-120	1.41	0.35	0.41	10.4	25.1	64.5
120-180	1.45	0.32	0.39	16.2	26.3	57.5

Table 4.2: APSIM maize and soybean cultivar parameters.

Crop/Cultivar	**Parameter**
Maize	Thermal time from flowering to physiological maturity (ºC-days)
CRM 110	812
CRM 105	732
CRM 100	652
CRM 95	572
CRM 90	492
Soybean	Thermal time from flowering to start grain fill (ºC-days)
GM IV	263, 351, 527, 1404
GM III	253, 338, 506, 1350
GM II	246, 328, 492, 1312
GM I	239, 318, 478, 1274
Soybean	Thermal time from start to end of grain fill (ºC-days)
GM IV	535, 713, 1069, 2852
GM III	514, 685, 1028, 2741
GM II	499, 666, 999, 2664
GM I	485, 646, 970, 2586

Chapter 5

Benchmarking maize-soybean yields in the US Corn Belt

* Manuscript in preparation

5.1 Abstract

Maize (*Zea mays* L.) typically receives more intensive management and inputs relative to soybeans (*Glycine max* L.) over a wide range of environmental conditions. However, to the extent of our knowledge, there are a very few studies benchmarking maize relative to soybean yields both grown under similar environments over a large spatial scale in recent decades. The aims of this study were to i) investigate the association between maize and soybean yields grown in similar environments under standard farming practices, ii) identify within the synthesized maize-soybean database the most relevant management, soil, and weather variables driving yield difference between crops, and iii) estimate the maize-to-soybean yield ratios at the county-level in Kansas and at the state-level for the US Corn Belt region. A large database of crop performance trials containing maize-soybean grown in the same site year and water regime (rainfed or irrigated) was collated for i) Kansas and ii) the entire US Corn Belt region and analyzed using a hierarchical Bayesian approach. Soybean yields

reached a plateau in high-yielding maize environments (>13.5 Mg ha^{-1}) in Kansas, which was attributed to optimal growing conditions such as irrigation and early planting dates. Similarly, we found a soybean yield deceleration relative to maize with major emphasis on high-yielding environments of the entire US Corn Belt region. Lastly, the maize to soybean yield ratio increased as the environment improved in the Corn Belt region, coinciding with the higher yield ratios achieved in irrigated counties in Kansas. Overall, we identified potential soybean yields deceleration and stagnation patterns relative to maize in the US Corn Belt region. This study highlights the need for investment in identifying soybean yield limiting factors in high-yielding maize environments. This information will be useful in understanding the resulting land crop allocation and in supporting future breeding efforts.

5.2 Introduction

Maize (*Zea mays* L.) and soybean (*Glycine max* L.) have historically been important crops in the United States (US) due to their high energy, protein, and oil content. Within the US, yields have steadily increased over the past 80 years at a rate of 87 kg ha^{-1} $year^{-1}$ for maize (S. Smith et al., 2015) and 23 kg ha^{-1} $year^{-1}$ for soybean (Specht et al., 2015). The factors attributed to these yield gains can be mainly divided into genetic improvement (e.g., improved stay-green during grain-filling for maize or increased lodging resistance in soybean; Duvick, 2005; Specht & Williams, 1984), improved management practices (e.g., higher plant density in maize or narrower row distance and more branching in soybean; De Bruin & Pedersen, 2008; Duvick, 2005) and potential changes in environmental conditions (e.g., rise in atmospheric CO2; Specht et al., 1999). As a result, the high attainable yields of these two crops, coupled with favorable prices, have displaced other crops in the rotation, such as sorghum (Sorghum bicolor L.; Mayor et al., 2023), alfalfa (Medicago sativa L.; Arora & Wolter, 2018), and grasslands (C. K. Wright & Wimberly, 2013). Nowadays, maize and soybean account for about 20% of the extensive cropland in the US and for 75% in the US Corn Belt region (United States Department of Agriculture (USDA), 2023).

The typical cropping system in the US Corn Belt involves a 2-year maize-soybean rotation, with maize usually planted earlier in the season (mid-April to mid-May) and soybean planting starting 12-15 days later (Grassini et al., 2015). Recently, however, this trend is changing across the US with soybeans being planted before maize with the goal of boosting soybean yields (longer growing season). In addition, this trend helps provide maize with a a better soil temperature environment for improved plant-to-plant uniformity. For maize, the critical period for yield determination, centered around flowering which occurs from 227 growing degree days (GDD) before silking to 100 GDD after silking (Otegui & Bonhomme, 1998), is typically centered in July. In the case of soybean, the critical period (from R_3 to R_6; Kantolic et al., 2013) is typically centered in August. Thus, these critical periods coincide with high solar radiation and optimal temperature conditions (lower for soybean during the critical period occurrence) that, along with a monsoonal rainfall pattern concentrated in the summer-crop growing season and sometimes supplemented by irrigation (mainly in Kansas and Nebraska), allow for achieving high yields for both crops.

In this context, maize typically outperforms soybean in terms of yield over a wide range of environmental conditions. This is mainly explained by differences in: i) carbon fixation metabolism (C_4 vs. C_3), which in turn affects photosynthetic rate (Laing et al., 1974); ii) canopy architecture (leaf arrangement and expansion), which affects solar radiation capture (F. H. Andrade, 1995); iii) energy content of both vegetative and reproductive organs, with high protein levels for soybean seeds (Sinclair & De Wit, 1975); and iv) use of more energy as carbohydrates to sustain nitrogen fixation process for soybeans. Egli (2008) reported maize-soybean yield ratios ranging from 2.9 to 3.2 using USDA-NASS data from six US Corn Belt states between the 1970s-1980s and 2005. Similarly, Specht et al. (1999) reported an average ratio of 2.8 for irrigated fields in Nebraska between 1972 and 1997, and Evans (1996) reported a value of 3.3 using data from record yields. However, to the extent of our knowledge, no studies have synthesized existing information to benchmark maize and soybean yields grown under similar environments over a large spatial scale in recent decades. The information produced by such an analysis will provide foundational insights on the major factors driving yields between these crops and better strategizing land allocation, future strategies for both crop intensification and diversification within the US Corn Belt region.

Following this rationale, this research study proposed the use of a Bayesian approach using data collated from crop performance trials. Initially, by focusing on the state of Kansas to better study the major drivers of yield trends, and then extending this work to the major maize-soybean producing states within the US Corn Belt region. These trials, conducted annually by universities in each state, evaluate multiple genotypes at multiple locations but only selecting those with both maize-soybean grown in similar geography, providing valuable data over large temporal and spatial scales. The objectives of this study were to: i) investigate the association between maize and soybean yields grown in similar geography under standard farming practices, ii) identify within the synthesized maize-soybean database the most relevant management, soil, and weather variables driving yield difference between crops, and iii) estimate the maize-to-soybean yield ratios at the county-level in Kansas and at the state-level for the US Corn Belt region.

5.3 Materials and Methods

5.3.1 Data sources

Kansas crop performance trials

The first data set used in this study was obtained from the Kansas crop performance trials collected from 1991 to 2021 (https://www.agronomy.k-state.edu/outreach-and-services/crop-performance-tests/, accessed in May 2023) and included maize and soybean grown in the same site-year and water regime (rainfed or irrigated). A total of 212 site by year by water regime combinations occur in the dataset, with a relatively balanced distribution between rainfed and irrigated trials (99 and 113 data points, respectively) in twelve counties (Finney, Franklin, Greeley, Harvey, Labette, Nemaha, Neosho, Reno, Republic, Saline, and Thomas). The spatial distribution of the number of observations by county and their respective proportions of rainfed and irrigated trials are shown in Figure 5.1A.

Crop management for these performance trials was applied to match those used by producers in each production region of the state. Maize was typically planted (Figure C.1A) and harvested (Figure C.1B) earlier in the season than soybean. Average plant densities were 6.3 pl m^{-2} for maize and 37.5 pl m^{-2} for soybean (Figure C.1C and C.1D). Nitrogen (N), phosphorus (P), and potassium (K) were applied as synthetic fertilizers as needed, and weeds were controlled with a combination of pre- and post-emergence herbicides. Insecticides and fungicides were occasionally applied as needed. At each site, the experimental design in all the trials was a randomized complete block design (RCBD) with three to four replications (blocks), with a harvested area ranging from 9.3 to 20.9 m^2 for maize and from 4.1 to 13 m^2 for soybean, depending on the site-year. Yield values (for maize referring to grain yield and for soybeans to seed yield) were obtained from the average yield of all genotypes evaluated for each crop on each site by year by water regime combination and expressed at 15.5% moisture for maize and 13% moisture for soybean.

Daily incident solar radiation (MJ m^{-2}), mean air temperature (°C), and precipitation (mm) data were obtained from the Global Historical Climatology Network (`https://www.ncei.noaa.gov/products/land-based-station/global-historical-climatology-network-daily`), and for each site, the nearest weather station with at least 30 years of data was selected. In addition, the photothermal quotient (PTQ) was calculated as the mean solar radiation divided the difference between the mean temperature and the crops base temperature (10°C for both maize and soybean; R. Fischer, 1985), and the extreme temperature events were calculated as the number of days with temperatures above 35°C (Berry & Bjorkman, 1980; Commuri & Jones, 2001). The weather data was transformed into bi-monthly basis (sum or average) (Carter et al., 2018; Correndo et al., 2021), resulting in three main periods: i) April-May, ii) June-July and iii) August-September. Soil texture data (clay, silt and sand contents at 0-15 cm) were retrieved from SSURGO using the reported latitude-longitude coordinates of each trial.

Corn Belt crop performance trials

The second dataset used in this study was obtained from the crop performance trials collected from 2000 to 2022 in 11 states of the US Corn Belt (Illinois, Iowa, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin; URLs in Table C.1) and included maize and soybean grown in the same site-year and water regime (rainfed or irrigated). A total of 773 site by year by water regime combinations comprised the dataset, with a higher proportion of rainfed than irrigated trials (701 and 72 observations, respectively). The spatial distribution of these data by state and their respective proportion of rainfed and irrigated trials are shown in Figure 5.1B.

Similar to the Kansas dataset, crop management for these performance trials aimed to match those used by producers in each production region of each state. Maize was typically planted earlier than soybean (Figure C.2A), but with similar harvest dates (Figure C.1B). N, P and K were applied as synthetic fertilizers as needed, and weeds were controlled with a combination of pre- and post-emergence herbicides. Insecticides and fungicides were applied as needed. The experimental design in the trials was either a RCBD or an alpha lattice design with three to five replications, with a harvested area from 9.29 to 11.61 m^{-2} for maize and from 4.64 to 13.93 m^{-2} for soybean. Yield values were obtained from the average yield of all genotypes evaluated for each crop on each site by year by water regime combination and expressed at 15.5% moisture for maize and 13% moisture for soybean.

5.3.2 Statistical analyses

Hierarchical Bayesian models provide a framework to construct bespoke statistically valid models that are tailored to answer specific research questions (see Ch. 1 in Hobbs & Hooten, 2015). This is important in our study because our analysis, as explained below, combines two commonly used statistical models into a single analysis in a statistically valid manner. While each individual component model is not novel, the combination of the two is novel and the hierarchical Bayesian framework provides a coherent process for us to combine the two. In addition, Bayesian models effortlessly enable uncertainty quantification about predicted and estimated qualities (e.g., a splot parameter). This uncertainty quantification is critical to enabling valid statistical inference.

More specifically for our analysis, a hierarchical Bayesian framework was used to model the relationship of soybean yield (Mg ha^{-1}) as a function of maize yield (Mg ha^{-1}) for both the Kansas and Corn Belt crop performance trial datasets. For this model, the response variable was the soybean yield data (y_i), where i is the i^{th} site by year by water regime combination. We assumed that y_i follows a normal distribution with expected value μ_i and variance σ^2, written as:

$$y_i \sim N(\mu_i, \sigma^2). \tag{5.1}$$

Following the hierarchical Bayesian framework, the underlying process model of the Kansas crop performance trials data, μ_i was defined following a linear-plateau function, where β_0 and β_1 are the intercept and slope of the linear component, θ is the inflection point. The x_i is the maize yield for the i^{th} site by year by water regime combination. This linear-plateau model can be written as:

$$\mu_i = \begin{cases} \beta_0 + \beta_1 x_i, & \text{if } x_i < \theta, \\ \beta_0 + \beta_1 \theta, & \text{if } x_i \geq \theta. \end{cases} \tag{5.2}$$

The final component of our hierarchical Bayesian model for the Kansas crop performance trials included a model for the parameters (e.g, β_1), known as the prior distribution. Uniformly distributed priors were defined for the parameters β_0, β_1, θ, while a Half-student-t (ν, μ, σ) prior was defined for σ, where ν, μ and σ represent the shape, the location, and the scale parameters, respectively. More specifically, the priors can be written as:

$$\begin{aligned} \beta_0 &\sim \text{Uniform}(-4, 4), \\ \beta_1 &\sim \text{Uniform}(0, 1), \\ \theta &\sim \text{Uniform}(0, 20), \\ \sigma &\sim \text{Half-student-t}(3, 0, 2.5). \end{aligned} \tag{5.3}$$

We used a similar, but slightly different hierarchical Bayesian for the Corn Belt performance trial dataset. The same distribution was used for the soybean yield data (i.e.,

$y_i \sim N(\mu_i, \sigma^2)$. However, for the underlying process model, μ_i was defined according to a power-law function, with parameters α and ϕ, and where x_i is the observed maize yield for the i^{th} site by year by water regime combination. This equation can be written as:

$$\mu_i = \alpha x_i^{\phi}. \tag{5.4}$$

Finally, normally and uniformly distributed priors were defined for the parameters α and ϕ, respectively, while a Half-student-t (ν, μ, σ) prior was defined for σ, where ν, μ and σ represent the shape, the location, and the scale parameters, respectively, which can be written as:

$$\begin{aligned}
&\alpha \sim \text{Normal}(0, 1000), \\
&\phi \sim \text{Uniform}(0, 1), \\
&\sigma \sim \text{Half-student-t}(3, 0, 2.5).
\end{aligned} \tag{5.5}$$

The two Bayesian models were fitted using R software (R Core Team, 2023) and the `brm` function from the `brms` package (Bürkner, 2017), using 48000 Markov Chain Monte Carlo samples with four chains of length 12000, and discarding the first 8000 samples to warm up. The posterior distribution of the model parameters and their respective credible intervals are shown in Figure C.3 and Figure C.4.

After performing the analysis of the Kansas crop performance trials dataset using the linear plateau model, a Bayesian model for binary "data" was used to model the presence or absence of soybean yield on the plateau component with year, management, soil, and weather variables as predictor variables (Figure C.5). Here we used quotation marks around data because the data were not observed, but rather imputed using the posterior predictive distribution. Imputing missing or unobserved data, as in our example, is a common technique used in Bayesian analyses (Gelman et al., 2013). Following the hierarchical structure, the presence or absence, defined as 1 or 0, respectively, of the soybean yield data on the predicted plateau component ($Z_i^{(k)}$), where i is the i^{th} posterior distribution and k is the k^{th} prediction (i.e., k^{th} draw) for a specific site by year by water regime combination, was assumed to follow a Bernoulli distribution with probability p_i and a logit link function to describe the data model, which can be written as:

$$Z_i^{(k)} \sim \text{Bern}(p_i). \tag{5.6}$$

For the underlying process model, p_i was defined as a combination of linear effects, where γ_0 is the intercept and γ_m is the linear parameter for the m^{th} predictor variable, and v_m is the observed value of the m^{th} variable, which can be written as:

$$\text{logit}(p_i) = \gamma_0 + \gamma_1 v_{i,1} + \ldots + \gamma_m v_{i,m}. \tag{5.7}$$

The following predictor variables were included in the model: year, soybean planting date (day of the year), water regime (rainfed or irrigated), incident solar radiation, mean temperature, extreme temperature events (>35°C), photothermal quotient and precipitation in April-May, June-July, and August-September, and clay, silt and sand content at 0-15 cm. All the predictor variables, except for year and water regime, were scaled by subtracting their mean and dividing by their standard deviation due to the large difference in magnitude and variation.

Normally distributed priors were defined for the linear parameters γ, while a Half-student-t (ν, μ, σ) prior was defined for σ, where ν, μ and σ represent the shape, the location, and the scale parameters, respectively, which can be written as:

$$\begin{aligned} \gamma &\sim \text{Normal}(0, 2.25), \\ \sigma &\sim \text{Half-student-t}(3, 0, 2.5). \end{aligned} \tag{5.8}$$

The Bayesian model was fitted using R software (R Core Team, 2023), and the `brm_multiple` function from the `brms` package (Bürkner, 2017), using 48000 Markov Chain Monte Carlo samples with four chains of length 12000, and discarding the first 8000 samples to warm up.

In addition to the analyses described above, our final analysis was separate (i.e., not connecting to multiple models) and used a hierarchical Bayesian model to model the maize to soybean yield ratio for each site by water regime combination in the Kansas crop performance trials dataset and each state in the US Corn Belt performance trials dataset. For the latter, Michigan, Minnesota, and Ohio were not included in the analysis due to the low representation of these states in the dataset (<1%). This yield ratio was calculated as $w_i = y_i/x_i$, and transformed by dividing it by a constant (i.e., $q_i = w_i/m$, where $m = 20$) which enabled the use of a beta distribution. As such, we assumed to follow a beta distribution with parameters μ and φ and a logit link function to describe the data model, which can be written as:

$$q_i \sim \text{Beta}(\mu_i, \varphi). \tag{5.9}$$

For the underlying process model of the Kansas crop performance trials dataset, μ_i was defined as a combination of linear effects, with δ_c defined as the linear parameter for the c^{th} county, δ_r defined as the linear parameter for the r^{th} water regime, and δ_{cr} defined as the linear parameter for the interaction between the c^{th} county and the r^{th} water regime. This equation can be written as:

$$\text{logit}(\mu_i) = \delta_c x_c + \delta_r x_r + \delta_{cr} x_{cr}. \tag{5.10}$$

For the underlying process model of the Corn Belt crop performance trials dataset, μ_i was defined as a linear effect, with δ_s defined as the linear parameter for the s^{th} state. This equation can be written as:

$$\text{logit}(\mu_i) = \delta_s x_s. \tag{5.11}$$

Normally distributed priors were defined for the linear parameters δ, while a Half-student-t (ν, μ, σ) prior was defined for σ, where ν, μ and σ represent the shape, the location, and the scale parameters, respectively, which can be written as:

$$
\begin{aligned}
\delta &\sim \text{Normal}(0, 2.25), \\
\sigma &\sim \text{Half-student-t}(3, 0, 2.5).
\end{aligned}
\tag{5.12}
$$

The two Bayesian models were fitted using R software (R Core Team, 2023) and the `brm` function from the `brms` package (Bürkner, 2017), using 48000 Markov Chain Monte Carlo samples with four chains of length 12000, and discarding the first 8000 samples to warm up. The mean and length of the 95% credible intervals of the posterior distributions at the treatment level were calculated to visualize the model-based estimates

5.4 Results

5.4.1 Relationship between maize and soybean yields in Kansas

For the state of Kansas, soybean yield was linearly related to the maize yield for values of maize yields below 13.53 Mg ha^{-1} (CI$_{95\%}$: 12.02 - 15.87) (Figure 5.2). The lowest maize yields were observed under rainfed conditions while yields under irrigated trials started at values of 7.5 Mg ha^{-1}. Moreover, for the soybean-maize relationship the plateau was reached at a soybean yield of 4.2 Mg ha-1 (CI$_{95\%}$: 2.69 - 5.69) and consisted mostly of trials under irrigated conditions (94% of the data points).

5.4.2 Management, soil, and weather variables driving the soybean yield plateau

The variables that had the largest positive coefficients from the Bayesian binary model were year, irrigation, and cumulative precipitation in April-May, while planting presented the largest negative coefficient (Figure 5.3). In addition, the soil coefficients showed higher uncertainty on the Binary model.

5.4.3 Maize to soybean yield ratios in Kansas

Greater maize to soybean yield ratios were observed in the western part of the state, mostly under irrigated conditions (e.g., 4.11 mean ratio for Finney County) (Figure 5.4). On the other hand, the lowest yield ratios (<2.7) were observed in Harvey, Shawnee, and Franklin counties under rainfed conditions (Figure 5.4). Moreover, within a given county, irrigated trials presented a greater yield ratio than rainfed trials (Shawnee and Republic counties).

5.4.4 Relationship between maize and soybean yields in the US Corn Belt

For the Corn Belt dataset, soybean yield showed a deceleration when expressed as a function of maize yield (Figure 5.5). In addition, the mean maize to soybean yield ratio ranged from 2.7 to 3.4, while its magnitude of uncertainty ranged between 0.18 and 0.7 (Figure 5.6). Lastly, the yield ratios obtained from the crop performance trials datasets were benchmarked against those documented by USDA-NASS, with slightly lower ratios for this dataset relative to those from USDA-NASS data (Table 5.1), which ranged from 3.2 to 3.9.

5.5 Discussion

This study provides new insights on the maize and soybean yield performances. This information is foundational for guiding future breeding efforts and targeted investment on research portfolio to better understand major causes impacting soybean yields under high yielding environments across the major US producing region for these field crops.

Previous studies have reported and raised concerns about the yield deceleration and stagnation of maize and soybean in very specific US regions (Kucharik et al., 2020; Ray et al., 2012). This study contributed to identify a soybean yield plateau in high-yielding maize environments in Kansas, which was attributed to optimal growing conditions such as, early planting dates, early season precipitation (April-May), and irrigation. Kukal & Irmak (2019) reported normalized irrigation-limited yield gaps (difference between irrigated and rainfed production) of 1.7 and 0.7 for maize and soybean, respectively. In addition, soybeans have been shown to be relatively less responsive to increased water supply than maize in local field studies (Schlegel et al., 2016). This suggests that the difference between these crops would tend to be exacerbated under optimal water supply, explaining the plateau behavior of soybean in high-yielding maize environments. Similarly, for the entire US Corn Belt region, we found a yield deceleration of soybean relative to maize. Historically (from 1930s to the present), maize yields have increased more proportionally (in relative terms) relative to soybeans (United States Department of Agriculture (USDA), 2023). Even during the most recent decade, the greater relative yield gain of maize compared to soybean over the last decade (2009-2019) (~ 0.8 and ~ 0.6 % year^{-1}, respectively; Egli, 2023) might be an additional contributing factor for this deceleration pattern for soybeans.

Our reported maize to soybean yield ratios for the Corn Belt are similar when considering the Crop Performance Trials dataset, or slightly higher when considering the USDA-NASS dataset, compared to previous studies, with reported ratios ranging from 2.9 to 3.2 (Karlen et al., 1995; Mallarino et al., 1991; Porter et al., 1998; West et al., 1996). However, the novelty from our study is the trend toward greater yield ratios as the yield environment improves (Figure 5.7), which is consistent with the higher yield ratios achieved in irrigated counties in Kansas. In contrast, Egli (2008) found no differences in the ratios ($\sim$3) between high- (Indiana, Illinois and Iowa) and low- (Kentucky, Missouri and Tennessee) yield potential states for the early 2000s. This dissimilarity with our study may reflect the fact that recent relative yield gains have differed between contrasting yield environments for maize but not for soybean (Lobell & Azzari, 2017), reflecting more stable variation documented for soybeans across many producing regions.

Under low yielding environments, it may be apparent that the lower maize to soybean yield ratio is supported by the higher plasticity of soybean relative to maize (e.g., Vega et al., 2000 or Sadras & Calviño, 2001). However, recent advances in maize vegetative and reproductive plasticity (Ross et al., 2020; Rotili et al., 2021; Veenstra et al., 2021) and stress tolerance (Di Matteo et al., 2016; Messina et al., 2020), as well as the introduction of new genetic traits (Barten et al., 2022; Clark et al., 2020; Fernandez et al., 2022; Gaffney et al., 2015; Schussler et al., 2022), are factors to consider for improving yield stability under more resource-limited conditions. Recent studies have highlighted the improvement of maize in terms of yield and stability under these conditions (Messina et al., 2022), and its subsequent expansion into low-yielding environments historically dominated by other summer crops (Mayor et al., 2023; Rotili et al., 2019). On the other hand, maize yield has significantly increased in under high yielding environments (Assefa et al., 2017). A few plausible pathways to increase attainable soybean yield under high yielding environments can include: i) improving photosynthetic efficiency (Peterhansel et al., 2008; Zhu et al., 2010), situation that can enhance N fixation (Friel & Friesen, 2019; Lam et al., 2012; Sanz-sáez et al., 2015), ii) exploring more efficient strains for nitrogen fixation to reduce the overall costs of carbohydrates for the crop (Dixon & Kahn, 2004; Holland et al., 2023; Kiers et al., 2003; Martins da Costa et al., 2020), iii) optimizing carbon supply and use (Borrás et al., 2004; Ho, 1988), and iv) improving flower initiation (mainly also via maintaining adequate crop N status; Brevedan et al., 1978) and reducing abortion (Egli & Bruening, 2002). In addition, anticipating reproductive growth stages (Cooper, 2003), enhancing early plant growth rate to take advantage of anticipated planting dates, improving management of cyst nematode problems (Arjoune et al., 2022), and micronutrient deficiencies (Thapa et al., 2021) are factors that should be considered for future gains in attainable soybean yield.

