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# Integrating Field Data and a Modeling Approach to Inform Optimum Planting Date × Maturity Group for Soybeans under Current and Future Weather Conditions in Kansas

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**Abstract:** Optimizing planting date by maturity group (PD × MG) is critical to increase productivity and reduce production risks. Understanding the effect of management, not only under current, but also future weather conditions, is even more relevant for developing effective mitigation strategies. This paper provides an analysis of the optimum combinations of soybean PD × MG management in the central-eastern region of Kansas (United States) for both current and future weather conditions. Three geographical clusters illustrating the main environmental and management characteristics were defined within the central-eastern region of Kansas. The Agricultural Production Systems Simulator platform was employed to explore PD × MG combinations (PD from mid-April to mid-July; MG from III to VI) comparing current (2011–2021) and future (2042–2052) weather conditions. Overall, early planting dates produce greater yields, but reduce their stability over time (with a 15% increase in yield variation relative to late planting) across the clusters. Late planting dates resulted in a reduction close to 27% for soybean yields relative to those obtained by planting at early dates under current weather conditions. Furthermore, longer maturity groups (IV, V, and VI) resulted in a reduced yield penalty when planting time was delayed under the current weather conditions. However, this combination did not always represent the strategy that maximized yields.

**Keywords:** soybean seed yield; crop modeling; management practices; future weather

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## 1. Introduction

Soybean (*Glycine max L. (Merr.)*) is an important crop due to its contribution as a source of protein and oil [1]. Improvements in crop management increased soybean yields [2] in concert with the increasing demand for global food production. The optimization of management technologies is still a challenge for many growers, with a high degree of uncertainty in the process of selecting the main factors influencing crop production [3,4]. Less information is available for the western region of the main producing soybean area in the United States (US). Within this region, Kansas ranked 9th as a major producer of soybeans in the US, highlighting the importance of providing critical information on management technologies for increased production.

Soybean seed yield is impacted by various production factors, including the selection of genotypes, planting date, and the seeds' interaction with the growing environment (soils and weather conditions