Future research should focus on better understanding genotype, management, and environmental factors that may be imposing a limitation to soybean yields, mainly under high yielding maize environments. For example, some aspects to consider are the relationship between plant N fixation and carbon dynamics (Sinclair & de Wit, 1976) or the thermo-photoperiodic conditions during the growing season (Cooper, 2003). In addition, in the current context of climate change (e.g., rising temperature and CO_2), it will be critical to compare maize and soybean performance under different weather scenarios. There is no consensus in the scientific literature on the magnitude of the impact this could have on yields for either crop (Arora et al., 2020; Burchfield et al., 2020; Lesk et al., 2020; T.-S. Lin et al., 2021; Malikov et al., 2020; Schlenker & Roberts, 2009; C. Yu et al., 2021). Finally, another point to consider is expanding the study of maize and soybean yield comparisons to different regions within the United States and around the world. Land allocation will be critical to offsetting the effects of climate change in the future (Rising & Devineni, 2020).

5.6 Conclusions

Our study provides a comprehensive yield comparison analysis of the two major crops in the US Corn Belt region, maize and soybean, over a large spatial and temporal scale. We found a soybean yield plateau in high-yielding maize environments in Kansas, which was attributed to optimal growing conditions such as irrigation and early planting dates. When the analysis was extended to the entire Corn Belt region, we found a soybean yield deceleration relative to maize with major emphasis under high yielding environments. Thus, yield difference for maize and soybean was maximized as the yield environment improved. Future studies should focus on studying the main limiting factors restricting to increase soybean yields, as well as extending this comparative study to other production regions.

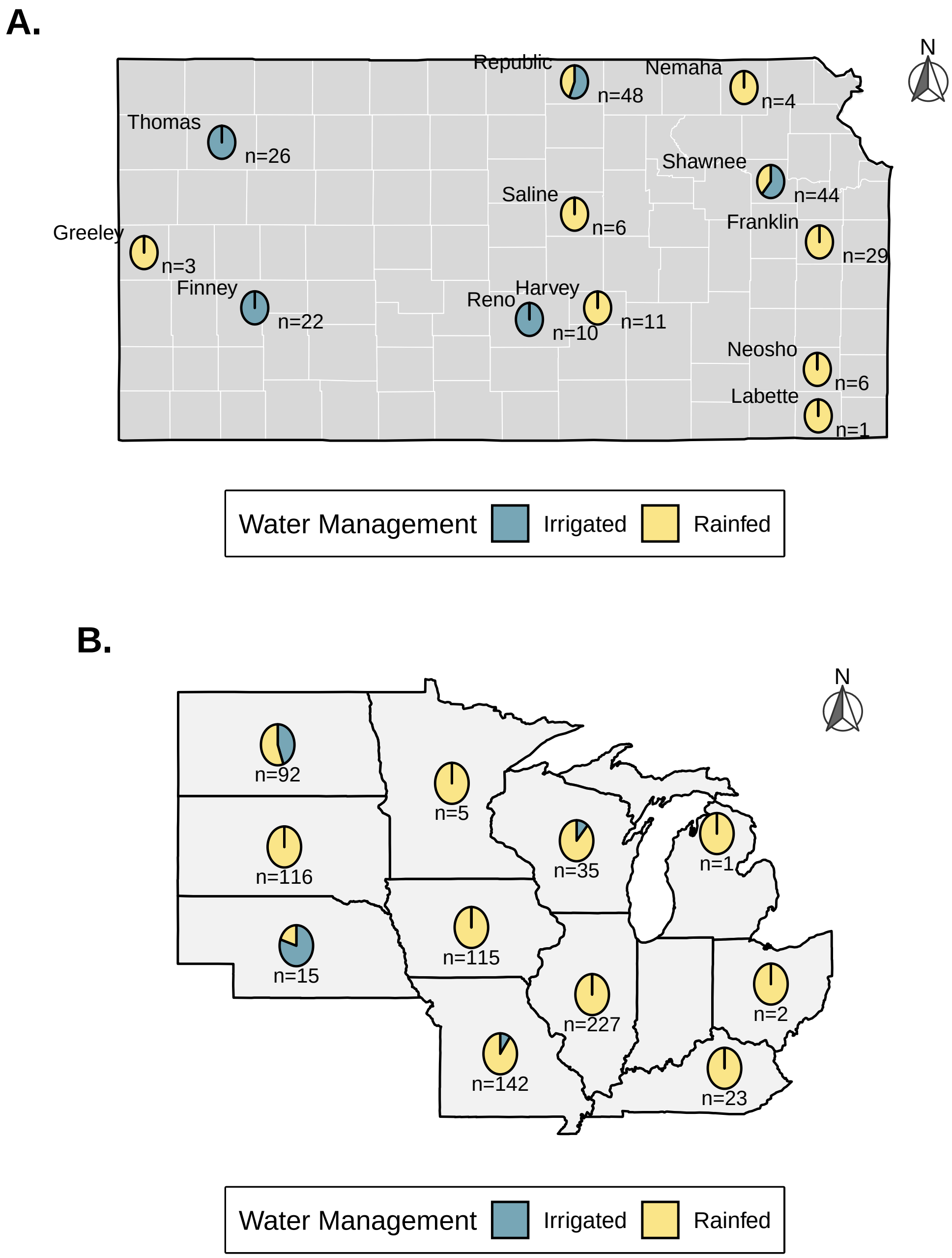

Figure 5.1: Spatial distribution of crop performance trials conducted in Kansas between 1991 and 2021 per county (**A**) and crop performance trials conducted in 11 US Corn Belt states (Illinois, Iowa, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin) per state (**B**), and the respective proportions of rainfed (yellow) and irrigated (blue) conditions. The total number of trials in each county or state is indicated as n.

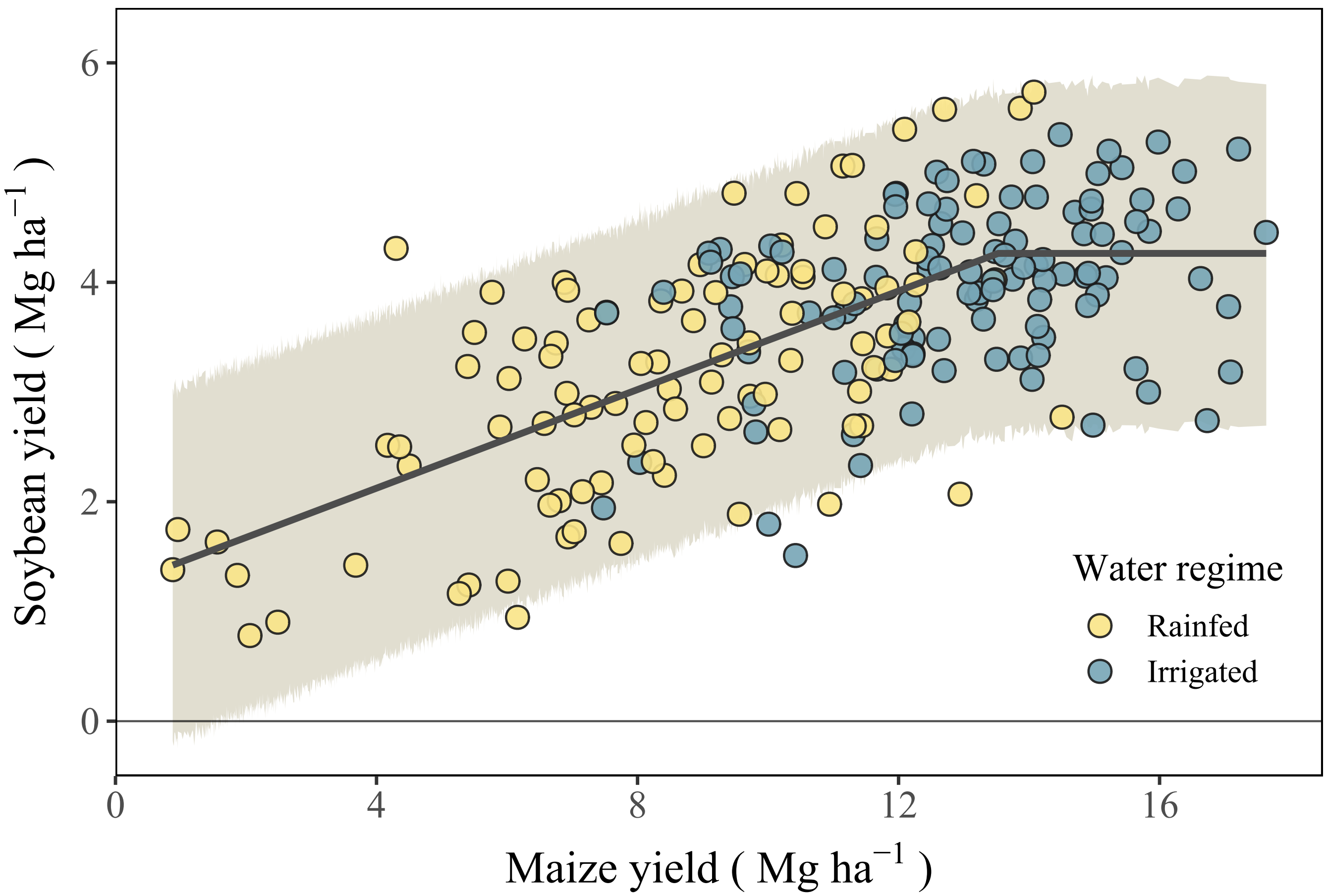

Figure 5.2: Relationship of soybean yield (Mg ha^{-1}) as a function of maize yield (Mg ha^{-1}) for Kansas crop performance trials conducted between 1991 and 2021. Yellow circles indicate trials conducted under rainfed conditions while blue points indicate trials conducted under irrigated conditions. The black line shows the expected linear-plateau regression model, and the shadowed area shows the predicted draws that fall into the 95% quantile.

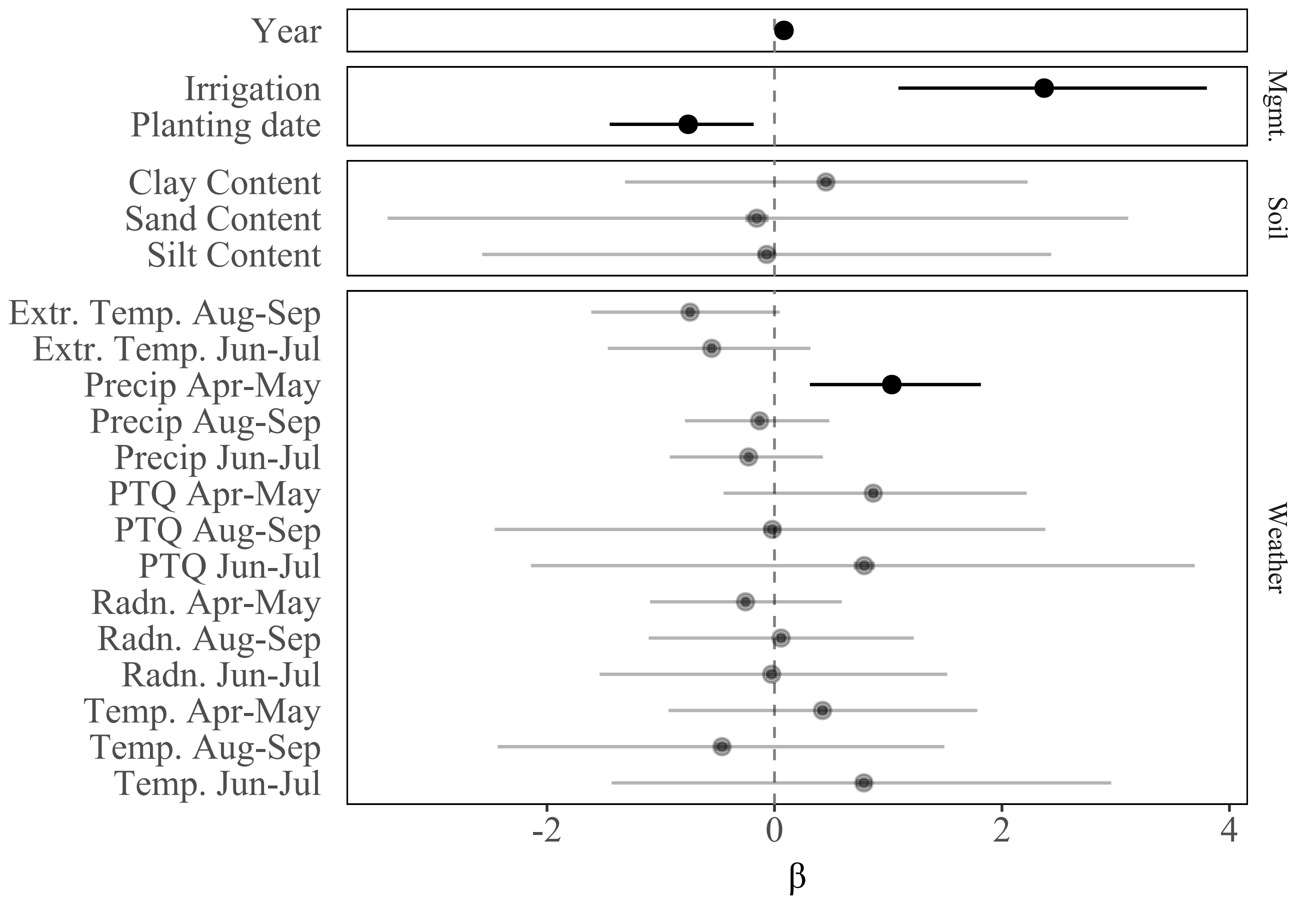

Figure 5.3: Coefficients from the Bayesian binary model for year, management (Mgmt.), soil, and weather variables. The points represent the medians with their respective 95% posterior credible intervals (horizontal lines). The black color indicates the coefficients for which the 95% posterior credible intervals do not contain zero.

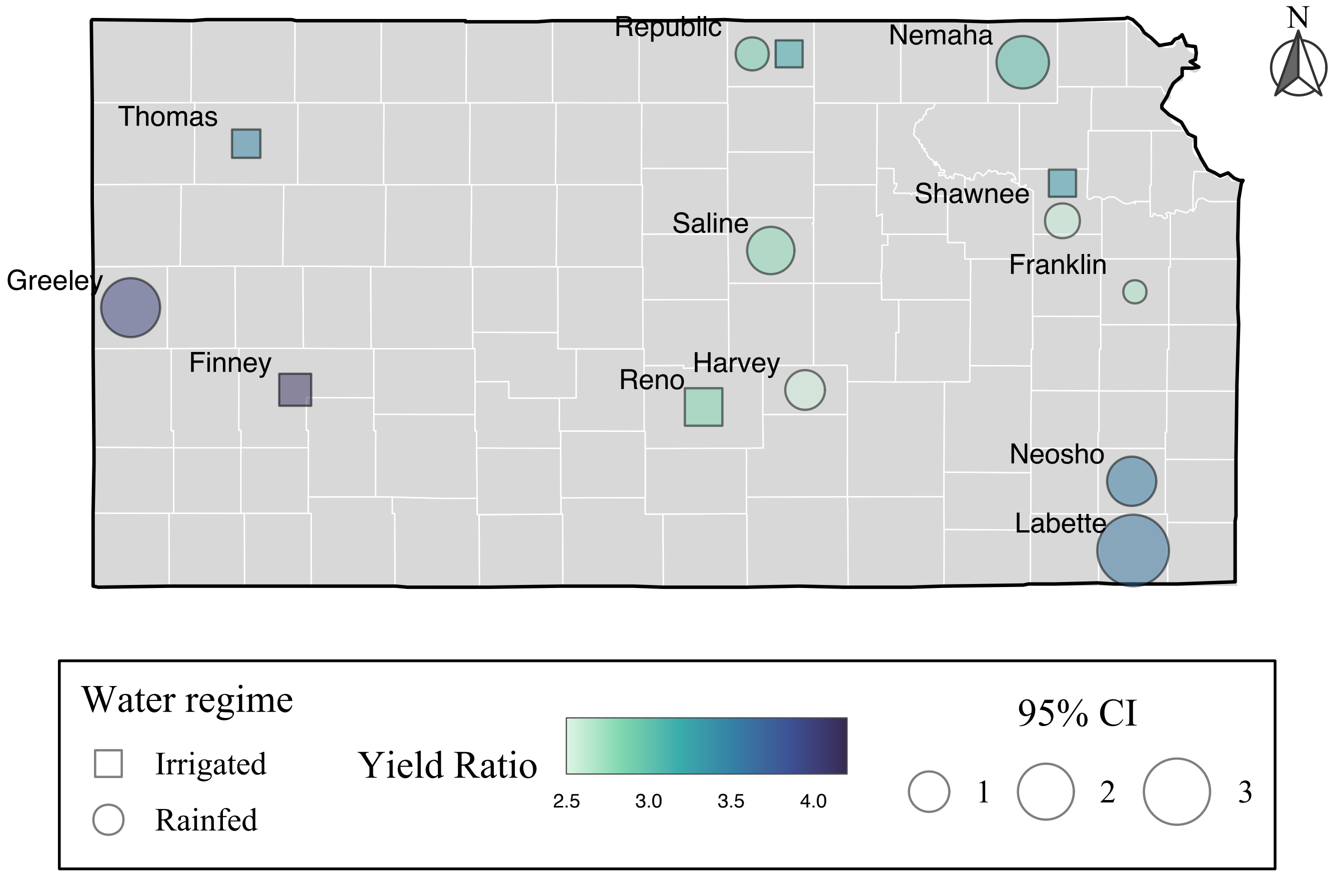

Figure 5.4: Spatial distribution of the mean maize to soybean yield ratios in Kansas by county (a darker color indicates a higher yield ratio). Circles represent rainfed conditions, while squares represent irrigated conditions. The size of the shape represents the length of the 95% credible interval from the posterior distributions.

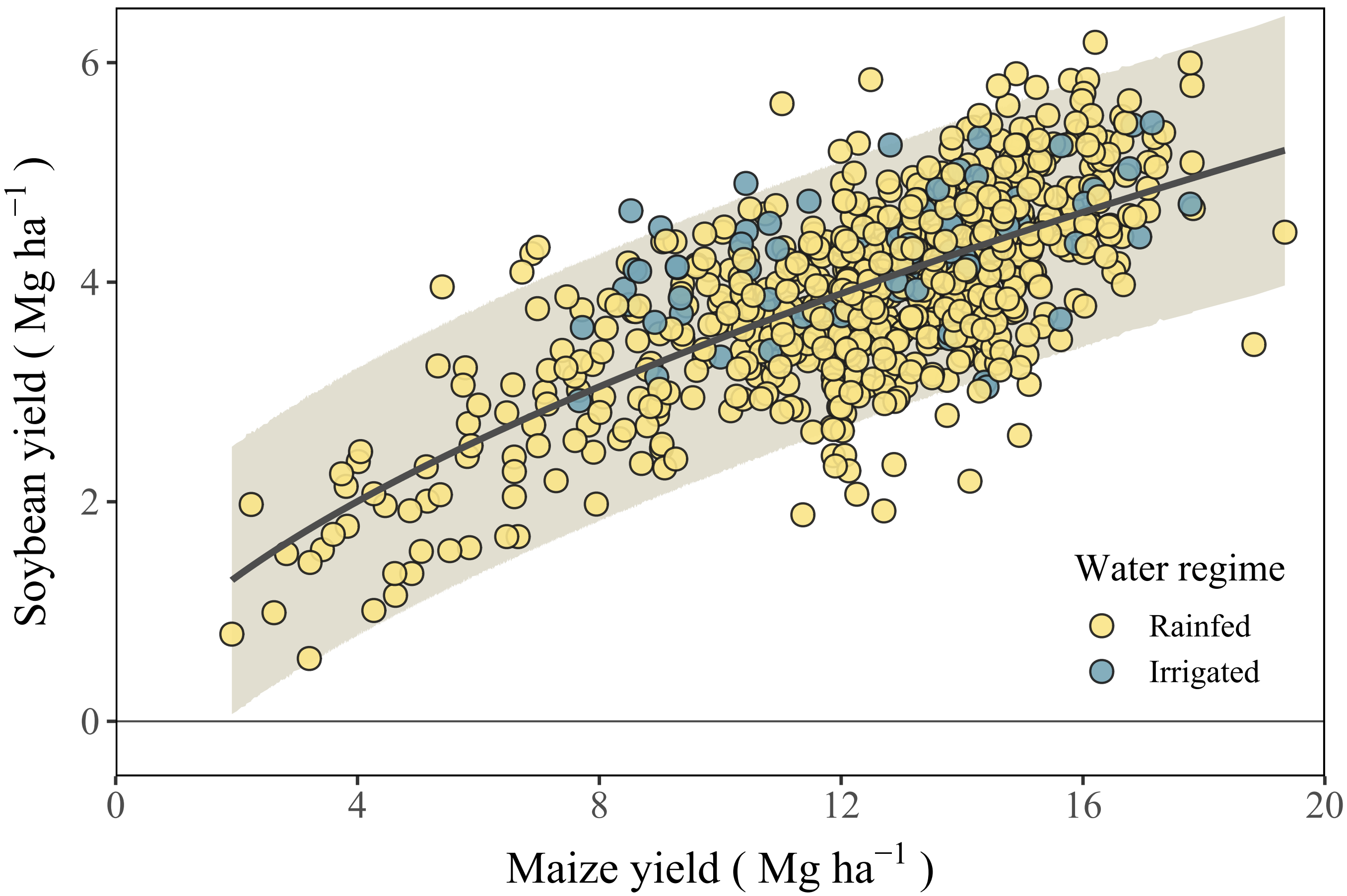

Figure 5.5: Relationship of soybean yield (Mg ha^{-1}) as a function of maize yield (Mg ha^{-1}) for crop performance trials conducted in 11 states of the US Corn Belt (Illinois, Iowa, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin) between 2000 and 2022. Yellow circles indicate trials conducted under rainfed conditions while blue points indicate trials conducted under irrigated conditions. The black line shows the expected power law function, and the shadowed area shows the predicted draws that fall into the 95% quantile.

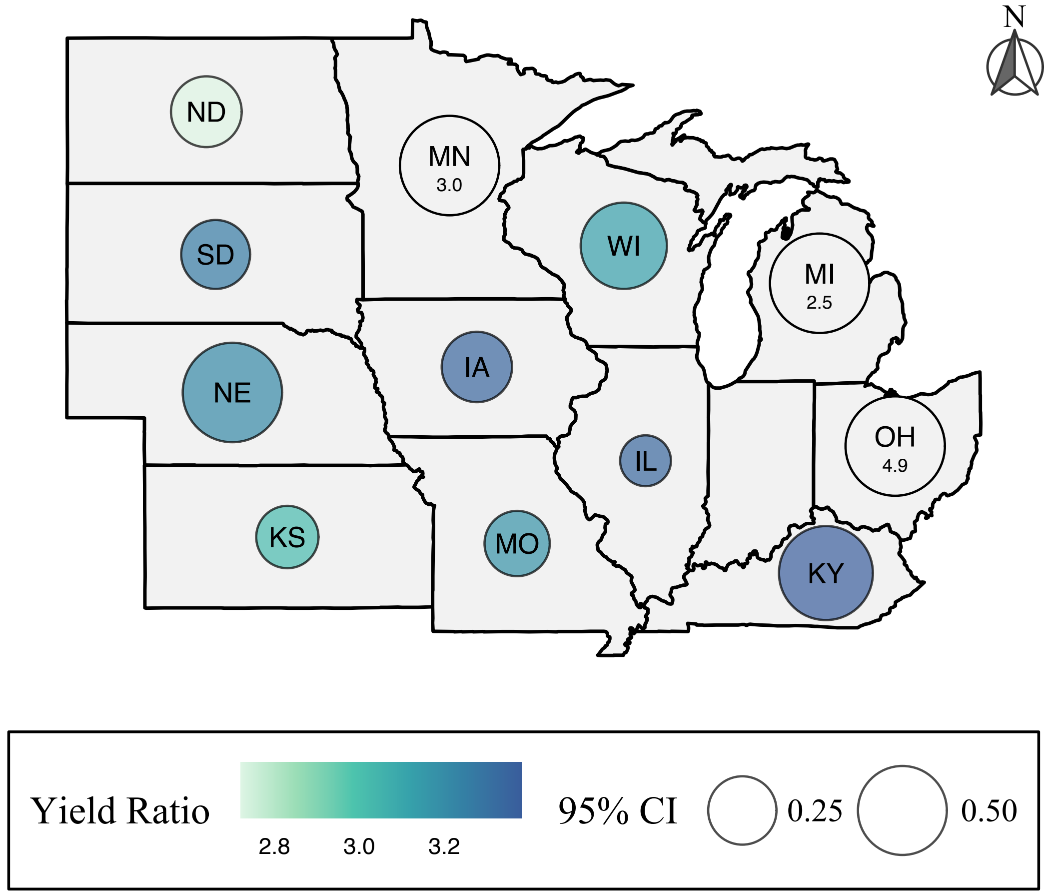

Figure 5.6: Spatial distribution of the mean maize to soybean yield ratios in the United States (US) Corn-Belt region by state from 2000 to 2022 (a darker color indicates a greater yield ratio). The size of the circles represents the length of the 95% credible interval from the posterior distributions. States with gray circles (Michigan, Minnesota, and Ohio) were not included in the analysis due to their low representation in the dataset (<1%), and the values shown below the abbreviations represent their calculated average maize to soybean yield ratio.

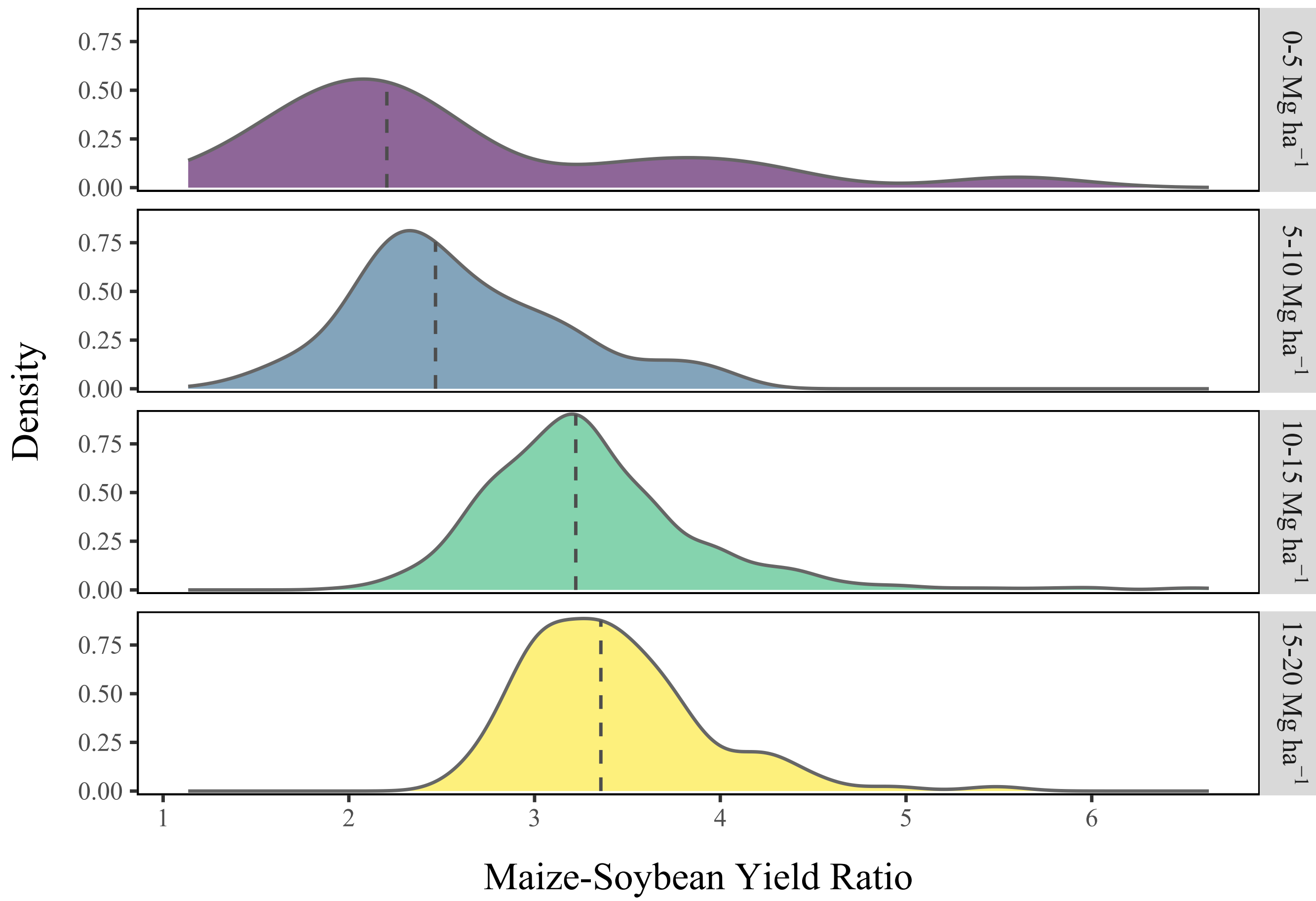

Figure 5.7: Density plots for maize to soybean yield ratios in the US Corn Belt for four maize yield categories (0-5, 5-10, 10-15, and 15-20 Mg ha^{-1}). The peak of the density curve represents the highest concentration of data points, and the dashed gray line indicates the median. The corresponding density plots of soybean yield for the four maize yield categories are shown in Figure C.6.

Table 5.1: Comparison of mean maize to soybean yield ratios by state obtained from the performance trials dataset and USDA-NASS (https://quickstats.nass.usda.gov/) in the US Corn Belt from 2000 to 2022.

State	**Mean yield ratio from crop performance trials dataset**	**Mean yield ratio from USDA-NASS dataset**
Illinois	3.3	3.4
Iowa	3.3	3.5
Kansas	3.0	3.9
Kentucky	3.4	3.4
Missouri	3.2	3.4
Nebraska	3.2	3.2
North Dakota	2.7	3.8
South Dakota	3.3	3.4
Wisconsin	3.1	3.5

Chapter 6

Final remarks

Crop intensification is a key aspect for achieving global food security and exploring options for optimizing land use and environmental resources. The focus of this dissertation was to examine different case studies of crop intensification within major production regions of the United States. Thus, we have considered the following alternatives to increase production without increasing land area: i) increasing the yield of a single crop per year per unit of land area (Chapters 2 and 5), and/or ii) increasing the number of crops harvested per year (Chapters 3 and 4).

In Chapter 2, we have demonstrated the importance of optimizing maize crop management (planting date and hybrid maturity) within a target environment of the US central Great Plains region. Our crop modeling analysis showed that long-maturity hybrids combined with early planting dates maximize grain yield in eastern environments, while late planting may be a strategy to maintain yield and increase stability in central environments. In addition, the use of short-season hybrids with reduced yield penalties may provide new opportunities in maize-based cropping systems to increase the number of crops harvested per unit of time.

In Chapter 3, we have focused on the traditional continuous winter wheat rotation of the US central Great Plains region and the adoption of more intensified and diversified cropping systems. Water inefficiency during summer fallow in the traditional system presents an opportunity for alternative rotations to increase overall productivity, especially for those with a high frequency of forage crops. However, from an economic standpoint, winter wheat combined with a double-cropped cereal rotation presented the highest positive economic returns, while more productive rotations attained negative margins. Finally, we have shown the importance of optimizing nitrogen management as a key component of crop intensification.

In chapter 4, we shifted the focus to the Southern US region to assess the feasibility of the unexplored maize-soybean double-crop. We reported land equivalent ratios greater than one for both field data and crop model analyses, indicating an advantage for the tested cropping system over the respective monocultures. In addition, we made progress in identifying the best maturity combination and explored the risk of success of the system across planting dates.

Lastly, the analysis presented in Chapter 5 revealed patterns of soybean yield deceleration and stagnation relative to maize for Kansas and the entire Corn Belt. The novelty of this analysis lies in the use of a large dataset covering 11 states over 20 years (Corn Belt dataset), which allowed the development of a comprehensive yield comparison analysis of the two major crops in the region. The information generated is fundamental to guiding future breeding efforts and targeted investments in the research portfolio to better understand the key drivers of soybean yield in high-yielding environments across the major U.S. production region for these crops.

Some of the major research limitations throughout this dissertation were related to i) restricted availability of data for calibration and validation of the crop model, especially for short-season genotypes and late planting dates (Chapter 2), ii) limited number and combination of crops, less focused on the aspect of crop diversification (Chapter 3) or crop maturities (Chapter 4) due to the exponential combination of choices regarding funding and labor, and iii) the limitation to only one data source (crop performance trials) for the maize-soybean yield comparison (Chapter 5). The use of more data sources (e.g., on-farm strip trials) could provide a more complete understanding of the relationship between corn and soybean yields across different yielding environments.

Future research should focus on testing the intensification alternatives (with their optimized crop management strategies) presented in this dissertation at on-farm scale. In this regard, the integration of inter- and multidisciplinary teams would allow these alternatives to be studied from different perspectives (e.g., economic, environmental, social, etc.), thus enriching the evaluation and allowing for their improvement in a more holistic approach. Another point to consider is expanding the study of these alternatives to different regions within the US and globally. Finally, under the current scenario of climate change (e.g., rising temperatures or CO_2), future studies should address its effects on the performance of the intensification alternatives, and their interactions with management practices as a strategy to mitigate future climate-driven yield reductions.

References

Abendroth, L., Elmore, R., Boyer, M., & Marlay, S. (2011). *Corn growth and development*. Ames: Iowa State University.

Abendroth, L., Miguez, F. E., Castellano, M. J., Carter, P. R., Messina, C. D., Dixon, P. M., & Hatfield, J. L. (2021). Lengthening of maize maturity time is not a widespread climate change adaptation strategy in the us midwest. *Global Change Biology*, *27*(11), 2426–2440. doi: 10.1111/gcb.15565

Abendroth, L., Woli, P. P., Myers, A. J., & Elmore, R. W. (2017). Yield-based corn planting date recommendation windows for iowa. *Crop, Forage & Turfgrass Management*, *3*(1), 1–7. doi: 10.2134/cftm2017.02.0015

Abrahão, G. M., & Costa, M. H. (2018). Evolution of rain and photoperiod limitations on the soybean growing season in brazil: The rise (and possible fall) of double-cropping systems. *Agricultural and Forest Meteorology*, *256*, 32–45. doi: 10.1016/j.agrformet.2018.02.031

Acosta-Martinez, V., Mikha, M. M., & Vigil, M. F. (2007). Microbial communities and enzyme activities in soils under alternative crop rotations compared to wheat–fallow for the central great plains. *Applied Soil Ecology*, *37*(1-2), 41–52. doi: 10.1016/j.apsoil.2007.03.009

Aiken, R. M., O'Brien, D. M., Olson, B. L., & Murray, L. (2013). Replacing fallow with continuous cropping reduces crop water productivity of semiarid wheat. *Agronomy Journal*, *105*(1), 199–207. doi: 10.2134/agronj2012.0165

Ali, Z., Ahmed, S., Salahin, M., Yasmin, N., Alam, A., & Islam, M. (2017). Evaluation of yield potential of maize-soybean intercropping in drought-prone areas of bangladesh. *Fundamental and Applied Agriculture*, *2*(2), 271–276.

Anderson, R. L. (2008). Diversity and no-till: keys for pest management in the us great plains. *Weed Science*, *56*(1), 141–145. doi: 10.1614/ws-07-007.1

Anderson, R. L., Bowman, R. A., Nielsen, D., Vigil, M. F., Aiken, R. M., & Benjamin, J. G. (1999). Alternative crop rotations for the central great plains. *Journal of Production Agriculture*, *12*(1), 95–99. doi: 10.2134/jpa1999.0095

Anderson, R. L., Tanaka, D. L., & Merrill, S. D. (2003). Yield and water use of broadleaf crops in a semiarid climate. *Agricultural Water Management*, *58*(3), 255–266. doi: 10.1016/s0378-3774(02)00085-9

Andrade, F. H. (1995). Analysis of growth and yield of maize, sunflower and soybean grown at balcarce, argentina. *Field Crops Research*, *41*(1), 1–12. doi: 10.1016/0378-4290(94)00107-n

Andrade, F. H. (2011). *La tecnología y la producción agrícola*. Ediciones INTA.

Andrade, J., Ermacora, M., & Satorre, E. (2022). Assessing benefits of land use intensification on extensive grain cropping systems of the Pampas. *European Journal of Agronomy*, *135*, 126484. doi: 10.1016/j.eja.2022.126484

Andrade, J., & Satorre, E. (2015). Single and double crop systems in the Argentine Pampas: Environmental determinants of annual grain yield. *Field Crops Research*, *177*, 137 147. doi: 10.1016/j.fcr.2015.03.008

Andrade, J. F., Poggio, S. L., Ermácora, M., & Satorre, E. H. (2015). Productivity and resource use in intensified cropping systems in the rolling pampa, argentina. *European Journal of Agronomy*, *67*, 37–51.

Andrade, J. F., Poggio, S. L., Ermácora, M., & Satorre, E. H. (2017). Land use intensification in the rolling pampa, argentina: Diversifying crop sequences to increase yields and resource use. *European Journal of Agronomy*, *82*, 1–10. doi: 10.1016/j.eja.2016.09.013

Angus, J., Hasegawa, S., Hsiao, T., Liboon, S., & Zandstras, H. (1983). The water balance of post-monsoonal dryland crops. *Journal of Agricultural Science*, *101*(3), 699–710. doi: 10.1017/s0021859600038739

Archontoulis, S., Miguez, F., & Moore, K. (2014). Evaluating APSIM Maize, Soil Water, Soil Nitrogen, Manure, and Soil Temperature Modules in the Midwestern United States. *Agronomy Journal,*, *106*(3), 1025–1040. doi: 10.2134/agronj2013.0421

Arjoune, Y., Sugunaraj, N., Peri, S., Nair, S. V., Skurdal, A., Ranganathan, P., & Johnson, B. (2022). Soybean cyst nematode detection and management: a review. *Plant Methods*, *18*(1), 1–39. doi: 10.1186/s13007-022-00933-8

Arora, G., Feng, H., Anderson, C., & Hennessy, D. (2020). Evidence of climate change impacts on crop comparative advantage and land use. *Agricultural Economics*, *51*(2), 221–236. doi: 10.1111/agec.12551

Arora, G., & Wolter, P. (2018). Tracking land cover change along the western edge of the u.s. corn belt from 1984 through 2016 using satellite sensor data: observed trends and contributing factors. *Journal of Land Use Science*, *13*(1-2), 59–80. doi: 10.1080/1747423x.2018.1466001

Arvor, D., Dubreuil, V., Ronchail, J., Simões, M., & Funatsu, B. (2014). Spatial patterns of rainfall regimes related to levels of double cropping agriculture systems in Mato Grosso (Brazil). *International Journal of Climatology*, *34*(8), 2622–2633. doi: 10.1002/joc.3863

Arvor, D., Meirelles, M., Dubreuil, V., Bégué, A., & Shimabukuro, Y. (2012). Analyzing the agricultural transition in Mato Grosso, Brazil, using satellite-derived indices. *Applied Geography*, *32*(2), 702–713. doi: 10.1016/j.apgeog.2011.08.007

Assefa, Y., Prasad, P. V., Carter, P., Hinds, M., Bhalla, G., Schon, R., ... Ciampitti, I. A. (2017). A new insight into corn yield: Trends from 1987 through 2015. *Crop Science*, *57*(5), 2799–2811. doi: 10.2135/cropsci2017.01.0066

Assefa, Y., Vara Prasad, P., Carter, P., Hinds, M., Bhalla, G., Schon, R., ... Ciampitti, I. (2016). Yield responses to planting density for US modern corn hybrids: A synthesis-analysis. *Crop Science*, *56*(5), 2802 2817. doi: 10.2135/cropsci2016.04.0215

Balboa, G., Archontoulis, S., Salvagiotti, F., Garcia, F., Stewart, W., Francisco, E., ... Ciampitti, I. (2019). A systems-level yield gap assessment of maize-soybean rotation under high- and low-management inputs in the Western US Corn Belt using APSIM. *Agricultural Systems*, *174*, 145–154. doi: 10.1016/j.agsy.2019.04.008

Ban, N. C., Mills, M., Tam, J., Hicks, C. C., Klain, S., Stoeckl, N., ... others (2013). A social–ecological approach to conservation planning: embedding social considerations. *Frontiers in Ecology and the Environment*, *11*(4), 194–202. doi: 10.1890/110205

Barrett, C. (2010). Measuring food insecurity. *Science*, *327*(5967), 825–828. doi: 10.1126/science.1182768

Barten, T. J., Kosola, K. R., Dohleman, F. G., Eller, M., Brzostowski, L., Mueller, S., ... Renaud, A. (2022). Short-stature maize reduced wind damage during the 2020 midwestern derecho, improving yields and greenhouse gas outcomes. *Crop Science*, *62*(6), 2439–2450. doi: 10.1002/csc2.20823

Basche, A., Archontoulis, S., Kaspar, T., Jaynes, D., Parkin, T., & Miguez, F. (2016). Simulating long-term impacts of cover crops and climate change on crop production and environmental outcomes in the Midwestern United States. *Agriculture, Ecosystems Environment,*, *218*, 95 106. doi: 10.1016/j.agee.2015.11.011

Bateman, N. R., Catchot, A. L., Gore, J., Cook, D. R., Musser, F. R., & Irby, J. T. (2020). Effects of planting date for soybean growth, development, and yield in the southern usa. *Agronomy*, *10*(4), 596. doi: 10.3390/agronomy10040596

Battisti, R., Ferreira, M., Tavares, , Knapp, F., Bender, F., Casaroli, D., & Alves Júnior, J. (2020). Rules for grown soybean-maize cropping system in Midwestern Brazil: Food production and economic profits. *Agricultural Systems*, *182*, 102850. doi: 10.1016/j.agsy.2020.102850

Baum, M., Archontoulis, S., & Licht, M. (2019). Planting Date, Hybrid Maturity, and Weather Effects on Maize Yield and Crop Stage. *Agronomy Journal*, *111*(1), 303 313. doi: 10.2134/agronj2018.04.0297

Baum, M., Licht, M., Huber, I., & Archontoulis, S. (2020). Impacts of climate change on the optimum planting date of different maize cultivars in the central US Corn Belt. *European Journal of Agronomy*, *119*, 126101. doi: 10.1016/j.eja.2020.126101

Berry, J., & Bjorkman, O. (1980). Photosynthetic response and adaptation to temperature in higher plants. *Annual Review of Plant Physiology*, *31*(1), 491–543. doi: 10.1146/annurev.pp.31.060180.002423

Berti, M., Gesch, R., Johnson, B., Ji, Y., Seames, W., Aponte, A., et al. (2015). Double- and relay-cropping of energy crops in the northern great plains, usa. *Industrial Crops and Products*, *75*, 26–34. doi: 10.1016/j.indcrop.2015.05.012

Bezdek, J., Ehrlich, R., & Full, W. (1984). FCM: The fuzzy c-means clustering algorithm. *Computers Geosciences*, *10*(2–3), 191 203. doi: 10.1016/0098-3004(84)90020-7

Blanco-Canqui, H., Holman, J. D., Schlegel, A. J., Tatarko, J., & Shaver, T. M. (2013). Replacing fallow with cover crops in a semiarid soil: Effects on soil properties. *Soil Science Society of America Journal*, *77*(3), 1026–1034. doi: 10.2136/sssaj2013.01.0006

Blanco-Canqui, H., Shaver, T. M., Lindquist, J. L., Shapiro, C. A., Elmore, R. W., Francis, C. A., & Hergert, G. W. (2015). Cover crops and ecosystem services: Insights from studies in temperate soils. *Agronomy Journal*, *107*(6), 2449–2474. doi: 10.2134/agronj15.0086

Borrás, L., Slafer, G., & Otegui, M. (2004). Seed dry weight response to source–sink manipulations in wheat, maize and soybean: a quantitative reappraisal. *Field Crops Research*, *86*(2–3), 131–146. doi: 10.1016/j.fcr.2003.08.002

Bowman, R. A., & Halvorson, A. D. (1997). Crop rotation and tillage effects on phosphorus distribution in the central great plains. *Soil Science Society of America Journal*, *61*(5), 1418–1422. doi: 10.2136/sssaj1997.03615995006100050020x

Brevedan, R., Egli, D., & Leggett, J. (1978). Influence of n nutrition on flower and pod abortion and yield of soybeans. *Agronomy Journal*, *70*(1), 81–84. doi: 10.2134/agronj1978.00021962007000010019x

Bringezu, S., Schütz, H., Pengue, W., O'Brien, M., Garcia, F., Sims, R., … Herrick, J. (2014). *Assessing global land use: balancing consumption with sustainable supply.* Nairobi: United Nations Environment Programme.

Brooker, R., Bennett, A., Cong, W.-F., Daniell, T., George, T., Hallett, P., … White, P. (2015). Improving intercropping: a synthesis of research in agronomy, plant physiology and ecology. *New Phytologist*, *206*(1), 107–117. doi: 10.1111/nph.13132

Brown, A., & Perkins, H. (1979). Single vs. double cropping under two levels of fertilization with and without irrigation. *Communications in Soil Science and Plant Analysis*, *10*(10), 1279–1289. doi: 10.1080/00103627909366982

Brown, H., Huth, N., Holzworth, D., Teixeira, E., Zyskowski, R., Hargreaves, J., & Moot, D. (2014). Plant Modelling Framework: Software for building and running crop models on the APSIM platform. *Environmental Modelling Software*, *62*, 385 398. doi: 10.1016/j.envsoft.2014.09.005

Brown, M. E., Carcedo, A. J. P., Eggen, M., Grace, K. L., Neff, J., & Ciampitti, I. A. (2023). Integrated modeling framework for sustainable agricultural intensification. *Frontiers in Sustainable Food Systems*, *6*, 1039962. doi: 10.3389/fsufs.2022.1039962

Brumatti, L., Pires, G., & Santos, A. (2020). Challenges to the adaptation of double cropping agricultural Systems in Brazil under changes in climate and land cover. *Atmosphere*, *11*(12), 1310. doi: 10.3390/atmos11121310

Bruns, H., & Abbas, H. (2006). Planting date effects on Bt and non-Bt corn in the Mid-South USA. *Agronomy Journal*, *98*(1), 100–106. doi: 10.2134/agronj2005.0143

Burchfield, E., Matthews-Pennanen, N., Schoof, J., & Lant, C. (2020). Changing yields in the central united states under climate and technological change. *Climatic Change*, *159*(3), 329–346. doi: 10.1007/s10584-019-02567-7/figures/6

Bürkner, P. (2017). brms: An r package for bayesian multilevel models using stan. *Journal of Statistical Software*, *80*, 1–28. doi: 10.18637/jss.v080.i01

Burton Jr, R. O., Crisostomo, M. F., Berends, P. T., Kelley, K. W., & Buller, O. H. (1996). Risk/return analysis of double-cropping and alternative crop rotations with and without government programs. *Review of Agricultural Economics*, 681–692. doi: 10.2307/1349599

Bushong, J. A., Griffith, A. P., Peeper, T. F., & Epplin, F. M. (2012). Continuous winter wheat versus a winter canola–winter wheat rotation. *Agronomy Journal*, *104*(2), 324–330. doi: 10.2134/agronj2011.0244

Campbell, C. A., Zentner, R. P., Basnyat, P., Wang, H., Selles, F., McConkey, B. G., ... Cutforth, H. W. (2007). Water use efficiency and water and nitrate distribution in soil in the semiarid prairie: Effect of crop type over 21 years. *Canadian Journal of Plant Science*, *87*(4), 815–827. doi: 10.4141/cjps06034

Capristo, P., Rizzalli, R., & Andrade, F. (2007). Ecophysiological yield components of maize hybrids with contrasting maturity. *Agronomy Journal*, *99*(4), 1111–1118. doi: 10.2134/agronj2006.0360

Carr, P. M., Bell, J. M., Boss, D. L., DeLaune, P., Eberly, J. O., Edwards, L., ... Liebig, M. (2021). Annual forage impacts on dryland wheat farming in the great plains. *Agronomy Journal*, *113*(1), 1–25. doi: 10.1002/agj2.20513

Carter, E., Melkonian, J., Steinschneider, S., & Riha, S. (2018). Rainfed maize yield response to management and climate covariability at large spatial scales. *Agricultural and Forest Meteorology*, *256–257*, 242–252. doi: 10.1016/j.agrformet.2018.02.029

Castro, C., & Leite, R. M. V. B. C. (2018). Main aspects of sunflower production in brazil. *Oilseeds fats crops and lipids*, *25*(1), D104. doi: 10.1051/ocl/2017056

Caviglia, O., & Andrade, F. (2010). Sustainable intensification of agriculture in the Argentinean Pampas: capture and use efficiency of environmental resources. *The Americas Journal of Plant Science and Biotechnology*, *3*(1), 1–8.

Caviglia, O., Rizzalli, R. H., Monzon, J. P., García, F. O., Melchiori, R. J. M., Martinez, J. J., ... Andrade, F. H. (2019). Improving resource productivity at a crop sequence level. *Field Crops Research*, *235*, 129–141. doi: 10.1016/j.fcr.2019.02.011

Caviglia, O., Sadras, V. O., & Andrade, F. H. (2011). Yield and quality of wheat and soybean in sole-and double-cropping. *Agronomy Journal*, *103*(4), 1081–1089. doi: 10.2134/agronj2011.0019

Ciampitti, I. A., & Lemaire, G. (2022). From use efficiency to effective use of nitrogen: A dilemma for maize breeding improvement. *Science of the Total Environment*, *826*, 154125. doi: 10.1016/j.scitotenv.2022.154125

Clark, J., Fernández, F., Veum, K., Camberato, J., Carter, P., et al. (2020). Adjusting corn nitrogen management by including a mineralizable-nitrogen test with the preplant and presidedress nitrate tests. *Agronomy Journal*, *112*(4), 3050–3064. doi: 10.1002/agj2.20228

Cohn, A., VanWey, L., Spera, S., & Mustard, J. (2016). Cropping frequency and area response to climate variability can exceed yield response. *Nature Climate Change*, *6*(6), 601–604. doi: 10.1038/nclimate2934

Commuri, P., & Jones, R. (2001). High temperatures during endosperm cell division in maize: A genotypic comparison under in vitro and field conditions. *Crop Science*, *41*(4), 1122–1130. doi: 10.2135/cropsci2001.4141122x

Congreves, K. A., Hayes, A., Verhallen, E. A., & Van Eerd, L. L. (2015). Long-term impact of tillage and crop rotation on soil health at four temperate agroecosystems. *Soil & Tillage Research*, *152*, 17–28. doi: 10.1016/j.still.2015.03.012

Cooper, R. (2003). A delayed flowering barrier to higher soybean yields. *Field Crops Research*, *82*(1), 27–35. doi: 10.1016/s0378-4290(03)00003-0

Correndo, A. A., Rosso, L. H. M., Hernandez, C. H., Bastos, L. M., Nieto, L., Holzworth, D., & Ciampitti, I. A. (2022). metrica: an r package to evaluate prediction performance of regression and classification point-forecast models. *Journal of Open Source Software*, *7*(79), 4655. Retrieved from `https://joss.theoj.org/papers/10.21105/joss.04655` doi: 10.21105/joss.04655

Correndo, A. A., Rotundo, J. L., Tremblay, N., Archontoulis, S., Coulter, J. A., Ruiz-Diaz, D., . . . Ciampitti, I. A. (2021). Assessing the uncertainty of maize yield without nitrogen fertilization. *Field Crops Research*, *260*, 107985. doi: 10.1016/j.fcr.2020.107985

Cutforth, L. B., Francis, C. A., Lynne, G. D., Mortensen, D. A., & Eskridge, K. M. (2001). Factors affecting farmers' crop diversity decisions: An integrated approach. *American Journal of Alternative Agriculture*, *16*(4), 168–176. doi: 10.1017/s0889189300009164

De Bruin, J., & Pedersen, P. (2008). Effect of row spacing and seeding rate on soybean yield. *Agronomy Journal*, *100*(3), 704–710. doi: 10.2134/agronj2007.0106

Deines, J. M., Kendall, A. D., Crowley, M. A., Rapp, J., Cardille, J. A., & Hyndman, D. W. (2019). Mapping three decades of annual irrigation across the us high plains aquifer using landsat and google earth engine. *Remote Sensing of Environment*, *233*, 111400. doi: 10.1016/j.rse.2019.111400

de La Vega, A. J., & Hall, A. J. (2002). Effects of planting date, genotype, and their interactions on sunflower yield: I. determinants of oil-corrected grain yield. *Crop Science*, *42*(4), 1191–1201. doi: 10.2135/cropsci2002.1191

Deng, J., Zhang, Z., Liang, Z., Li, Z., Yang, X., Wang, Z., ... Shen, Y. (2020). Replacing summer fallow with annual forage improves crude protein productivity and water use efficiency of the summer fallow-winter wheat cropping system. *Agricultural Water Management*, *230*, 105980. doi: 10.1016/j.agwat.2019.105980

Dewes, C. F., Rangwala, I., Barsugli, J. J., Hobbins, M. T., & Kumar, S. (2017). Drought risk assessment under climate change is sensitive to methodological choices for the estimation of evaporative demand. *PloS one*, *12*(3), e0174045. doi: 10.1371/journal.pone.0174045

Dhuyvetter, K. C., Thompson, C. R., Norwood, C. A., & Halvorson, A. D. (1996). Economics of dryland cropping systems in the great plains: A review. *Journal of Production Agriculture*, *9*(2), 216–222. doi: 10.2134/jpa1996.0216

Di Matteo, J., Ferreyra, J., Cerrudo, A., Echarte, L., & Andrade, F. (2016). Yield potential and yield stability of argentine maize hybrids over 45 years of breeding. *Field Crops Research*, *197*, 107–116. doi: 10.1016/j.fcr.2016.07.023

Dixon, R., & Kahn, D. (2004). Genetic regulation of biological nitrogen fixation. *Nature Reviews Microbiology*, *2*(8), 621–631. doi: 10.1038/nrmicro954

Duvick, D. N. (1989). Possible genetic causes of increased variability in us maize yields. *Variability in grain yields: implications for agricultural research and policy in developing countries.*, 147–156.

Duvick, D. N. (2005). The contribution of breeding to yield advances in maize (*zea mays* l.). *Advances in Agronomy*, *86*, 83–145. doi: 10.1016/s0065-2113(05)86002-x

Duvick, D. N., Smith, J. S. C., & Cooper, M. (2004). Long-term selection in a commercial hybrid maize breeding program. *Plant breeding reviews*, *24*(2), 109–152.

Egli, D. B. (2008). Comparison of corn and soybean yields in the united states: Historical trends and future prospects. *Agronomy Journal*, *100*, S–79. doi: 10.2134/agronj2006.0286c

Egli, D. B. (2023). Yield improvement and yield components: A comparison of corn and soybean. *Crop Science*, *63*(3), 1019–1029. doi: 10.1002/csc2.20925

Egli, D. B., & Bruening, W. (1992). Planting date and soybean yield: evaluation of environmental effects with a crop simulation model: SOYGRO. *Agricultural and Forest Meteorology*, *62*(1–2), 19–29. doi: 10.1016/0168-1923(92)90003-m

Egli, D. B., & Bruening, W. (2002). Flowering and fruit set dynamics at phloem-isolated nodes in soybean. *Field Crops Research*, *79*(1), 9–19. doi: 10.1016/s0378-4290(02)00016-3

Evans, L. T. (1996). *Crop evolution, adaptation and yield*. Cambridge university press.

Evett, S. R., Tolk, J. A., & Howell, T. A. (2006). Soil profile water content determination: Sensor accuracy, axial response, calibration, temperature dependence, and precision. *Vadose Zone Journal*, *5*(3), 894–907. doi: 10.2136/vzj2005.0149

Fang, Q., Ma, L., Yu, Q., Malone, R., Saseendran, S., & Ahuja, L. (2008). Modeling nitrogen and water management effects in a wheat-maize double-cropping system. *Journal of Environmental Quality*, *37*(6), 2232–2242. doi: 10.2134/jeq2007.0601

Farahani, H., Peterson, G., Westfall, D., Sherrod, L., & Ahuja, L. (1998). Soil water storage in dryland cropping systems: the significance of cropping intensification. *Soil Science Society of America Journal*, *62*(4), 984–991. doi: 10.2136/sssaj1998.03615995006200040020x

Feekes, W. (1941). *De tarwe en haar milieu.* Groningen: Vers XVII Tech. Tarwe. Comm.

Fehr, W., & Caviness, C. (1977). *Stages of soybean development* (Tech. Rep.). Iowa State University Cooperative Extension Service, Special Report 80.

Fernandez, J., Habben, J., Schussler, J., Masek, T., Weers, B., et al. (2022). zmm28 transgenic maize increases both n uptake- and n utilization-efficiencies. *Communications Biology*, *2022*(181), 1–9. doi: 10.1038/s42003-022-03501-x

Fernandez de C., F., Gepts, P., & Lopez, M. (1986). *Etapas de desarrollo de la planta de frijol comun (phaseolus vulgaris l.).* Cali, CO: Centro Internacional de Agricultura Tropical (CIAT).

Fick, G. W., & Mueller, S. C. (1989). *Alfalfa: Quality, maturity, and mean stage of development* (Tech. Rep.). Department of Agronomy, College of Agriculture and Life Sciences, Cornell University.

Fischer, R. (1985). Number of kernels in wheat crops and the influence of solar radiation and temperature. *Journal of Agricultural Science*, *105*(2), 447–461. doi: 10.1017/s0021859600056495

Fischer, T., Byerlee, D., & Edmeades, G. (2014). Crop yields and global food security. In *ACIAR: Canberra* (pp. 8–11).

Fox, J., & Weisberg, S. (2019). *An R companion to applied regression* (Third ed.). Sage publications.

Friel, C., & Friesen, M. (2019). Legumes modulate allocation to rhizobial nitrogen fixation in response to factorial light and nitrogen manipulation. *Frontiers in Plant Science*, *10*, 1316. doi: 10.3389/fpls.2019.01316

Gaba, S., Lescourret, F., Boudsocq, S., Enjalbert, J., Hinsinger, P., Journet, E., ... Ozier-Lafontaine, H. (2015). Multiple cropping systems as drivers for providing multiple ecosystem services: from concepts to design. *Agron. Sustain. Dev*, *35*, 607–623. doi: 10.1007/s13593-014-0272-z

Gaffney, J., Schussler, J., Löffler, C., Cai, W., Paszkiewicz, S., Messina, C., ... Cooper, M. (2015). Industry-scale evaluation of maize hybrids selected for increased yield in drought-stress conditions of the us corn belt. *Crop Science*, *55*(4), 1608–1618. doi: 10.2135/cropsci2014.09.0654

Gan, Y., Hamel, C., O'Donovan, J. T., Cutforth, H., Zentner, R. P., Campbell, C. A., ... Poppy, L. (2015). Diversifying crop rotations with pulses enhances system productivity. *Scientific Reports*, *5*(1), 14625. doi: 10.1038/srep14625

Garba, I. I., & Williams, A. (2023). Integrating diverse cover crops for fallow replacement in a subtropical dryland: Implications on subsequent cash crop yield, grain quality, and gross margins. *Agronomy*, *13*(1), 271. doi: 10.3390/agronomy13010271

Garbelini, L., Debiasi, H., Junior, A., Franchini, J., Coelho, A., & Telles, T. (2022). Diversified crop rotations increase the yield and economic efficiency of grain production systems. *European Journal of Agronomy*, *137*, 126528. doi: 10.1016/j.eja.2022.126528

Garcia, R., Ceccon, G., Sutier, G. S., & Santos, A. (2018). Sucessão soja/milho em função da época de semeadura. *Pesquisa Agropecuária Brasileira*, *53*(1), 22–29. doi: 10.1590/s0100-204x2018000100003

Garnett, T. (2013). Food sustainability: problems, perspectives and solutions. *Proceedings of the nutrition society*, *72*(1), 29–39. doi: 10.1017/s0029665112002947

Gaudin, A. C. M., Janovicek, K., Deen, B., & Hooker, D. C. (2015). Wheat improves nitrogen use efficiency of maize and soybean-based cropping systems. *Agriculture, Ecosystems & Environment*, *210*, 1–10. doi: 10.1016/j.agee.2015.04.034

Gelb, J., & Apparicio, P. (2021). Contribution of the spatial c-means fuzzy classification in geography: a socio-residential and environmental taxonomy in Lyon Cybergeo. *Cybergeo: European Journal of Geography*, *972*.

Gelman, A., Carlin, J., Stern, H., Dunson, D., Vehtari, A., & B.Rubin, D. (2013). *Bayesian data analysis* (3rd ed.). CRC Press. doi: 10.1201/b16018

Giménez, V. D., Micheloud, J. R., & Maddonni, G. Á. (2018). Climatic constraints for the maize-soybean system in the humid subtropical region of argentina. *Theoretical and Applied Climatology*, *134*, 753–767. doi: 10.1007/s00704-017-2302-7

Graham, R., Nelson, R., Sheehan, J., Perlack, R., & Wright, L. (2007). Current and Potential U.S. Corn Stover Supplies. *Agrononmy Journal*, *99*(1), 1 11. doi: 10.2134/agronj2005.0222

Grassini, P., Specht, J., Tollenaar, M., Ciampitti, I., & Cassman, K. (2015). High-yield maize–soybean cropping systems in the us corn belt. *Crop Physiology: Applications for Genetic Improvement and Agronomy*, 17–41. doi: 10.1016/b978-0-12-417104-6.00002-9

Grassini, P., Thorburn, J., Burr, C., & Cassman, K. (2011). High-yield irrigated maize in the Western U.S. Corn Belt: I. On-farm yield, yield potential, and impact of agronomic practices. *Field crops research*, *120*(1), 142 150. doi: 10.1016/j.fcr.2010.09.012

Graß, R., Heuser, F., Stülpnagel, R., Piepho, H., & Wachendorf, M. (2013). Energy crop production in double-cropping systems: Results from an experiment at seven sites. *European Journal of Agronomy*, *51*, 120–129. doi: 10.1016/j.eja.2013.08.004

Gu, D., Andreev, K., & Dupre, M. (2021). Major trends in population growth around the world. *China CDC Weekly*, *3*(28), 604. doi: 10.46234/ccdcw2021.160

Gupta, H. V., Kling, H., Yilmaz, K., & Martinez, G. (2009). Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of hydrology*, *377*(1–2), 80 91. doi: 10.1016/j.jhydrol.2009.08.003

Gupta, H. V., Sorooshian, S., & Yapo, P. O. (1999). Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. *Journal of hydrologic engineering*, *4*(2), 135–143. doi: 10.1061/(asce)1084-0699(1999)4:2(135)

Gupta, R., Bhattarai, R., Coppess, J. W., Jeong, H., Ruffatti, M., & Armstrong, S. D. (2022). Modeling the impact of winter cover crop on tile drainage and nitrate loss using dssat model. *Agricultural Water Management*, *272*, 107862. doi: 10.1016/j.agwat.2022.107862

Halvorson, A. D., Peterson, G. A., & Reule, C. A. (2002). Tillage system and crop rotation effects on dryland crop yields and soil carbon in the central great plains. *Agronomy Journal*, *94*(6), 1429–1436. doi: 10.2134/agronj2002.1429

Hammer, G., Dong, Z., McLean, G., Doherty, A., Messina, C., Schussler, J., ... Cooper, M. (2009). Can changes in canopy and/or root system architecture explain historical maize yield trends in the us corn belt? *Crop Science*, *49*(1), 299 312. doi: 10.2135/cropsci2008.03.0152

Hampf, A. C., Stella, T., Berg-Mohnicke, M., Kawohl, T., Kilian, M., & Nendel, C. (2020). Future yields of double-cropping systems in the southern amazon, brazil, under climate change and technological development. *Agricultural Systems*, *177*, 102707. doi: 10.1016/j.agsy.2019.102707

Hansen, N. C., Allen, B. L., Baumhardt, R. L., & Lyon, D. J. (2012). Research achievements and adoption of no-till, dryland cropping in the semi-arid u.s. great plains. *Field Crops Research*, *132*, 196–203. doi: 10.1016/j.fcr.2012.02.021

Hare, A., Jordan, D., Edmisten, K., Leon, R., Post, A., Vann, R., ... Washburn, D. (2020). Response of agronomic crops to planting date and double-cropping with wheat. *Agronomy Journal*, *112*(3), 1972–1980. doi: 10.1002/agj2.20164

Heald, C. L., & Spracklen, D. V. (2015). Land use change impacts on air quality and climate. *Chemical reviews*, *115*(10), 4476–4496. doi: 10.1021/cr500446g

Ho, L. (1988). Metabolism and compartmentation of imported sugars in sink organs in relation to sink strength. *Annual Review of Plant Physiology and Plant Molecular Biology*, *39*(1), 355–378. doi: 10.1146/annurev.pp.39.060188.002035

Hobbs, N., & Hooten, M. (2015). Bayesian models: a statistical primer for ecologists.

Holland, B., Matthews, M., Bota, P., Sweetlove, L., Long, S., et al. (2023). A genome-scale metabolic reconstruction of soybean and bradyrhizobium diazoefficiens reveals the cost–benefit of nitrogen fixation. *New Phytologist*, *240*(2), 744–756. doi: 10.1111/nph.19203

Holman, J. D., Schlegel, A., & Obour, A. K. (2020). Dryland cropping system impact on forage accumulation, nutritive value, and rainfall use efficiency. *Crop Science*, *60*(6), 3395–3409. doi: 10.1002/csc2.20251

Holman, J. D., Schlegel, A., Obour, A. K., & Assefa, Y. (2018). Can cover or forage crops replace fallow in the semiarid central great plains? *Crop Science*, *58*(2), 932–944. doi: 10.2135/cropsci2017.05.0324

Holzworth, D., Huth, N., deVoil, P., Zurcher, E., Herrmann, N., McLean, G., ... Keating, B. (2014). APSIM – Evolution towards a new generation of agricultural systems simulation. *Environmental Modelling Software*, *62*, 327–350. doi: 10.1016/j.envsoft.2014.07.009

Holzworth, D., Huth, N., Fainges, J., Brown, H., Zurcher, E., Cichota, R., ... Snow, V. (2018). APSIM Next Generation: Overcoming challenges in modernising a farming systems model. *Environmental Modelling Software*, *103*, 43–51. doi: 10.1016/j.envsoft.2018.02.002

Horn, K. M., Rocateli, A. C., Warren, J. G., Turner, K. E., & Antonangelo, J. A. (2020). Introducing grazeable cover crops to the winter wheat systems in oklahoma. *Agronomy Journal*, *112*(5), 3677–3694. doi: 10.1002/agj2.20326

Howell, T., Tolk, J., Schneider, A., & Evett, S. (1998). Evapotranspiration, yield, and water use efficiency of corn hybrids differing in maturity. *Agronomy Journal*, *90*(1), 3–9. doi: 10.2134/agronj1998.00021962009000010002x

Hu, X., Næss, J., Iordan, C., Huang, B., Zhao, W., & Cherubini, F. (2021). Recent global land cover dynamics and implications for soil erosion and carbon losses from deforestation. *Anthropocene*, *34*, 100291. doi: 10.1016/j.ancene.2021.100291

Hunter, M., Smith, R., Schipanski, M., Atwood, L., & Mortensen, D. (2017). Agriculture in 2050: recalibrating targets for sustainable intensification. *Bioscience*, *67*(4), 386–391. doi: 10.1093/biosci/bix010

Jacques, S., Bacon, R., & Parsch, L. (1997). Comparison of single cropping, relay cropping and double cropping of soyabeans with wheat using cultivar blends. *Experimental Agriculture*, *33*(4), 477–486. doi: 10.1017/s0014479797004043

Jaenisch, B. R., Munaro, L. B., Bastos, L. M., Moraes, M., Lin, X., & Lollato, R. P. (2021). On-farm data-rich analysis explains yield and quantifies yield gaps of winter wheat in the u.s. central great plains. *Field Crops Research*, *272*, 108287. doi: 10.1016/j.fcr.2021.108287

Jat, H. S., Kumar, V., Datta, A., Choudhary, M., Kakraliya, S. K., Poonia, T., ... Sharma, P. C. (2020). Designing profitable, resource use efficient and environmentally sound cereal based systems for the western indo-gangetic plains. *Scientific reports*, *10*(1), 19267. doi: 10.1038/s41598-020-76035-z

Jensen, E., Carlsson, G., & Hauggaard-Nielsen, H. (2020). Intercropping of grain legumes and cereals improves the use of soil N resources and reduces the requirement for synthetic fertilizer N: A global-scale analysis. *Agronomy for sustainable development*, *40*, 1–9. doi: 10.1007/s13593-020-0607-x/tables/3

Jiang, W., Thapa, S., Jessup, K., Hao, B., Hou, X., Marek, T., … Xue, Q. (2020). Corn response to later than traditional planting dates in the Texas High Plains. *Crop Science*, *60*(2), 1004–1020. doi: 10.1002/csc2.20042

Kantolic, A., Peralta, G., & Slafer, G. (2013). Seed number responses to extended photoperiod and shading during reproductive stages in indeterminate soybean. *European Journal of Agronomy*, *51*, 91–100. doi: 10.1016/j.eja.2013.07.006

Karlen, D., Colvin, T., & Duffy, M. (1995). Nutrient, labor, energy and economic evaluations of two farming systems in iowa. *Journal of Production Agriculture*, *8*(4), 540–546. doi: 10.2134/jpa1995.0540

Keating, B., Carberry, P., Hammer, G., Probert, M., Robertson, M., Holzworth, D., … McCown (2003). An overview of APSIM, a model designed for farming systems simulation. *European Journal of Agronomy*, *18*(3), 267–288. doi: 10.1016/s1161-0301(02)00108-9

Keeney, D. (1982). Nitrogen-availability indices. In *Methods of Soil Analysis. Part 2. Chemical and Microbiological Properties. ASA and SSSA* (pp. 711–733).

Kelly, C., Schipanski, M. E., Tucker, A., Trujillo, W., Holman, J. D., Obour, A. K., … Fonte, S. J. (2021). Dryland cover crop soil health benefits are maintained with grazing in the u.s. high and central plains. *Agriculture, Ecosystems & Environment*, *313*, 107358. doi: 10.1016/j.agee.2021.107358

Kiers, E., Rousseau, R., West, S., & Denlson, R. (2003). Host sanctions and the legume–rhizobium mutualism. *Nature*, *425*(6953), 78–81. doi: 10.1038/nature01931

Kling, H., Fuchs, M., & Paulin, M. (2012). Runoff conditions in the upper Danube basin under an ensemble of climate change scenarios. *Journal of hydrology*, *424*, 264–277. doi: 10.1016/j.jhydrol.2012.01.011

Ko, J., Ahuja, L. R., Saseendran, S. A., Green, T. R., Ma, L., Nielsen, D., & Walthall, C. L. (2012). Climate change impacts on dryland cropping systems in the central great plains, usa. *Climatic Change*, *111*, 445–472. doi: 10.1007/s10584-011-0175-9/figures/11

Kröbel, R., Campbell, C. A., Zentner, R. P., Lemke, R., Steppuhn, H., Desjardins, R. L., & De Jong, R. (2012). Nitrogen and phosphorus effects on water use efficiency of spring wheat grown in a semi-arid region of the canadian prairies. *Canadian Journal of Soil Science*, *92*(4), 573–587. doi: 10.4141/cjss2011-055/asset/images/cjss2011-055tab5.gif

Krupinsky, J., Bailey, K., McMullen, M., Gossen, B., & Turkington, T. (2002). Managing plant disease risk in diversified cropping systems. *Agronomy Journal*, *94*(2), 198 209. doi: 10.2134/agronj2002.1980

Kucharik, C. (2008). Contribution of planting date trends to increased maize yields in the central united states. *Agronomy Journal*, *100*(2), 328 336. doi: 10.2134/agronj2007.0145

Kucharik, C., Ramiadantsoa, T., Zhang, J., & Ives, A. (2020). Spatiotemporal trends in crop yields, yield variability, and yield gaps across the usa. *Crop Science*, *60*(4), 2085–2101. doi: 10.1002/csc2.20089

Kukal, M., & Irmak, S. (2019). Irrigation-limited yield gaps: trends and variability in the united states post-1950. *Environmental Research Communications*, *1*(6), 061005. doi: 10.1088/2515-7620/ab2aee

Kumar, V., Obour, A., Jha, P., Liu, R., Manuchehri, M. R., Dille, J. A., . . . Stahlman, P. W. (2020). Integrating cover crops for weed management in the semiarid u.s. great plains: opportunities and challenges. *Weed Science*, *68*(4), 311–323. doi: 10.1017/wsc.2020.29

Lacoste, M., Cook, S., McNee, M., Gale, D., Ingram, J., Bellon-Maurel, V., . . . Hall, A. (2022). On-farm experimentation to transform global agriculture. *Nature Food*, *3*(1), 11–18. doi: 10.1038/s43016-021-00424-4

Lafitte, H., & Edmeades, G. (1997). Temperature effects on radiation use and biomass partitioning in diverse tropical maize cultivars. *Field Crops Research*, *49*(2–3), 231–247. doi: 10.1016/s0378-4290(96)01005-2

Laing, W., Ogren, W., & Hageman, R. (1974). Regulation of soybean net photosynthetic co2 fixation by the interaction of co2, o2, and ribulose 1,5-diphosphate carboxylase. *Plant Physiology*, *54*(5), 678–685. doi: 10.1104/pp.54.5.678

Lam, S., Chen, D., Norton, R., Armstrong, R., & Mosier, A. (2012). Nitrogen dynamics in grain crop and legume pasture systems under elevated atmospheric carbon dioxide concentration: A meta-analysis. *Global Change Biology*, *18*(9), 2853–2859. doi: 10.1111/j.1365-2486.2012.02758.x

Lambin, E., & Meyfroidt, P. (2011). Global land use change, economic globalization, and the looming land scarcity. *Proceedings of the National Academy of Sciences*, *108*(9), 3465–3472. doi: 10.1073/pnas.1100480108

Lanning-Rush, J. L. (2016). *Irrigation water use in kansas, 2013* (Tech. Rep.). US Geological Survey. doi: 10.3133/ds981

Lark, T., Spawn, S., Bougie, M., & Gibbs, H. (2020). Cropland expansion in the United States produces marginal yields at high costs to wildlife. *Nature communications*, *11*(1), 4295. doi: 10.1038/s41467-020-18045-z

Larson, E. (2013). What is the Cut-Off Date for Planting Corn? Retrieved from https://www.mississippi-crops.com/2014/04/11/what-is-the-cut-off-date-for-planting-corn-2/

Lenth, R., Bolker, B., Buerkner, P., Giné-Vázquez, I., Herve, M., Jung, M., ... Singmann, H. (2023). *emmeans: Estimated Marginal Means, aka Least-Squares Means.*

Lesk, C., Coffel, E., & Horton, R. (2020). Net benefits to us soy and maize yields from intensifying hourly rainfall. *Nature Climate Change*, *10*(9), 819–822. doi: 10.1038/s41558-020-0830-0

Li, L., Li, S.-M., Sun, J.-H., Zhou, L.-L., Bao, X.-G., Zhang, H.-G., & Zhang, F.-S. (2007). Diversity enhances agricultural productivity via rhizosphere phosphorus facilitation on phosphorus-deficient soils. *Proceedings of the National Academy of Sciences*, *104*(27), 11192–11196.

Li, T., Zhang, X., Liu, Q., Yan, P., Liu, J., Chen, Y., & Sui, P. (2022). Yield and yield stability of single cropping maize under different sowing dates and the corresponding changing trends of climatic variables. *Field Crops Research*, *285*, 108589. doi: 10.1016/j.fcr.2022.108589

Lin, R., & Chen, C. (2014). Tillage, crop rotation, and nitrogen management strategies for wheat in central montana. *Agronomy Journal*, *106*(2), 475–485. doi: 10.2134/agronj2013.0316

Lin, T.-S., Song, Y., Lawrence, P., Kheshgi, H. S., & Jain, A. K. (2021). Worldwide maize and soybean yield response to environmental and management factors over the 20th and 21st centuries. *Journal of Geophysical Research: Biogeosciences*, *126*(11), e2021JG006304. doi: 10.1029/2021jg006304

Litsinger, J., & Moody, K. (1976). Integrated pest management in multiple cropping systems. *Multiple cropping*, *27*, 293–316. doi: 10.2134/asaspecpub27.c15

Liu, L., Xu, X., Zhuang, D., Chen, X., & Li, S. (2013). Changes in the potential multiple cropping system in response to climate change in china from 1960–2010. *PloS one*, *8*(12), e80990. doi: 10.1371/journal.pone.0080990

Liu, S., Yang, J., Zhang, X., Drury, C., Reynolds, W., & Hoogenboom, G. (2013). Modelling crop yield, soil water content and soil temperature for a soybean–maize rotation under conventional and conservation tillage systems in northeast china. *Agricultural water management*, *123*, 32–44. doi: 10.1016/j.agwat.2013.03.001

Liu, Y., Cruz-Morales, P., Zargar, A., Belcher, M., Pang, B., Englund, E., ... Keasling, J. (2021). Biofuels for a sustainable future. *Cell*, *184*(6), 1636–1647. doi: 10.1016/j.cell.2021.01.052

Lobell, D., & Azzari, G. (2017). Satellite detection of rising maize yield heterogeneity in the us midwest. *Environmental Research Letters*, *12*(1), 014014. doi: 10.1088/1748-9326/aa5371

Lobell, D., Deines, J., & Tommaso, S. (2020). Changes in the drought sensitivity of US maize yields. *Nature Food*, *1*(1), 729–735. doi: 10.1038/s43016-020-00165-w

Lollato, R. P., Bavia, G. P., Perin, V., Knapp, M., Santos, E. A., Patrignani, A., & DeWolf, E. D. (2020). Climate-risk assessment for winter wheat using long-term weather data. *Agronomy Journal*, *112*(3), 2132–2151. doi: 10.1002/agj2.20168

Lollato, R. P., Jaenisch, B. R., & Silva, S. R. (2021). Genotype-specific nitrogen uptake dynamics and fertilizer management explain contrasting wheat protein concentration. *Crop Science*, *61*(3), 2048–2066. doi: 10.1002/csc2.20442

Long, N. V., Assefa, Y., Schwalbert, R., & Ciampitti, I. A. (2017). Maize yield and planting date relationship: A synthesis-analysis for us high-yielding contest-winner and field research data. *Frontiers in plant science*, *8*, 2106. doi: 10.3389/fpls.2017.02106/bibtex

Loomis, R., & Amthor, J. (1999). Yield potential, plant assimilatory capacity, and metabolic efficiencies. *Crop Science*, *39*(6), 1584–1596. doi: 10.2135/cropsci1999.3961584x

Lotze-Campen, H., Popp, A., Beringer, T., Müller, C., Bondeau, A., Rost, S., & Lucht, W. (2010). Scenarios of global bioenergy production: the trade-offs between agricultural expansion, intensification and trade. *Ecological Modelling*, *221*(18), 2188–2196. doi: 10.1016/j.ecolmodel.2009.10.002

Lyon, D. J., Nielsen, D., Felter, D. G., & Burgener, P. A. (2007). Choice of summer fallow replacement crops impacts subsequent winter wheat. *Agronomy Journal*, *99*(2), 578–584. doi: 10.2134/agronj2006.0287

Malikov, E., Miao, R., & Zhang, J. (2020). Distributional and temporal heterogeneity in the climate change effects on u.s. agriculture. *Journal of Environmental Economics and Management*, *104*, 102386. doi: 10.1016/j.jeem.2020.102386

Mallarino, A., Webb, J., & Blackmer, A. (1991). Corn and soybean yields during 11 years of phosphorus and potassium fertilization on a high-testing soil. *Journal of Production Agriculture*, *4*(3), 312–316. doi: 10.2134/jpa1991.0312

Marten, G., Shenk, J., & Barton, F. (1985). *Near infrared reflectance spectroscopy (nirs): analysis of forage quality* (No. 643). US Department of Agriculture, Agricultural Research Service.

Martinez-Feria, R. A., Licht, M. A., Ordóñez, R. A., Hatfield, J. L., Coulter, J. A., & Archontoulis, S. V. (2019). Evaluating maize and soybean grain dry-down in the field with predictive algorithms and genotype-by-environment analysis. *Scientific reports*, *9*(1), 7167. doi: 10.1038/s41598-019-43653-1

Martin-Guay, M.-O., Paquette, A., Dupras, J., & Rivest, D. (2018). The new green revolution: sustainable intensification of agriculture by intercropping. *Science of the total environment*, *615*, 767–772. doi: 10.1016/j.scitotenv.2017.10.024

Martins da Costa, E., Almeida Ribeiro, P. R., Soares de Carvalho, T., Pereira Vicentin, R., Balsanelli, E., Maltempi de Souza, E., … de Souza Moreira, F. M. (2020). Efficient nitrogen-fixing bacteria isolated from soybean nodules in the semi-arid region of northeast brazil are classified as bradyrhizobium brasilense (symbiovar sojae). *Current Microbiology*, *77*(8), 1746–1755. doi: 10.1007/s00284-020-01993-6

Matsuura, M. I. F., Dias, F. R., Picoli, J. F., Lucas, K. R. G., de Castro, C., & Hirakuri, M. H. (2017). Life-cycle assessment of the soybean-sunflower production system in the brazilian cerrado. *The International Journal of Life Cycle Assessment*, *22*, 492–501. doi: 10.1007/s11367-016-1089-6

Mayor, L., Demarco, P., Lira, S., Fang, Y., Abadie, T., Gambin, B. L., … Messina, C. (2023). Retrospective study in us commercial sorghum breeding: I. genetic gain in relation to relative maturity. *Crop Science*, *63*(2), 501–510. doi: 10.1002/csc2.20897

Mercau, J. L., & Otegui, M. (2014). A modeling approach to explore water management strategies for late-sown maize and double-cropped wheat–maize in the rainfed pampas region of argentina. In *Practical applications of agricultural system models to optimize the use of limited water* (pp. 351–373). Wiley Online Library. doi: 10.2134/advagricsyst-model5.c13

Messina, C. D., Ciampitti, I. A., Berning, D., Bubeck, D., Hammer, G., & Cooper, M. (2022). Sustained improvement in tolerance to water deficit accompanies maize yield increase in temperate environments. *Crop Science*, *62*(6), 2138–2150. doi: 10.1002/csc2.20781

Messina, C. D., Cooper, M., Hammer, G. L., Berning, D., Ciampitti, I., Clark, R., … van Eeuwijk, F. (2020). Two decades of creating drought tolerant maize and underpinning prediction technologies in the us corn-belt: review and perspectives on the future of crop design. *BioRxiv*, 2020–10. doi: 10.1101/2020.10.29.361337

Messina, C. D., Hammer, G. L., McLean, G., Cooper, M., van Oosterom, E. J., Tardieu, F., ... Gho, C. (2019). On the dynamic determinants of reproductive failure under drought in maize. *in silico Plants*, *1*(1), diz003. doi: 10.1093/insilicoplants/diz003

Messina, C. D., Sinclair, T. R., Hammer, G. L., Curan, D., Thompson, J., Oler, Z., ... Cooper, M. (2015). Limited-transpiration trait may increase maize drought tolerance in the us corn belt. *Agronomy Journal*, *107*(6), 1978–1986. doi: 10.2134/agronj15.0016

Meza, F. J., Silva, D., & Vigil, H. (2008). Climate change impacts on irrigated maize in mediterranean climates: evaluation of double cropping as an emerging adaptation alternative. *Agricultural systems*, *98*(1), 21–30. doi: 10.1016/j.agsy.2008.03.005

Miceli-Garcia, J. (2010). *Comparing cropping system productivity between fixed rotations and a flexible fallow system using modeling and historical weather data in the semi-arid central great plains* (Master's thesis, University of Nebraska, Lincoln). Retrieved from `http://digitalcommons.unl.edu/agronhortdiss/38`

Middendorf, B. J., Prasad, P. V., & Pierzynski, G. M. (2020). Setting research priorities for tackling climate change. *Journal of Experimental Botany*, *71*(2), 480–489. doi: 10.1093/jxb/erz360

Miguez, F. E. (2022). *apsimx: Inspect, Read, Edit and Run APSIM Next Generation and APSIM Classic.*

Mikha, M. M., Vigil, M. F., & Benjamin, J. G. (2013). Long-term tillage impacts on soil aggregation and carbon dynamics under wheat-fallow in the central great plains. *Soil Science Society of America Journal*, *77*(2), 594–605. doi: 10.2136/sssaj2012.0125

Mirsky, S., Curran, W., Mortenseny, D., Ryany, M., & Shumway, D. L. (2011). Timing of cover-crop management effects on weed suppression in no-till planted soybean using a roller-crimper. *Weed Science*, *59*(3), 380–389. doi: 10.1614/ws-d-10-00101.1

Mohanty, M., Probert, M., Reddy, K. S., Dalal, R., Mishra, A., Rao, A. S., ... Menzies, N. (2012). Simulating soybean–wheat cropping system: Apsim model parameterization and validation. *Agriculture, ecosystems & environment*, *152*, 68–78. doi: 10.1016/j.agee.2012.02.013

Monzon, J., Mercau, J., Andrade, J., Caviglia, O., Cerrudo, A., Cirilo, A., ... Calviño, P. (2014). Maize–soybean intensification alternatives for the Pampas. *Field Crops Research*, *162*, 48–59. doi: 10.1016/j.fcr.2014.03.012

Moraine, M., Duru, M., & Therond, O. (2017). A social-ecological framework for analyzing and designing integrated crop–livestock systems from farm to territory levels. *Renewable agriculture and food systems*, *32*(1), 43–56. doi: 10.1017/s1742170515000526

Morris, R. A., Villegas, A., Polthanee, A., & Centeno, H. (1990). Water use by monocropped and intercropped cowpea and sorghum grown after rice. *Agronomy journal*, *82*(4), 664–668. doi: 10.2134/agronj1990.00021962008200040003x

NASA Prediction Of Worldwide Energy Resources. (2021). Retrieved from `https://power.larc.nasa.gov/`

National Oceanic and Atmospheric Administration. (2021). Retrieved from `https://www.noaa.gov/` (Accessed 9.19.21.)

Nelder, J. A., & Mead, R. (1965). A simplex method for function minimization. *The computer journal*, *7*(4), 308–313. doi: 10.1093/comjnl/7.4.308

Nicoloso, R. S., Amado, T. J., & Rice, C. W. (2020). Assessing strategies to enhance soil carbon sequestration with the dssat-century model. *European Journal of Soil Science*, *71*(6), 1034–1049. doi: 10.1111/ejss.12938

Nielsen, D., & Aiken, R. (1998). Wind speed above and within sunflower stalks varying in height and population. *Journal of Soil and Water Conservation*, *53*(4), 347–352.

Nielsen, D., Unger, P. W., & Miller, P. R. (2005). Efficient water use in dryland cropping systems in the great plains. *Agronomy Journal*, *97*(2), 364–372. doi: 10.2134/agronj2005.0364

Nielsen, D., & Vigil, M. (2018). Wheat yield and yield stability of eight dryland crop rotations. *Agronomy Journal*, *110*(2), 594–601. doi: 10.2134/agronj2017.07.0407

Nielsen, D., & Vigil, M. F. (2010). Precipitation storage efficiency during fallow in wheat-fallow systems. *Agronomy Journal*, *102*(2), 537–543. doi: 10.2134/agronj2009.0348

Nielsen, D., Vigil, M. F., & Benjamin, J. G. (2006). Forage yield response to water use for dryland corn, millet, and triticale in the central great plains. *Agronomy Journal*, *98*(4), 992–998. doi: 10.2134/agronj2005.0356

Nielsen, D., Vigil, M. F., & Benjamin, J. G. (2011). Evaluating decision rules for dryland rotation crop selection. *Field Crops Research*, *120*(2), 254–261. doi: 10.1016/j.fcr.2010.10.011

Nielsen, D., Vigil, M. F., & Hansen, N. C. (2016). Evaluating potential dryland cropping systems adapted to climate change in the central great plains. *Agronomy Journal*, *108*(6), 2391–2405. doi: 10.2134/agronj2016.07.0406

Norwood, C. A. (2001). Planting date, hybrid maturity, and plant population effects on soil water depletion, water use, and yield of dryland corn. *Agronomy Journal*, *93*(5), 1034–1042. doi: 10.2134/agronj2001.9351034x

Novelli, L. E., Caviglia, O., & Piñeiro, G. (2017). Increased cropping intensity improves crop residue inputs to the soil and aggregate-associated soil organic carbon stocks. *Soil and Tillage Research*, *165*, 128–136. doi: 10.1016/j.still.2016.08.008

Nóia Júnior, R. S., & Sentelhas, P. (2019). Soybean-maize succession in Brazil: Impacts of sowing dates on climate variability, yields and economic profitability. *European Journal of Agronomy*, *103*, 140–151. doi: 10.1016/j.eja.2018.12.008

Ojeda, J. J., Volenec, J. J., Brouder, S. M., Caviglia, O., & Agnusdei, M. G. (2018). Modelling stover and grain yields, and subsurface artificial drainage from long-term corn rotations using apsim. *Agricultural Water Management*, *195*, 154–171. doi: 10.1016/j.agwat.2017.10.010

Oligini, K. F., Batista, V. V., Lemes, E. S., Silva, É. J. d., & Adami, P. F. (2021). Sowing date and maturity groups on the economic feasibility of soybean-maize double summer crop system. *Revista de Economia e Sociologia Rural*, *59*. doi: 10.1590/1806-9479.2021.235472

Otegui, M., & Bonhomme, R. (1998). Grain yield components in maize: I. ear growth and kernel set. *Field Crops Research*, *56*(3), 247–256. doi: 10.1016/s0378-4290(97)00093-2

Otegui, M., Riglos, M., & Mercau, J. L. (2021). Genetically modified maize hybrids and delayed sowing reduced drought effects across a rainfall gradient in temperate argentina. *Journal of Experimental Botany*, *72*(14), 5180–5188. doi: 10.1093/jxb/erab139

O'Donoghue, E. J., Roberts, M. J., & Key, N. (2009). Did the federal crop insurance reform act alter farm enterprise diversification? *Journal of Agricultural Economics*, *60*(1), 80–104. doi: 10.1111/j.1477-9552.2008.00166.x

Patrignani, A., Godsey, C. B., & Ochsner, T. E. (2019). No-till diversified cropping systems for efficient allocation of precipitation in the southern great plains. *Agrosystems, Geosciences & Environment*, *2*(1), 1–8. doi: 10.2134/age2018.08.0026

Patrignani, A., Knapp, M., Redmond, C., & Santos, E. (2020). Technical overview of the kansas mesonet. *Journal of Atmospheric and Oceanic Technology*, *37*(12), 2167–2183. doi: 10.1175/jtech-d-19-0214.1

Patrignani, A., Lollato, R. P., Ochsner, T. E., Godsey, C. B., & Edwards, J. T. (2014). Yield gap and production gap of rainfed winter wheat in the southern great plains. *Agronomy Journal*, *106*(4), 1329–1339. doi: 10.2134/agronj14.0011

Paulsen, M. R., Pinto, F. A., de Sena Jr, D. G., Zandonadi, R. S., Ruffato, S., Costa, A., ... Danao, M.-G. C. (2013). Measurement of combine losses for corn and soybeans in brazil. In *American society of agricultural and biological engineers annual international meeting, 2013.* doi: 10.13031/aim.20131570965

Paut, R., Sabatier, R., & Tchamitchian, M. (2020). Modelling crop diversification and association effects in agricultural systems. *Agriculture, Ecosystems & Environment*, *288*, 106711. doi: 10.1016/j.agee.2019.106711

Peng, B., Guan, K., Chen, M., Lawrence, D. M., Pokhrel, Y., Suyker, A., ... Lu, Y. (2018). Improving maize growth processes in the community land model: Implementation and evaluation. *Agricultural and forest meteorology*, *250*, 64–89. doi: 10.1016/j.agrformet.2017.11.012

Peterhansel, C., Niessen, M., & Kebeish, R. (2008). Metabolic engineering towards the enhancement of photosynthesis. *Photochemistry and Photobiology*, *84*(6), 1317–1323. doi: 10.1111/j.1751-1097.2008.00427.x

Petersen, B., & Snapp, S. (2015). What is sustainable intensification? views from experts. *Land use policy*, *46*, 1–10. doi: 10.1016/j.landusepol.2015.02.002

Peterson, G. A., Schlegel, A. J., Tanaka, D. L., & Jones, O. R. (1996). Precipitation use efficiency as affected by cropping and tillage systems. *Journal of Production Agriculture*, *9*(2), 180–186. doi: 10.2134/jpa1996.0180

Peterson, G. A., & Westfall, D. G. (2004). Managing precipitation use in sustainable dryland agroecosystems. *Annals of Applied Biology*, *144*(2), 127–138. doi: 10.1111/j.1744-7348.2004.tb00326.x

Philbrook, B., & Oplinger, E. (1989). Soybean field losses as influenced by harvest delays. *Agronomy Journal*, *81*(2), 251–258. doi: 10.2134/agronj1989.00021962008100020023x

Pinstrup-Andersen, P. (2009). Food security: definition and measurement. *Food security*, *1*(1), 5–7. doi: 10.1007/s12571-008-0002-y

Pires, G. F., Abrahão, G. M., Brumatti, L. M., Oliveira, L. J., Costa, M. H., Liddicoat, S., ... Ladle, R. J. (2016). Increased climate risk in brazilian double cropping agriculture systems: Implications for land use in northern brazil. *Agricultural and forest meteorology*, *228*, 286–298. doi: 10.1016/j.agrformet.2016.07.005

Pires, M. V., da Cunha, D. A., de Matos Carlos, S., & Costa, M. H. (2015). Nitrogen-use efficiency, nitrous oxide emissions, and cereal production in brazil: current trends and forecasts. *PloS one*, *10*(8), e0135234. doi: 10.1371/journal.pone.0135234

Poeplau, C., & Don, A. (2015). Carbon sequestration in agricultural soils via cultivation of cover crops–a meta-analysis. *Agriculture, Ecosystems & Environment*, *200*, 33–41. doi: 10.1016/j.agee.2014.10.024

Porter, P., Lauer, J., Huggins, D., Oplinger, E., & Crookston, R. (1998). Assessing spatial and temporal variability of corn and soybean yields. *Journal of Production Agriculture*, *11*(3), 359–363. doi: 10.2134/jpa1998.0359

Potapov, P., Turubanova, S., Hansen, M. C., Tyukavina, A., Zalles, V., Khan, A., ... Cortez, J. (2022). Global maps of cropland extent and change show accelerated cropland expansion in the twenty-first century. *Nature Food*, *3*(1), 19–28. doi: 10.1038/s43016-021-00429-z

Pretty, J., Attwood, S., Bawden, R., van den Berg, H., Bharucha, Z., Dixon, J., ... Yang, P. (2020). Assessment of the growth in social groups for sustainable agriculture and land management. *Global Sustainability*, *3*, e23. doi: 10.1017/sus.2020.19

Pretty, J., Benton, T. G., Bharucha, Z. P., Dicks, L. V., Flora, C. B., Godfray, H. C. J., … others (2018). Global assessment of agricultural system redesign for sustainable intensification. *Nature Sustainability*, *1*(8), 441–446. doi: 10.1038/s41893-018-0114-0

Pretty, J., & Bharucha, Z. P. (2014). Sustainable intensification in agricultural systems. *Annals of botany*, *114*(8), 1571–1596. doi: 10.1093/aob/mcu205

Puntel, L. A., Sawyer, J. E., Barker, D. W., Dietzel, R., Poffenbarger, H., Castellano, M. J., … Archontoulis, S. V. (2016). Modeling long-term corn yield response to nitrogen rate and crop rotation. *Frontiers in plant science*, *7*, 1630. doi: 10.3389/fpls.2016.01630/bibtex

R Core Team. (2022). *R: A Language Environment for Statistical Computer.* Retrieved from `https://www.r-project.org/`

R Core Team. (2023). *R: A Language Environment for Statistical Computer.* Retrieved from `https://www.r-project.org/`

Rao, S. C., & Northup, B. K. (2009). Water use by five warm-season legumes in the southern great plains. *Crop science*, *49*(6), 2317–2324. doi: 10.2135/cropsci2009.03.0134

Rao, V. N., Meinke, H., Craufurd, P., Parsons, D., Kropff, M., Anten, N. P., … Rego, T. (2015). Strategic double cropping on vertisols: a viable rainfed cropping option in the indian sat to increase productivity and reduce risk. *European Journal of Agronomy*, *62*, 26–37. doi: 10.1016/j.eja.2014.09.003

Ray, D. K., Mueller, N. D., West, P. C., & Foley, J. A. (2013). Yield trends are insufficient to double global crop production by 2050. *PloS one*, *8*(6), e66428. doi: 10.1371/journal.pone.0066428

Ray, D. K., Ramankutty, N., Mueller, N. D., West, P. C., & Foley, J. A. (2012). Recent patterns of crop yield growth and stagnation. *Nature communications*, *3*(1), 1293. doi: 10.1038/ncomms2296

Reckling, M., Hecker, J. M., Bergkvist, G., Watson, C. A., Zander, P., Schläfke, N., ... Bachinger, J. (2016). A cropping system assessment framework—evaluating effects of introducing legumes into crop rotations. *European Journal of Agronomy.*, *76*, 186–197. doi: 10.1016/j.eja.2015.11.005

Rhodes, E. C., Perotto-Baldivieso, H. L., Tanner, E. P., Angerer, J. P., & Fox, W. E. (2023). The declining ogallala aquifer and the future role of rangeland science on the north american high plains. *Rangeland Ecology & Management*, *87*, 83–96. doi: 10.1016/j.rama.2022.12.002

Rickson, R., Deeks, L., Graves, A., Harris, J., Kibblewhite, M., & Sakrabani, R. (2015). Input constraints to food production: the impact of soil degradation. *Food security*, *7*, 351–364. doi: 10.1007/s12571-015-0437-x

Rising, J., & Devineni, N. (2020). Crop switching reduces agricultural losses from climate change in the united states by half under rcp 8.5. *Nature Communications*, *11*(1), 1–7. doi: 10.1038/s41467-020-18725-w

Ritchie, S., Hanway, J., & Benson., G. (1986). How a corn plant develops. *Iowa Agric. Home Econ. Exp. Stn. Publ*, *48*, 1–21.

Robertson, M., Carberry, P., Huth, N., Turpin, J., Probert, M. E., Poulton, P., ... Brinsmead, R. (2002). Simulation of growth and development of diverse legume species in apsim. *Australian Journal of Agricultural Research*, *53*(4), 429–446. doi: 10.1071/ar01106

Robinson, T., & Pozzi, F. (2011). Mapping supply and demand for animal-source foods to 2030. *Animal production and health working paper*, *2*, 1–154.

Rod, K. S., Shockley, J., & Knott, C. A. (2021). Seed yield, seed quality, profitability, and risk analysis among double crop soybean maturity groups and seeding rates. *Agronomy Journal*, *113*(2), 1792–1802. doi: 10.1002/agj2.20626

Rodriguez, C., Carlsson, G., Englund, J., Flöhr, A., Pelzer, E., Jeuffroy, M., … Jensen, E. (2020). Grain legume-cereal intercropping enhances the use of soil-derived and biologically fixed nitrogen in temperate agroecosystems. A meta-analysis. *European Journal of Agronomy*, *118*, 126077. doi: 10.1016/j.eja.2020.126077

Rosenzweig, S. T., Carolan, M. S., & Schipanski, M. E. (2020). A dryland cropping revolution? linking an emerging soil health paradigm with shifting social fields among wheat growers of the high plains. *Rural Sociology*, *85*(2), 545–574. doi: 10.1111/ruso.12304

Rosenzweig, S. T., & Schipanski, M. E. (2019). Landscape-scale cropping changes in the high plains: economic and environmental implications. *Environmental Research Letters*, *14*(12), 124088. doi: 10.1088/1748-9326/ab5e8b

Rosenzweig, S. T., Stromberger, M. E., & Schipanski, M. E. (2018). Intensified dryland crop rotations support greater grain production with fewer inputs. *Agriculture, Ecosystems & Environment*, *264*, 63–72. doi: 10.1016/j.agee.2018.05.017

Ross, F., Di Matteo, J., & Cerrudo, A. (2020). Maize prolificacy: A source of reproductive plasticity that contributes to yield stability when plant population varies in drought-prone environments. *Field Crops Research*, *247*, 107699. doi: 10.1016/j.fcr.2019.107699

Rotili, D., Abeledo, L., DeVoil, P., Rodríguez, D., & Maddonni, G. (2021). Exploring the effect of tillers on the water economy, plant growth and kernel set of low-density maize crops. *Agricultural Water Management*, *243*, 106424. doi: 10.1016/j.agwat.2020.106424

Rotili, D., Giorno, A., Tognetti, P. M., & Maddonni, G. Á. (2019). Expansion of maize production in a semi-arid region of argentina: climatic and edaphic constraints and their implications on crop management. *Agricultural Water Management*, *226*, 105761. doi: 10.1016/j.agwat.2019.105761

Rotz, C. A. (2005). Postharvest changes in alfalfa quality. In *35th california alfalfa & forage symposium.* Visalia, CA.

Rotz, C. A., & Muck, R. E. (1994). Changes in forage quality during harvest and storage. *Forage quality, evaluation, and utilization*, 828–868. doi: 10.2134/1994.foragequality.c20

Russelle, M. P., Entz, M. H., & Franzluebbers, A. J. (2007). Reconsidering integrated crop–livestock systems in north america. *Agronomy Journal*, *99*(2), 325–334. doi: 10.2134/agronj2006.0139

Sadras, V. O., & Calviño, P. A. (2001). Quantification of grain yield response to soil depth in soybean, maize, sunflower, and wheat. *Agronomy Journal*, *93*(3), 577–583. doi: 10.2134/agronj2001.933577x

Sadras, V. O., & Roget, D. K. (2004). Production and environmental aspects of cropping intensification in a semiarid environment of southeastern australia. *Agronomy Journal*, *96*(1), 236–246. doi: 10.2134/agronj2004.2360

Sandler, L., Nelson, K. A., Dudenhoeffer, C., et al. (2015). Winter wheat row spacing and alternative crop effects on relay-intercrop, double-crop, and wheat yields. *International journal of agronomy*, *2015*. doi: 10.1155/2015/369243

Sanz-sáez, Á., Heath, K. D., Burke, P. V., & Ainsworth, E. A. (2015). Inoculation with an enhanced n2-fixing bradyrhizobium japonicum strain (usda110) does not alter soybean (glycine max merr.) response to elevated [co2]. *Plant, Cell & Environment*, *38*(12), 2589–2602. doi: 10.1111/pce.12577

Schlegel, A. J., Assefa, Y., Haag, L. A., Thompson, C. R., & Stone, L. R. (2019). Soil water and water use in long-term dryland crop rotations. *Agronomy journal*, *111*(5), 2590–2599. doi: 10.2134/agronj2018.09.0623

Schlegel, A. J., Assefa, Y., O'Brien, D., Lamm, F. R., Haag, L. A., & Stone, L. R. (2016). Comparison of corn, grain sorghum, soybean, and sunflower under limited irrigation. *Agronomy Journal*, *108*(2), 670–679. doi: 10.2134/agronj2015.0332

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of Sciences*, *106*(37), 15594–15598. doi: 10.1073/pnas.0906865106

Schussler, J. R., Weers, B., Wu, J., Mo, H., Lafitte, H. R., et al. (2022). Novel genetic variation through altered zmm28 expression improves maize performance under abiotic stress. *Field Crops Research*, *281*, 108486. doi: 10.1016/j.fcr.2022.108486

Searchinger, T., & Heimlich, R. (2009). Likely impacts of biofuel expansion on midwest land and water resources. *International Journal of Biotechnology*, *11*(1-2), 127–149. doi: 10.1504/ijbt.2009.028103

Searle, S. R., Speed, F. M., & Milliken, G. A. (2021). Estimated marginal means, aka least-squares means [r package emmeansversion 1.7.0]. *The American Statistician*, *34*(4), 216–221. doi: 10.1080/00031305.1980.10483031

Shenk, J. S., & Westerhaus, M. O. (1994). The application of near infrared reflectance spectroscopy (nirs) to forage analysis. In *Forage quality, evaluation, and utilization* (pp. 406–449). John Wiley & Sons, Ltd. doi: 10.2134/1994.foragequality.c10

Siebert, S., Portmann, F., & Döll, P. (2010). Global patterns of cropland use intensity. *Remote Sensing*, *2*(7), 1625–1643. doi: 10.3390/rs2071625

Silva, J. V., & Giller, K. E. (2020). Grand challenges for the 21st century: what crop models can and can't (yet) do. *The Journal of Agricultural Science*, *158*(10), 794–805. doi: 10.1017/s0021859621000150

Simão, L. M., Peterson, D., Roozeboom, K. L., Rice, C. W., Du, J., Lin, X., & Lollato, R. P. (2023). Crop rotation and tillage impact yield performance of soybean, sorghum, and wheat. *Agronomy Journal*, *115*(2), 658–673. doi: 10.1002/agj2.21237

Sinclair, T. R., & De Wit, C. T. (1975). Photosynthate and nitrogen requirements for seed production by various crops. *Science*, *189*(4202), 565–567. doi: 10.1126/science.189.4202.565

Sinclair, T. R., & de Wit, C. T. (1976). Analysis of the carbon and nitrogen limitations to soybean yield. *Agronomy Journal*, *68*(2), 319–324. doi: 10.2134/agronj1976.00021962006800020021x

Sinclair, T. R., & Rufty, T. W. (2012). Nitrogen and water resources commonly limit crop yield increases, not necessarily plant genetics. *Global Food Security*, *1*(2), 94–98. doi: 10.1016/j.gfs.2012.07.001

Sindelar, A. J., Schmer, M. R., Jin, V. L., Wienhold, B. J., & Varvel, G. E. (2016). Crop rotation affects corn, grain sorghum, and soybean yields and nitrogen recovery. *Agronomy Journal*, *108*(4), 1592–1602. doi: 10.2134/agronj2016.01.0005

Singh, H., Northup, B. K., & Prasad, P. V. V. (2023). Water storage and use efficiencies of rainfed winter wheat-summer green manure systems of the us southern great plains. *European Journal of Agronomy*, *146*, 126818. doi: 10.1016/j.eja.2023.126818

Smith, C. R. (1981). *Intercropping and double cropping of maize with legumes in north florida* (Thesis M.S.). University of Florida.

Smith, E. G., Young, D. L., et al. (2000). The economic and environmental revolution in semi-arid cropping in north america. *Annals of Arid Zone*, *39*(3).

Smith, S., Cooper, M., Gogerty, J., Löffler, C., Borcherding, D., et al. (2015). Maize. In *Yield gains major u.s. f. crop.* (pp. 125–171). doi: 10.2135/cssaspecpub33.c6

Soil Survey Manual. (2017). *USDA Natural Resources Conservation Service Soils.* Retrieved from https://www.nrcs.usda.gov/wps/portal/nrcs/main/soils/survey/

Specht, J. E., Diers, B. W., Nelson, R. L., de Toledo, J. F. F., Torrion, J. A., et al. (2015). Soybean. In *Yield gains in major us field crops* (Vol. 33, pp. 311–355). doi: 10.2135/cssaspecpub33.c12

Specht, J. E., Hume, D. J., & Kumudini, S. V. (1999). Soybean yield potential—a genetic and physiological perspective. *Crop Science*, *39*(6), 1560–1570. doi: 10.2135/cropsci1999.3961560x

Specht, J. E., & Williams, J. H. (1984). Contribution of genetic technology to soybean productivity — retrospect and prospect. In *Genetic contribution to yield gains five major crop plants* (pp. 49–74). doi: 10.2135/cssaspecpub7.c3

Spiertz, J., & Ewert, F. (2009). Crop production and resource use to meet the growing demand for food, feed and fuel: opportunities and constraints. *NJAS: Wageningen Journal of Life Sciences*, *56*(4), 281–300. doi: 10.1016/s1573-5214(09)80001-8

St. Luce, M., Lemke, R., Gan, Y., McConkey, B., May, W., Campbell, C., ... others (2020). Diversifying cropping systems enhances productivity, stability, and nitrogen use efficiency. *Agronomy Journal*, *112*(3), 1517–1536. doi: 10.1002/agj2.20162

Sun, H., Zhang, X., Wang, E., Chen, S., Shao, L., & Qin, W. (2016). Assessing the contribution of weather and management to the annual yield variation of summer maize using APSIM in the North China Plain. *Field Crops Research*, *194*, 94–102. doi: 10.1016/j.fcr.2016.05.007

Sutton, M. A., Howard, C. M., Kanter, D. R., Lassaletta, L., Móring, A., Raghuram, N., & Read, N. (2021). The nitrogen decade: mobilizing global action on nitrogen to 2030 and beyond. *One Earth*, *4*(1), 10–14. doi: 10.1016/j.oneear.2020.12.016

Tamagno, S., Eagle, A. J., McLellan, E. L., van Kessel, C., Linquist, B. A., Ladha, J. K., & Pittelkow, C. M. (2022). Quantifying n leaching losses as a function of n balance: A path to sustainable food supply chains. *Agriculture, Ecosystems & Environment*, *324*, 107714. doi: 10.1016/j.agee.2021.107714

Thapa, S., Bhandari, A., Ghimire, R., Xue, Q., Kidwaro, F., et al. (2021). Managing micronutrients for improving soil fertility, health, and soybean yield. *Sustainability*, *13*(21), 11766. doi: 10.3390/su132111766

Tilman, D., Balzer, C., Hill, J., & Befort, B. L. (2011). Global food demand and the sustainable intensification of agriculture. *Proceedings of the national academy of sciences*, *108*(50), 20260–20264. doi: doi.org/10.1073/pnas.1116437108

Tilman, D., Cassman, K. G., Matson, P. A., Naylor, R., & Polasky, S. (2002). Agricultural sustainability and intensive production practices. *Nature*, *418*(6898), 671–677. doi: 10.1038/nature01014

Trooien, T. P., Buschman, L., Sloderbeck, P., Dhuyvetter, K., & Spurgeon, W. (1999). Water use efficiency of different maturity corn hybrids and grain sorghum in the central great plains. *Journal of production agriculture*, *12*(3), 377–382. doi: 10.2134/jpa1999.0377

Tsai, Y., Mishoe, J., & Jones, J. (1987). Optimizing multiple cropping systems: Simulation studies. *Agricultural systems*, *25*(3), 165–176. doi: 10.1016/0308-521x(87)90018-7

Tsubo, M., Ogindo, H., & Walker, S. (2004). Yield evaluation of maize-bean intercropping in a semi-arid region of south africa. *African Crop Science Journal*, *12*(4), 351–358. doi: 10.4314/acsj.v12i4.27897

Unger, P. W. (2001). Alternative and opportunity dryland crops and related soil conditions in the southern great plains. *Agronomy Journal*, *93*(1), 216–226. doi: 10.2134/agronj2001.931216x

United States Department of Agriculture (USDA). (2014). *Keys to soil taxonomy* (Vol. 12) (No. 410). Conservation Service.

United States Department of Agriculture (USDA). (2017). *USDA/NASS QuickStats Ad-hoc Query Tool.* Retrieved from https://quickstats.nass.usda.gov/

United States Department of Agriculture (USDA). (2023). *USDA/NASS QuickStats Ad-hoc Query Tool.* Retrieved from https://quickstats.nass.usda.gov/

Vanderlip, R., & Reeves, H. (1972). Growth stages of sorghum [sorghum bicolor,(l.) moench.] 1. *Agronomy journal*, *64*(1), 13–16. doi: 10.2134/agronj1972.00021962006400010005x

Van Oort, P., Gou, F., Stomph, T.-J., & van der Werf, W. (2020). Effects of strip width on yields in relay-strip intercropping: a simulation study. *European Journal of Agronomy*, *112*, 125936. doi: 10.1016/j.eja.2019.125936

Van Opstal, N. V., Caviglia, O., & Melchiori, R. J. (2011). Water and solar radiation productivity of double-crops in a humid temperate area. *Australian Journal of Crop Science*, *5*(13), 1760–1766.

VanWey, L. K., Spera, S., de Sa, R., Mahr, D., & Mustard, J. F. (2013). Socioeconomic development and agricultural intensification in mato grosso. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *368*(1619), 20120168. doi: 10.1098/rstb.2012.0168

Veenstra, R. L., Messina, C. D., Berning, D., Haag, L. A., Carter, P., Hefley, T. J., ... Ciampitti, I. A. (2021). Effect of tillers on corn yield: Exploring trait plasticity potential in unpredictable environments. *Crop Science*, *61*(5), 3660–3674. doi: 10.1002/csc2.20576

Vega, C. R. C., Sadras, V. O., Andrade, F. H., & Uhart, S. A. (2000). Reproductive allometry in soybean, maize and sunflower. *Annals of Botany*, *85*(4), 461–468. doi: 10.1006/anbo.1999.1084

Vukicevich, E., Lowery, T., Bowen, P., Úrbez Torres, J. R., & Hart, M. (2016). Cover crops to increase soil microbial diversity and mitigate decline in perennial agriculture. a review. *Agronomy for Sustainable Development*, *36*(36), 1–14. doi: 10.1007/s13593-016-0385-7

Waha, K., Dietrich, J. P., Portmann, F. T., Siebert, S., Thornton, P. K., Bondeau, A., & Herrero, M. (2020). Multiple cropping systems of the world and the potential for increasing cropping intensity. *Global Environmental Change*, *64*, 102131. doi: 10.1016/j.gloenvcha.2020.102131

Wall, G. W., Amthor, J. S., & Kimball, B. A. (1994). Cotco2: a cotton growth simulation model for global change. *Agricultural and forest meteorology*, *70*(1-4), 289–342. doi: 10.1016/0168-1923(94)90064-7

Wallach, D. (2011). Crop model calibration: A statistical perspective. *Agronomy Journal*, *103*(4), 1144–1151. doi: 10.2134/agronj2010.0432

Wan, J., Li, R., Wang, W., Liu, Z., & Chen, B. (2016). Income diversification: A strategy for rural region risk management. *Sustainability*, *8*(10), 1064. doi: 10.3390/su8101064

West, T. D., Griffith, D. R., Steinhardt, G. C., Kladivko, E. J., & Parsons, S. D. (1996). Effect of tillage and rotation on agronomic performance of corn and soybean: Twenty-year study on dark silty clay loam soil. *Journal of Production Agriculture*, *9*(2), 241–248. doi: 10.2134/jpa1996.0241

Widstrom, N., & Young, J. (1980). Double cropping corn on the coastal plain of the southeastern united states 1. *Agronomy Journal*, *72*(2), 302–305. doi: 10.2134/agronj1980.00021962007200020012x

Widstrom, N., Young, J., Martin, W., & Shaver, D. (1984). Grain and forage yields of irrigated second-crop corn seeded on five planting dates 1. *Agronomy Journal*, *76*(6), 883–886. doi: 10.2134/agronj1984.00021962007600060006x

Williams, J. R., Pachta, M. J., Roozeboom, K. L., Llewelyn, R. V., Claassen, M. M., & Bergtold, J. S. (2012). Risk analysis of tillage and crop rotation alternatives with winter wheat. *Journal of Agricultural and Applied Economics*, *44*(4), 561–576. doi: 10.1017/s1074070800024111

Wood, S. (2017). *Generalized additive models: An introduction with r* (2nd ed.). Chapman and Hall/CRC. doi: 10.1201/9781315370279

Wright, C. K., & Wimberly, M. C. (2013). Recent land use change in the western corn belt threatens grasslands and wetlands. *Proceedings of the National Academy of Sciences*, *110*(10), 4134–4139. doi: 10.1073/pnas.1215404110

Wright, S., & Anderson, R. (2000). Aggregate stability and glomalin in alternative crop rotations for the central great plains. *Biology and Fertility of Soils*, *31*, 249–253. doi: 10.1007/s003740050653

Xiang, M., Yu, Q., Li, Y., Shi, Z., & Wu, W. (2022). Increasing multiple cropping for land use intensification: The role of crop choice. *Land Use Policy*, *112*, 105846. doi: 10.1016/j.landusepol.2021.105846

Xie, X. L., & Beni, G. (1991). A validity measure for fuzzy clustering. *IEEE Transactions on Pattern Analysis & Machine Intelligence*, *13*(08), 841–847. doi: 10.1109/34.85677

Xie, Y., & Lark, T. J. (2021). Mapping annual irrigation from landsat imagery and environmental variables across the conterminous united states. *Remote Sensing of Environment*, *260*, 112445. doi: 10.1016/j.rse.2021.112445

Xu, Z., Li, C., Zhang, C., Yu, Y., van der Werf, W., & Zhang, F. (2020). Intercropping maize and soybean increases efficiency of land and fertilizer nitrogen use; a meta-analysis. *Field Crops Research*, *246*, 107661. doi: 10.1016/j.fcr.2019.107661

Yamane, K., Ikoma, A., & Iijima, M. (2016). Performance of double cropping and relay intercropping for black soybean production in small-scale farms. *Plant Production Science*, *19*(4), 449–457. doi: 10.1080/1343943x.2016.1164574

Yang, X., Chen, F., Lin, X., Liu, Z., Zhang, H., Zhao, J., . . . others (2015). Potential benefits of climate change for crop productivity in china. *Agricultural and Forest Meteorology*, *208*, 76–84. doi: 10.1016/j.agrformet.2015.04.024

Yang, X., Li, Z., Cui, S., Cao, Q., Deng, J., Lai, X., & Shen, Y. (2020). Cropping system productivity and evapotranspiration in the semiarid loess plateau of china under future temperature and precipitation changes: An apsim-based analysis of rotational vs. continuous systems. *Agricultural Water Management*, *229*, 105959. doi: 10.1016/j.agwat.2019.105959

Yang, X., Xiong, J., Du, T., Ju, X., Gan, Y., Li, S., ... Butterbach-Bahl, K. (2024). Diversifying crop rotation increases food production, reduces net greenhouse gas emissions and improves soil health. *Nature Communications*, *151*(15), 1–14. doi: 10.1038/s41467-023-44464-9

Young, B. G. (2006). Changes in herbicide use patterns and production practices resulting from glyphosate-resistant crops. *Weed Technology*, *20*(2), 301–307. doi: 10.1614/wt-04-189.1

Yu, C., Miao, R., & Khanna, M. (2021). Maladaptation of u.s. corn and soybeans to a changing climate. *Scientific Reports*, *11*(1), 1–12. doi: 10.1038/s41598-021-91192-5

Yu, Y., Stomph, T.-J., Makowski, D., & van Der Werf, W. (2015). Temporal niche differentiation increases the land equivalent ratio of annual intercrops: a meta-analysis. *Field Crops Research*, *184*, 133–144. doi: 10.1016/j.fcr.2015.09.010

Zadoks, J. C., Chang, T. T., Konzak, C. F., et al. (1974). A decimal code for the growth stages of cereals. *Weed research*, *14*(6), 415–421.

Zhang, X., Davidson, E. A., Mauzerall, D. L., Searchinger, T. D., Dumas, P., & Shen, Y. (2015). Managing nitrogen for sustainable development. *Nature*, *528*(7580), 51–59. doi: 10.1038/nature15743

Zhu, X.-G., Long, S. P., & Ort, D. R. (2010). Improving photosynthetic efficiency for greater yield. *Annual Review of Plant Biology*, *61*, 235–261. doi: 10.1146/annurev-arplant-042809-112206

Zuber, S. M., Behnke, G. D., Nafziger, E. D., & Villamil, M. B. (2015). Crop rotation and tillage effects on soil physical and chemical properties in illinois. *Agronomy Journal*, *107*(3), 971–978. doi: 10.2134/agronj14.0465

Appendix A

Appendix A, Chapter 2

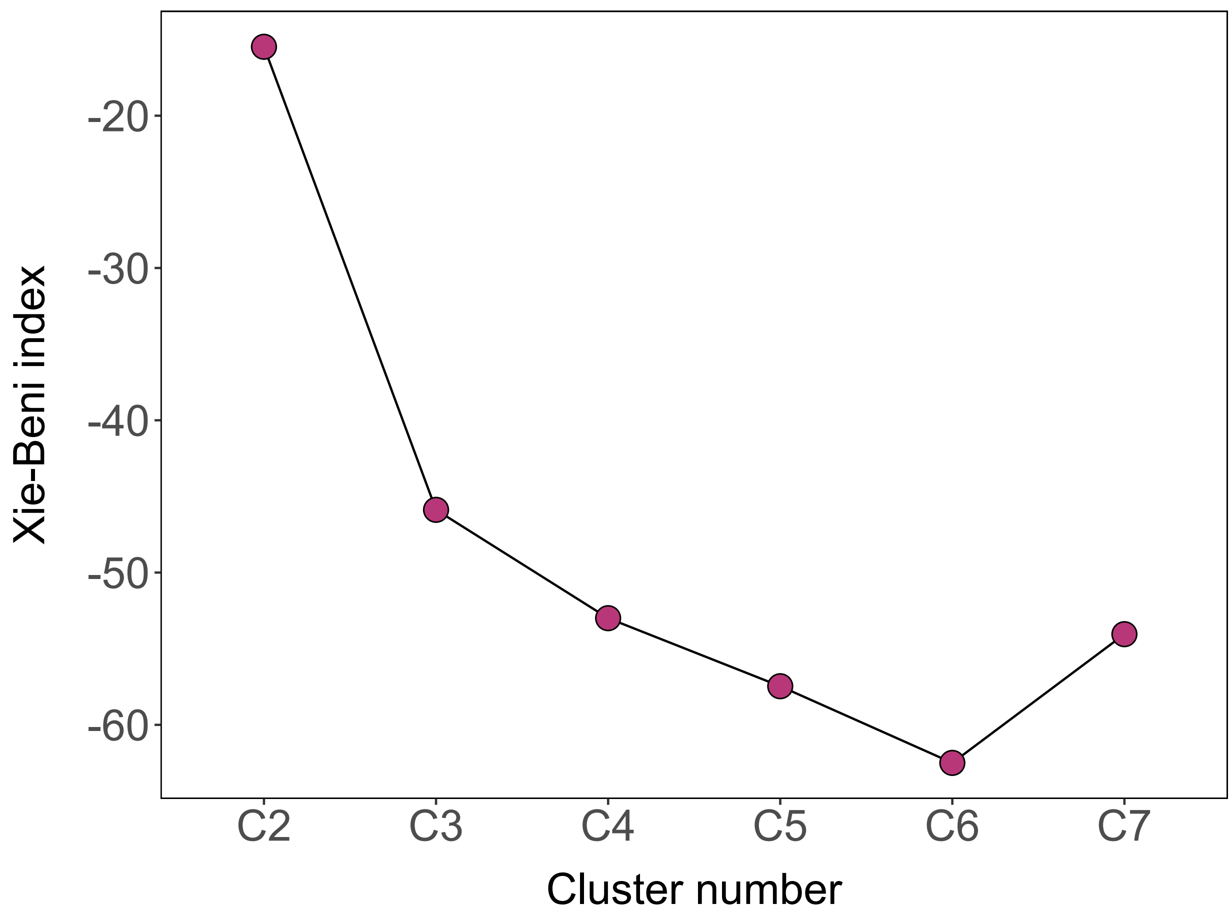

Figure A.1: Xie-beni index values versus number of clusters (2-7) used to define the optimum number of clusters from the spatial c-means (SFC) clustering technique based on mean grain yield and its corresponding standard deviation (30 years) for the optimal combination of planting date (April 1^{st}, April 15^{th}, May 1^{st}, May 15^{th}, June 1^{st}, June 15^{th}, and July 1^{st}) and hybrid maturity (CRM 72, 85 101 and, 115) at each site.

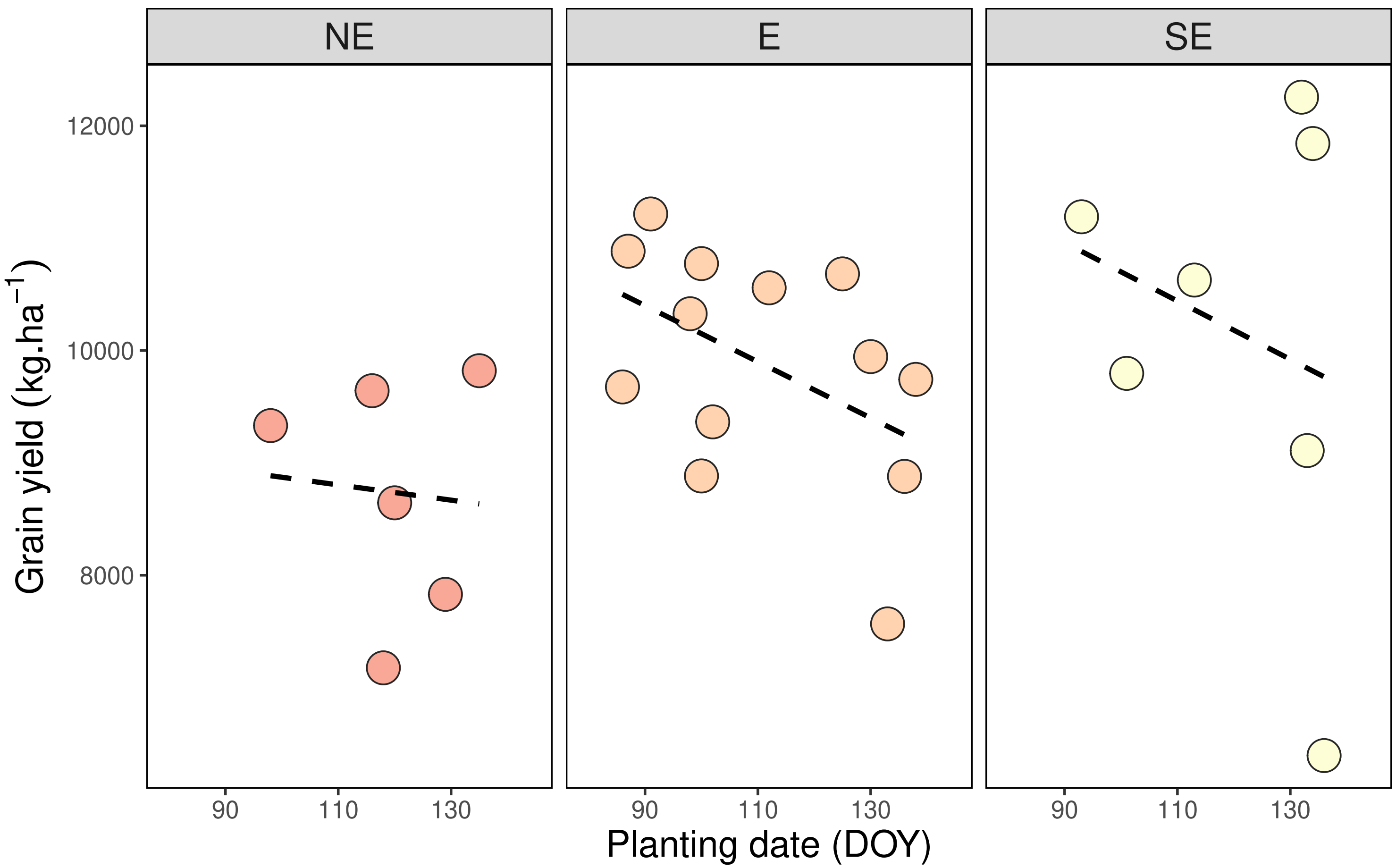

Figure A.2: Grain yield (kg ha^{-1}) as a function of planting date (DOY: day of the year) at three maize productivity environments (Southeastern: SE; Eastern: E; Northeastern: NE). Data provided by Kansas Corn Yield Contests and the Kansas entries from the National Corn Yield Contest. Dashed line indicates fitted linear function.

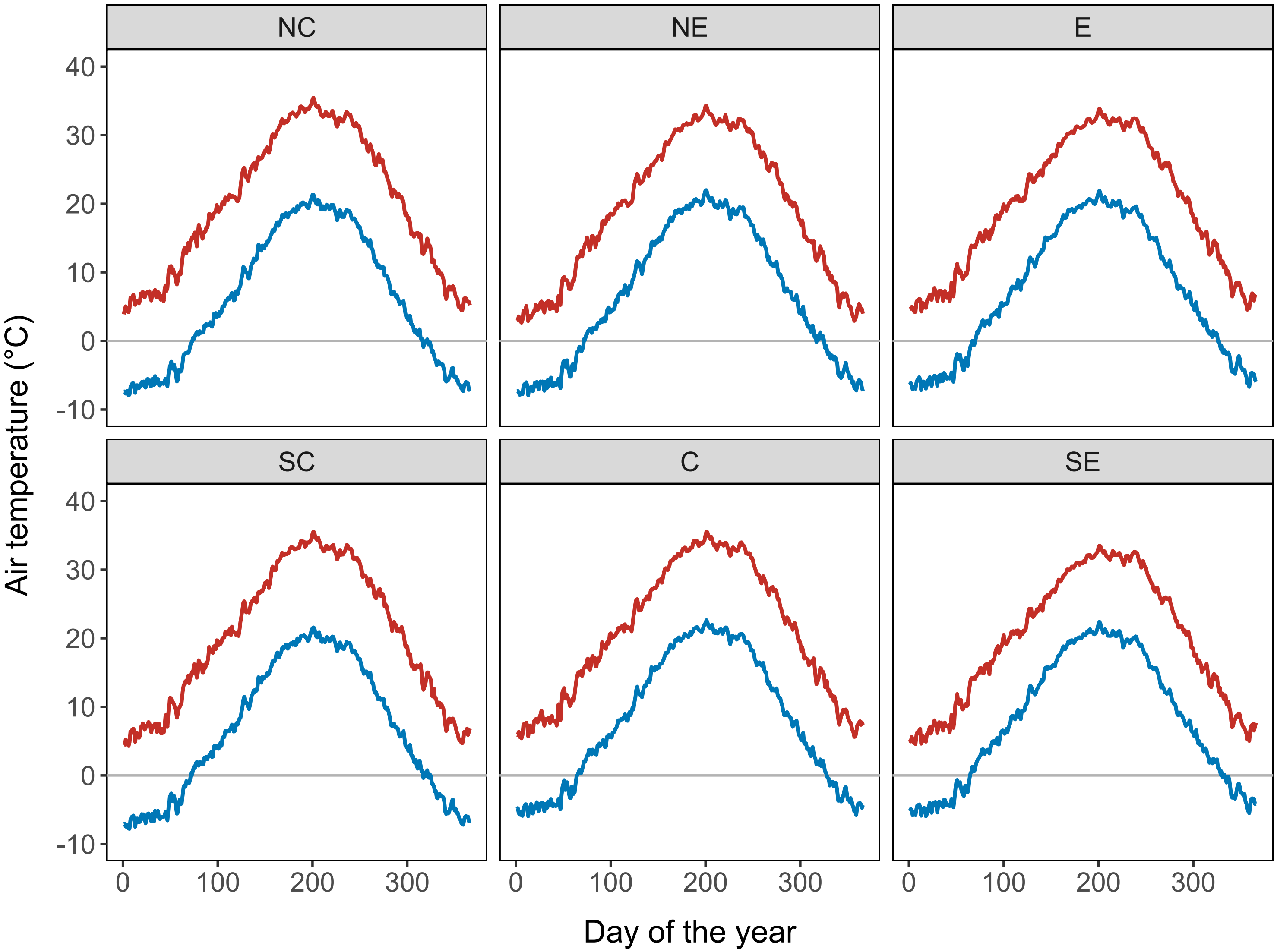

Figure A.3: Mean minimum (blue) and maximum (red) air temperature (°C) as a function of day of the year at six maize productivity environments (Southeastern: SE; Eastern: E; Northeastern: NE; Central: C; Southcentral: SC; Northcentral: NC).

Table A.1: Maize cultivar-specific calibrated parameters in APSIM Next Generation (Holzworth et al., 2018) for corn relative maturity (CRM) 72, 85, 101 and 115 hybrid maturities.

Parameter	**Maize genotype (CRM)**			
	72	**85**	**101**	**115**
Juvenile.Target.Fixed.Value.	154.3	223.5	261.5	316.2
GrainFilling.Target.Fixed.Value.	583.8	551.3	670.9	824.1

Table A.2: Metrics describing agreement between predicted and simulated days to silking (from planting to R_1) and grain yield (kg ha^{-1}) by the APSIM Next Generation model (Holzworth et al., 2018) for different site-years in Kansas state from 2014 to 2022.

Metric	**Days to silking (R_1)**	**Grain yield**
n	44	41
RMSE	9.93 days	2388 kg ha^{-1}
RRMSE	14%	25%
KGE	0.81	0.51
PBE	-11.28	-0.06

Table A.3: Data source and management description (planting date, nitrogen applied as fertilizer, and plant density and CRM) for the different site-years in Kansas state from 2013 to 2022 used in the validation of the model and in the on-farm planting date validation. PT: Kansas Maize Performance Trials; FE: Field experiment; YC: Yield contest.

Step	**Data source**	**Year**	**Site/County**	**Planting date**	**Nitrogen (kg ha^{-1})**	**Plant density (pl m^{-2})**	**CRM**
Validation of the model	PT	2014	Erie	17-Apr	224	3.4 - 4.7	101 and 115
	PT	2014	Hays	02-May	90	5 – 7.1	101
	PT	2014	Manhattan	18-Apr	179	5.1 – 5.8	101 and 115
	PT	2014	Ottawa	17-May	135	5.2 – 5.3	101 and 115
	PT	2014	Parsons	04-Apr	168	5 – 5.8	101
	PT	2014	Rossville	22-Apr	135	3.8 – 7	101
	PT	2014	Severance	22-Apr	202	5.8 – 6.5	101
	PT	2015	Erie	28-Apr	224	5 – 5.7	101
	PT	2015	Garden City	13-May	112	5.6 – 6.1	101
	PT	2015	Hays	22-Apr	112	4.1 – 6.3	101 and 115
	PT	2015	Manhattan	28-Apr	179	5.6	101
	PT	2015	Ottawa	17-Apr	135	5.7	101

Continued on next page

Table A.3 – Continued from previous page

Step	Data source	Year	Site/County	Planting date	Nitrogen (kg ha^{-1})	Plant density (pl m^{-2})	CRM
	PT	2015	Parsons	27-Apr	168	4.8 - 6.1	101 and 115
	PT	2015	Topeka	22-Apr	168	4.7 - 5.3	101 and 115
	PT	2016	Ottawa	12-Apr	157	5.3 – 6.5	101 and 115
	PT	2016	Rossville	11-Apr	217	5.2 – 5.9	101
	PT	2017	Erie	08-Jun	224	5.2 – 5.8	101 and 115
	PT	2017	Parsons	09-May	168	4.9 - 6	101
	PT	2017	Topeka	12-Apr	202	3.1 – 4	101 and 115
	PT	2018	Colby	01-May	90	5.3 – 5.9	101 and 115
	PT	2018	Ottawa	24-Apr	157	8.6	101 and 115
	PT	2018	Parsons	10-Apr	202	5.3 – 6	101 and 115
	PT	2019	Kiro	24-Apr	202	3.3 – 5	101
	PT	2019	Ottawa	26-Apr	157	4.9	101 and 115
	PT	2019	Parsons	11-Apr	202	4.9 – 5.3	101 and 115
	PT	2020	Parsons	07-Apr	202	3.4 – 4	101 and 115

Continued on next page

Table A.3 – Continued from previous page

Step	Data source	Year	Site/County	Planting date	Nitrogen (kg ha^{-1})	Plant density (pl m^{-2})	CRM
	FE	2021	Manhattan	29-Jul	67	8.1	85
	FE	2022	Manhattan	11-May	100	6.9 – 9.7	72, 85, 101 and 115
	FE	2022	Manhattan	02-Aug	34	10.3 – 11.11	72, 85 and 115
On-farm planting data validation	YC	2013	Anderson	16-May	-	6.3	105
	YC	2013	Anderson	13-May	-	6.4	111
	YC	2013	Anderson	14-May	-	6.2	114
	YC	2013	Labette	12-May	-	7.9	112
	YC	2013	Coffey	13-May	-	6.5	96
	YC	2013	Coffey	16-May	-	6.5	111
	YC	2013	Franklin	18-May	-	5.9	108
	YC	2013	Sedgwick	09-May	-	5.4	96
	YC	2013	Sedgwick	28-Apr	-	5.4	105
	YC	2013	Washington	15-May	-	6	108
	YC	2013	Washington	30-Apr	-	5.4	111

Continued on next page

Table A.3 – Continued from previous page

Step	Data source	Year	Site/County	Planting date	Nitrogen (kg ha^{-1})	Plant density (pl m^{-2})	CRM
	YC	2014	Labette	03-Apr	-	6.2	103
	YC	2014	Butler	27-Mar	-	5.4	105
	YC	2014	Butler	10-Apr	-	5.9	111
	YC	2014	Greenwood	12-Apr	-	6.7	114
	YC	2014	Saline	26-Apr	-	6.1	110
	YC	2014	Sedgwick	08-Apr	-	5.4	103
	YC	2015	Woodson	11-Apr	-	6.4	111
	YC	2015	Butler	10-Apr	-	5.4	111
	YC	2015	Butler	05-May	-	5.7	111
	YC	2015	Coffey	01-Apr	-	6.2	98
	YC	2015	Douglas	08-Apr	-	6.2	111
	YC	2015	Jefferson	22-Apr	-	6.7	111
	YC	2021	Anderson	23-Apr	-	5.9	112
	YC	2021	Butler	10-May	-	5.7	114

Continued on next page

Table A.3 – Continued from previous page

Step	**Data source**	**Year**	**Site/County**	**Planting date**	**Nitrogen (kg ha^{-1})**	**Plant density (pl m^{-2})**	**CRM**
	YC	2021	Cowley	28-Mar	-	5.9	115

Table A.4: Description of the maize productivity environments according to maize productivity (mean grain yield and standard deviation for simulations over 30 years), weather (mean annual cumulative precipitation and mean annual temperature) and soil characteristics (percentage of sand, clay, and silt at 0-20 cm. depth) across sites.

Variable	**Productivity environment**					
	NC	**SC**	**C**	**NE**	**E**	**SE**
Mean yield (kg ha^{-1})	7469	7690	9621	10035	11523	12458
GY standard deviation (kg ha^{-1})	3106	2830	2567	3071	2415	1766
Mean annual cumulative precipitation (mm)	688	728	861	849	990	1120
Mean annual temperature (°C)	12.6	14.4	14.2	13.1	13.6	13.9
Sand (%)	23.66	48.14	18.27	10.52	10.55	15.24
Clay (%)	25.14	17.71	31.72	33.62	37.87	37.45
Silt (%)	51.20	34.15	50.00	55.86	51.58	47.31

Table A.5: Means across sites and years (30) and ANOVA F-test probabilities for maize grain yield from the combination of productivity environments (Southeastern: SE; Eastern: E; Northeastern: NE; Central: C; Southcentral: SC; Northcentral: NC), planting dates (April 1st, April 15th, May 1st, May 15th, June 1st, June 15th, and July 1st), and hybrid maturities (72, 85, 101, and 115 corn relative maturity) obtained from simulations with the APSIM Next Generation model (Holzworth et al., 2018).

Environment	**Planting date**	**Maize hybrid maturity (CRM)**			
		72	**85**	**101**	**115**
	April 1st	9694 cB	11470 bAB	12425 aA	12483 aA
	April 15th	10435 cA	11670 bA	12268 aAB	12239 aAB
	May 1st	10099 cAB	11267 bAB	11977 aAB	12201 aAB
SE	May 15th	9659 cB	10935 bB	11829 aB	11752 aB
	June 1st	9018 cC	10282 bC	10992 aC	11189 aC
	June 15th	8458 cD	9915 bC	10849 aC	10747 aC
	July 1st	8207 bD	9847 aC	9962 aD	7774 bD
	April 1st	8832 cCD	10586 bA	11504 aA	11433 aA
	April 15th	9735 cA	10878 bA	11355 aA	11235 abAB
	May 1st	9676 cA	10663 bA	11174 aA	11261 aAB
E	May 15th	9348 cAB	10424 bA	11049 aA	10912 aBC

Continued on next page

Environment	Planting date	Maize hybrid maturity (CRM)			
		72	**85**	**101**	**115**
	June 1st	8895 cBC	9927 bB	10515 aB	10607 aC
	June 15th	8423 cDE	9738 bB	10462 aB	10035 bD
	July 1st	8196 bE	9564 aB	9338 aC	7186 cE
	April 1st	7235 cD	8990 bABC	9855 aA	9756 aA
	April 15th	8414 bA	9404 aA	9798 abA	9810 aA
	May 1st	8482 cA	9284 bAB	9733 aAB	9768 aA
NE	May 15th	8222 cAB	9104 bABC	9615 aAB	9547 aA
	June 1st	7907 cBC	8831 bBC	9337 aB	9449 aAB
	June 15th	7648 cCD	8839 bBC	9415 aAB	9016 abB
	July 1st	7577 bCD	8662 aC	8462 aC	6614 cC
	April 1st	7087 cD	8590 bAB	9624 aA	9439 aA
	April 15th	7844 bABC	9003 aA	9434 aAB	9236 aA
	May 1st	8119 bA	8906 aAB	9214 aAB	9253 aA
C	May 15th	7964 bAB	8718 aAB	9206 aAB	9139 aA

Continued on next page

Table A.5 – continued from previous page

Environment	**Planting date**	**Maize hybrid maturity (CRM)**			
		72	**85**	**101**	**115**
	June 1st	7596 bABCD	8442 aAB	8923 abBC	8997 aA
	June 15th	7380 cBCD	8314 bB	8875 abBC	8883 aA
	July 1st	7258 bCD	8344 aB	8546 aC	7327 bB
	April 1st	5321 cC	6653 bA	7619 aA	7484 aA
	April 15th	6094 bAB	7219 aA	7541 aA	7400 aA
	May 1st	6499 bA	7173 aA	7386 aA	7481 aA
SC	May 15th	6274 bAB	6991 aA	7390 aA	7418 aA
	June 1st	5919 cAB	6808 bA	7305 abA	7477 aA
	June 15th	5830 cBC	6844 bA	7402 aA	7521 aA
	July 1st	5790 cBC	6931 abA	7309 aA	6657 bB
	April 1st	4604 bB	6620 aA	7123 aA	7090 abA
	April 15th	6201 bA	6881 aA	7163 aA	7176 aA
	May 1st	6256 bA	6761 abA	7092 aA	7214 aA
NC	May 15th	6176 bA	6766 aA	7088 aA	7144 aA

Continued on next page

Table A.5 – continued from previous page

Environment	Planting date	Maize hybrid maturity (CRM)			
		72	85	101	115
	June 1st	6095 cA	6718 bA	7134 abA	7247 aA
	June 15th	6116 bA	6833 aA	7215 aA	6859 aA
	July 1st	5958 bA	6630 aA	6360 abB	5048 cB

Source of variation	ANOVA
Genotype (G)	***
Planting date (PD)	***
Environment (E)	***
G x PD	***
G x E	NS
PD x E	***
G x PD x E	***

[a] Within columns and environments, means followed by the same uppercase letter are not significantly different according to Tukey test ($p < 0.05$). The lack of letters in a comparison indicates no differences between planting dates for the same hybrid maturity.

[b] Within rows and environments, means followed by the same lowercase letter are not significantly different according to Tukey

test ($p < 0.05$). The lack of letters in a comparison indicates no differences between hybrid maturities for the same planting date.

*, **, ***, significant at the 0.05, 0.01, and 0.001 probability level, respectively.

NS, nonsignificant.

Appendix B

Appendix B, Chapter 3

Table B.1: Crop management (sowing date, stand count (pl m^{-2}) at emergence, genotype, and termination date (i.e., killing date for cover crops, mowing date for forage purpose crops, and maturity date for grain purpose crops) description for eleven cropping sequences in experiments conducted from October 2019 to October 2022. ContW: continuous wheat; Gr: grain purpose; GF: grain-forage purpose; For: forage purpose; Ba: base-intensive; Sem: semi-intensive; Int: intensive.

			Crop management			
Season	**Treatment**	**Crop**	**Sowing date**	**Stand count**	**Genotype**	**Termination date**
2019/20	ContW	Wheat	10/24/19	38	Zenda™	6/11/20
2019/20	Gr – Ba	Wheat	10/24/19	37	Zenda™	6/11/20
2019/20	Gr – Sem 1	Wheat	10/24/19	39	Zenda™	6/11/20
2019/20	Gr- Sem 2	Wheat	10/24/19	38	Zenda™	6/11/20
2019/20	Gr – Int	Wheat	10/24/19	39	Zenda™	6/11/20
2019/20	GF – Ba	Wheat	10/24/19	36	Zenda™	6/11/20
2019/20	GF – Sem 1	Wheat	10/24/19	41	Zenda™	6/11/20
2019/20	GF – Sem 2	Triticale	10/24/19	*	Zenda™	5/12/20
2019/20	GF – Int 1	Wheat	10/24/19	37	Zenda™	6/11/20
2019/20	GF – Int 2	Wheat	10/24/19	38	Zenda™	6/11/20
2019/20	For	Wheat	10/24/19	*	Zenda™	5/12/20
2020	ContW	Fallow	-	-	-	-

Continued on next page

Table B.1 – Continued from previous page

Season	Treatment	Crop	Crop management: Sowing date	Stand count	Genotype	Termination date
2020	Gr – Ba	Fallow	-	-	-	-
2020	Gr – Sem 1	Soybean	7/8/20	27		10/20/20
2020	Gr- Sem 2	Sorghum	7/8/20	21		11/3/20
2020	Gr – Int	Soybean	7/8/20	37		10/20/20
2020	GF – Ba	Fallow	-	-	-	-
2020	GF – Sem 1	Cowpea	7/8/20	33		10/20/20
2020	GF – Sem 2	Soybean	5/22/20	33		10/1/20
2020	GF – Int 1	Moth	7/8/20	8		10/20/20
2020	GF – Int 2	Tepary	7/8/20	13		10/20/20
2020	For	Forage soybean	7/8/20	27	Large Lad RR™	9/24/20
2020/21	ContW	Wheat	10/15/20	52	Zenda™	6/8/21
2020/21	Gr – Ba	Wheat	10/15/20	52	Zenda™	6/8/21
2020/21	Gr – Sem 1	Wheat	11/7/20	60	Zenda™	6/8/21
2020/21	Gr- Sem 2	Fallow	-	-	-	-
2020/21	Gr – Int	Wheat	11/7/20	66	Zenda™	6/8/21

Continued on next page

Table B.1 – Continued from previous page

			Crop management			
Season	**Treatment**	**Crop**	**Sowing date**	**Stand count**	**Genotype**	**Termination date**
2020/21	GF – Ba	Triticale	9/24/20	*		5/6/21
2020/21	GF – Sem 1	Wheat	11/7/20	65	Zenda™	6/8/21
2020/21	GF – Sem 2	Wheat	10/15/20	63	Zenda™	6/8/21
2020/21	GF – Int 1	Wheat	9/24/20	*	Zenda™	6/8/21
2020/21	GF – Int 2	Wheat	9/24/20	*	Zenda™	6/8/21
2020/21	For	Wheat	9/24/20	*	Zenda™	5/6/21
2021	ContW	Fallow	-	-	-	-
2021	Gr – Ba	Maize	7/6/21	9		10/29/21
2021	Gr – Sem 1	Fallow	-	-	-	-
2021	Gr- Sem 2	Soybean	5/14/21	*		9/21/21
2021	Gr – Int	Soybean	7/6/21	35		10/6/21
2021	GF – Ba	Soybean	5/14/21	*		9/21/21
2021	GF – Sem 1	Fallow	-	-	-	-
2021	GF – Sem 2	Fallow	-	-	-	-
2021	GF – Int 1	Forage soybean	7/6/21	35	Large Lad RR™	9/22/21

Continued on next page

Table B.1 – Continued from previous page

			Crop management			
Season	**Treatment**	**Crop**	**Sowing date**	**Stand count**	**Genotype**	**Termination date**
2021	GF – Int 2	Alfalfa	7/6/21	*	*	9/20/21
2021	For	Fallow	-	-	-	-
2021/22	ContW	Wheat	10/22/21	61	Zenda™	6/7/22
2021/22	Gr – Ba	Wheat	11/8/21	*	Zenda™	6/7/22
2021/22	Gr – Sem 1	Wheat	10/22/21	56	Zenda™	6/7/22
2021/22	Gr- Sem 2	Wheat	11/8/21	*	Zenda™	6/7/22
2021/22	Gr – Int	Triticale	11/8/21	*		5/11/22
2021/22	GF – Ba	Wheat	10/22/21	63	Zenda™	6/7/22
2021/22	GF – Sem 1	Wheat	11/8/21	*	Zenda™	6/7/22
2021/22	GF – Sem 2	Wheat	10/5/21	*	Zenda™	6/7/22
2021/22	GF – Int 1	Triticale	10/5/21	47		5/11/22
2021/22	GF – Int 2	Triticale	10/5/21	40		5/11/22
2021/22	For	Wheat	10/5/21	49	Zenda™	5/11/22
2022	ContW	Fallow	-	-	-	-
2022	Gr – Ba	Fallow	-	-	-	-

Continued on next page

Table B.1 – Continued from previous page

			Crop management			
Season	**Treatment**	**Crop**	**Sowing date**	**Stand count**	**Genotype**	**Termination date**
2022	Gr – Sem 1	Soybean	7/12/22	*	P40T19E™	10/18/22
2022	Gr- Sem 2	Maize	7/12/22	*	P0622AML™	10/18/22
2022	Gr – Int	Soybean	5/17/22	*	P40T19E™	9/27/22
2022	GF – Ba	Fallow	-	-	-	-
2022	GF – Sem 1	Forage soybean	7/12/22	*	Large Lad RR™	10/6/22
2022	GF – Sem 2	Soybean	7/12/22	*	P40T19E™	10/18/22
2022	GF – Int 1	Forage soybean	5/17/22	31	Large Lad RR™	9/15/22
2022	GF – Int 2	Alfalfa	-	-	*	**
2022	For	Forage soybean	5/17/22	25	Large Lad RR™	9/15/22

* Data not available. ** Multiple mowing dates: 6/13/2022 – 7/8/2022 – 8/7/2022 – 9/4/2022.

Table B.2: URLs and corresponding descriptions used in the economic analysis.

Description	**URL**
Kansas daily grain bids developed by USDA	https://mymarketnews.ams.usda.gov/viewReport/2886
Kansas direct hay report developed by USDA	https://mymarketnews.ams.usda.gov/viewReport/2885
Kansas historical budget report developed by Kansas State University	https://agmanager.info/kfma/kfma-enterprise-reports
Consumer price index inflation calculator developed by US Bureau of Labor Statistics	https://www.bls.gov/data/inflation_calculator.htm

In our first statistical analysis, we used a GLM specified as:

$$\begin{aligned} y_{ik} &\sim \text{gamma}(\mu_{ik}, \psi), \\ \log_e(\mu_{ik}) &= \mu + \alpha_i + \beta_k, \end{aligned} \tag{B.1}$$

where y_{ik} is the recorded dry matter, glucose-equivalent yield, or cumulative winter wheat yield (i.e., the response variables) for the i^{th} cropping sequence treatment level ($i = 1, 2, \ldots, 11$) in the k^{th} block ($k = 1, 2, 3, 4$). The μ_{ik} denotes the expected value and ψ denotes the dispersion parameter of the gamma distribution (i.e., $\text{E}(y_{ik}) = \mu_{ik}$ and $\text{Var}(y_{ik}) = \mu_{ik}\psi^{-1}$). The α_i denotes the effect of the i^{th} level of the treatment factor cropping sequence, and β_k denotes the effect of the k^{th} level of the block effect.

In our second statistical analysis, we used a GLM specified as:

$$\begin{aligned} y_{ijk} &\sim \text{gamma}(\mu_{ijk}, \psi), \\ \log_e(\mu_{ijk}) &= \mu + \alpha_i + \tau_j + \gamma_{ij} + \beta_k, \end{aligned} \tag{B.2}$$

where y_{ijk} is the recorded mean precipitation use efficiency or nitrogen partial factor productivity (i.e., the response variables) for the i^{th} cropping sequence treatment level ($i = 1, 2, \ldots, 11$) and the j^{th} nitrogen management treatment level ($j = 1, 2$) in the k^{th} block ($k = 1, 2, 3, 4$). The μ_{ijk} denotes the expected value and ψ denotes the dispersion parameter of the gamma distribution (i.e., $\text{E}(y_{ijk}) = \mu_{ijk}$ and $\text{Var}(y_{ijk}) = \mu_{ijk}\psi^{-1}$). The α_i denotes the effect of the i^{th} level of the treatment factor cropping sequence, τ_i denotes the effect of the j^{th} level of the treatment factor nitrogen management, γ_{ij} denotes the interaction effect between the i^{th} level of the treatment factor cropping sequence and the j^{th} level of the treatment factor nitrogen management, and β_k denotes the effect of the k^{th} level of the block effect.

Appendix C

Appendix C, Chapter 5

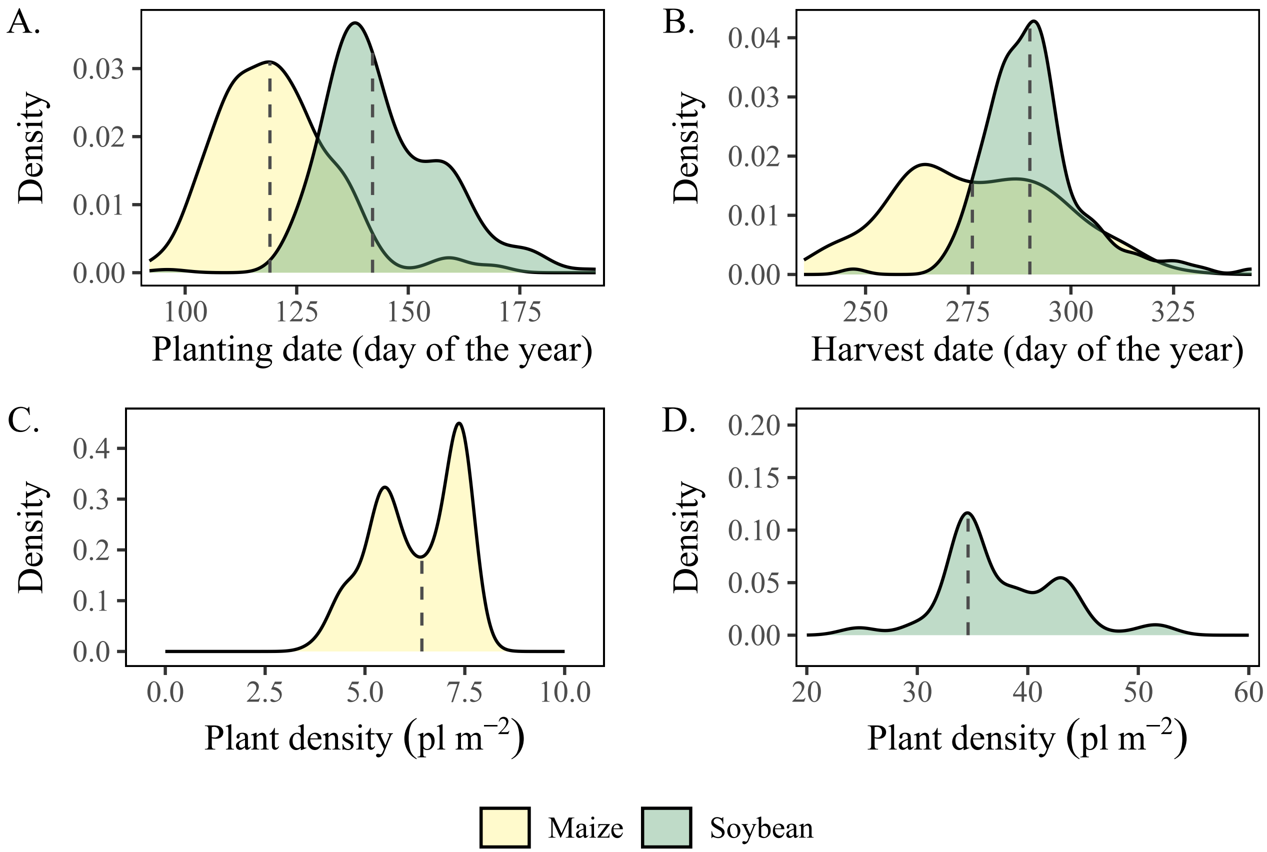

Figure C.1: Density plots for planting (**A**) and harvest (**B**) dates (day of the year) and plant densities (**C** and **D**) (pl m^{-2}) for maize (yellow) and soybean (green) in Kansas crop performance trials conducted between 1991 and 2021. The peak of the density curve represents the highest concentration of data points, and the dashed gray line indicates the median.

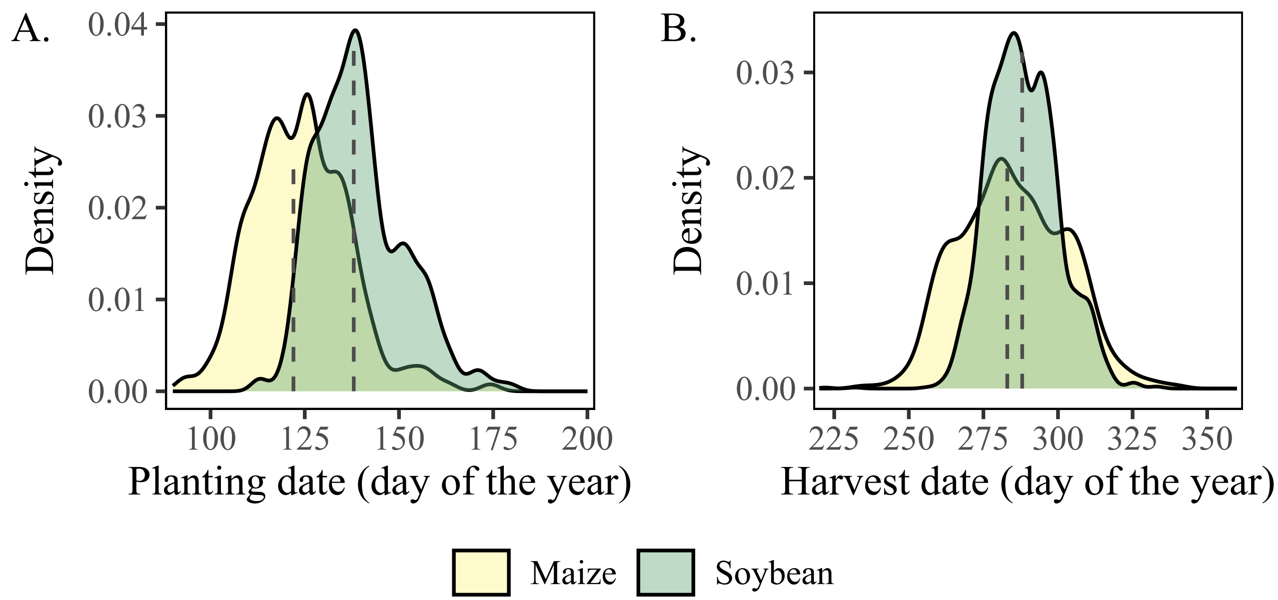

Figure C.2: Density plots for planting (**A**) and harvest (**B**) dates (day of the year) for maize (yellow) and soybean (green) in crop performance trials conducted in 11 states of the US Corn Belt (Illinois, Iowa, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin). The peak of the density curve represents the highest concentration of data points, and the dashed gray line indicates the median.

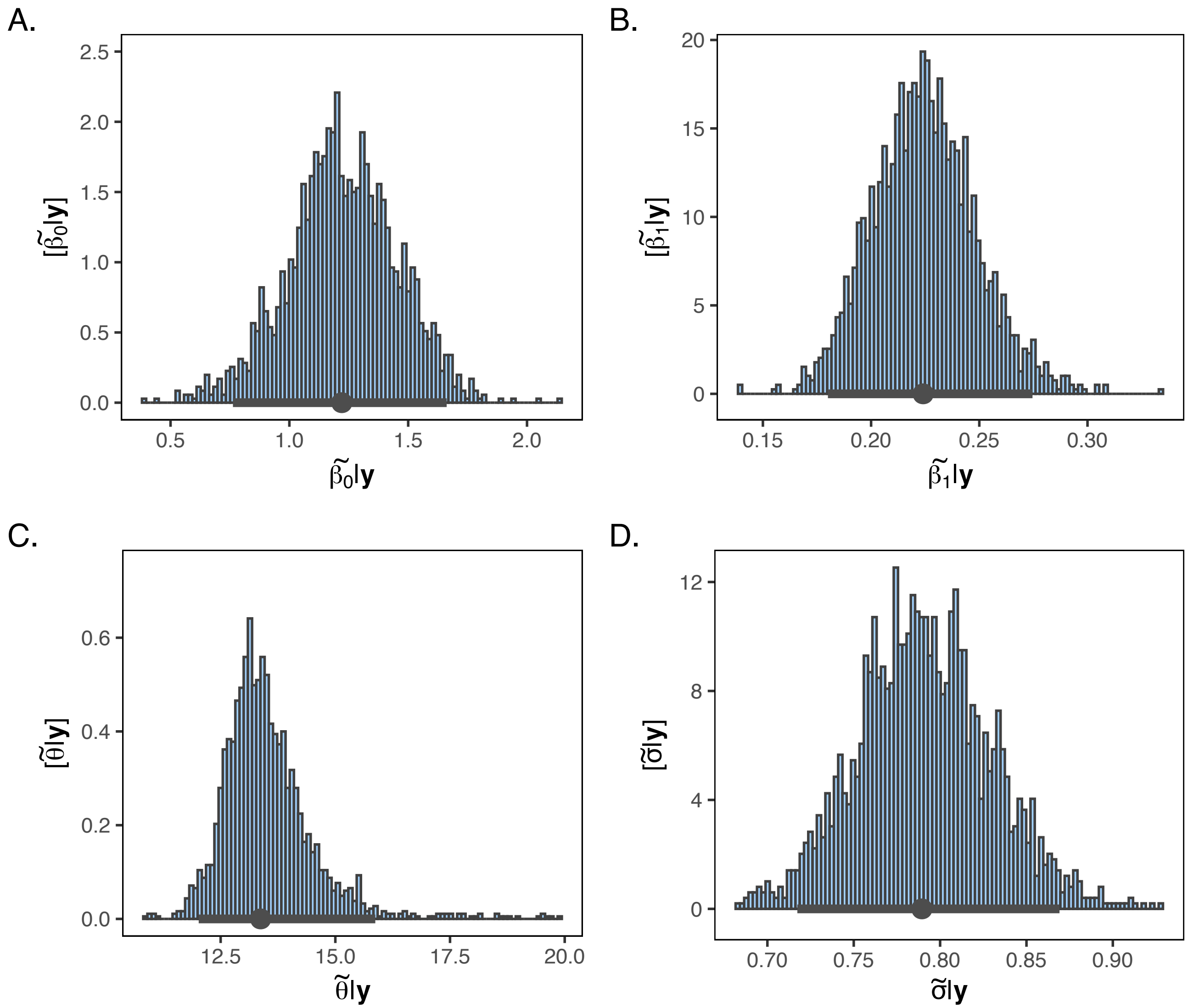

Figure C.3: Histogram of the posterior distribution of the parameters of the Bayesian linear-plateau model (**A**: β_0; **B**: β_1; **C**: θ; **D**: σ) for the relationship of soybean yield (Mg ha^{-1}) as a function of maize yield (Mg ha^{-1}) for Kansas crop performance trials conducted between 1991 and 2021. Estimated Bayesian linear-plateau model: $y = 1.22 + 0.22x$, if $x < 13.53$; $y = 4.2$, if $x \geq 13.53$. The gray line indicates the 95% credible interval, and the circle indicates the mean estimate for each parameter.

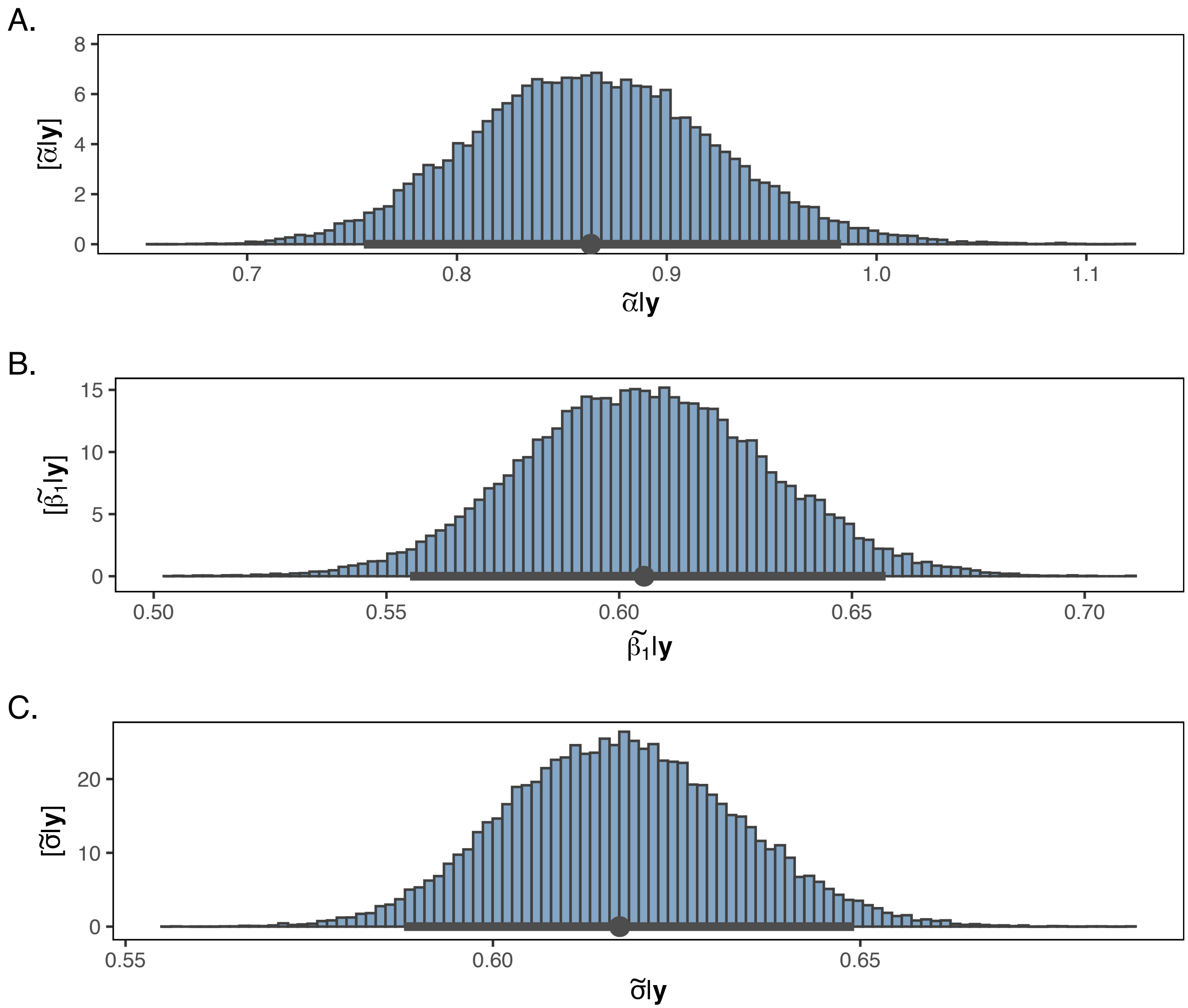

Figure C.4: Histogram of the posterior distribution of the parameters of the Bayesian power-law model (**A**: α; **B**: β_1; **C**: σ) for the relationship of soybean yield (Mg ha^{-1}) as a function of maize yield (Mg ha^{-1}) for crop performance trials conducted in 11 states of the US Corn Belt (Illinois, Iowa, Kentucky, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin). Estimated Bayesian power-law function: $y = 0.87x^{0.61}$. The gray line indicates the 95% credible interval, and the circle indicates the mean estimate for each parameter.

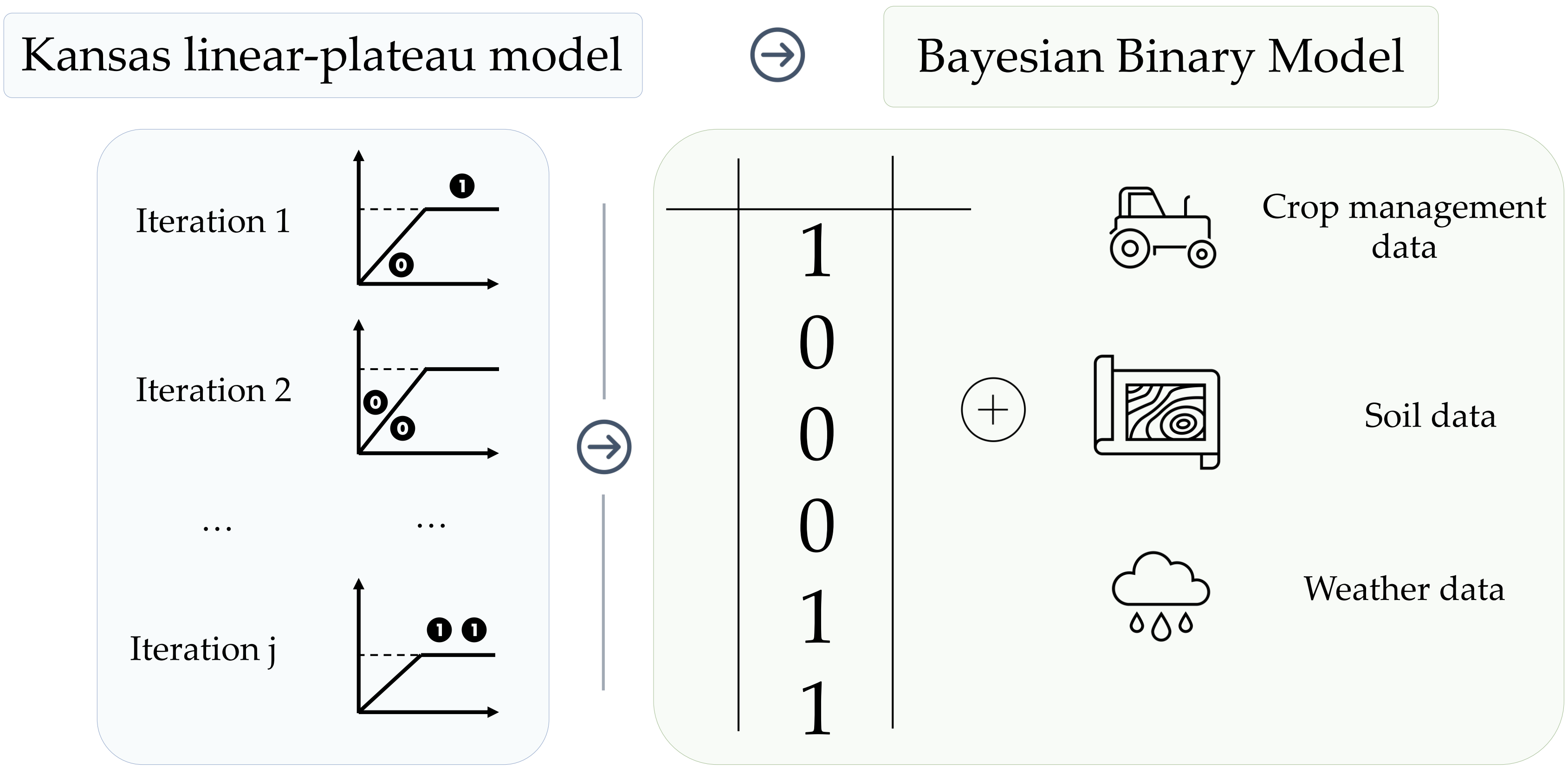

Figure C.5: Theoretical representation of the Bayesian binary model using the posterior distributions from the Bayesian linear plateau model developed for the Kansas crop performance trials dataset.

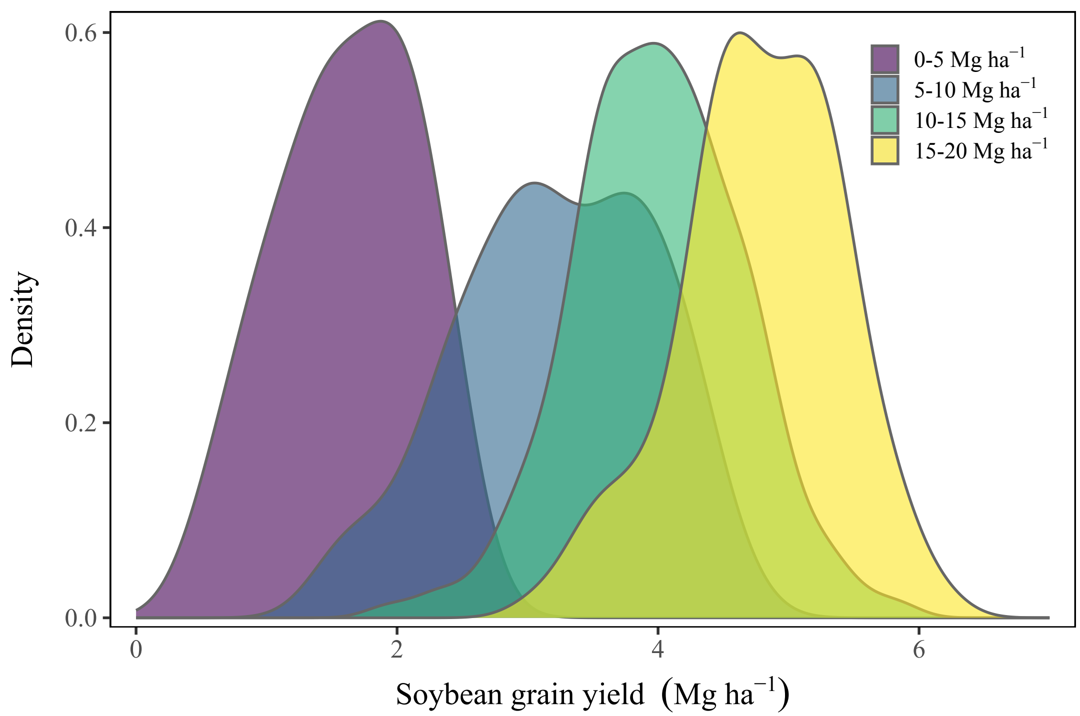

Figure C.6: Density plots of soybean yield (Mg ha^{-1}) corresponding to four maize yield categories (0-5, 5-10, 10-15, and 15-20 Mg ha^{-1}) for the US Corn Belt.

Table C.1: URLs used to access data from crop performance trials conducted in 11 US Corn Belt states.

State	URL
Illinois	https://vt.cropsci.illinois.edu/
Iowa	https://www.croptesting.iastate.edu/
Kentucky	https://graincrops.ca.uky.edu/variety-testing
Michigan	https://www.canr.msu.edu/varietytrials/
Minnesota	https://varietytrials.umn.edu/
Missouri	https://varietytesting.missouri.edu/
Nebraska	https://cropwatch.unl.edu/varietytest
North Dakota	https://vt.ag.ndsu.edu/
Ohio	https://u.osu.edu/perf/
South Dakota	https://extension.sdstate.edu/tags/crop-performance-testing
Wisconsin	-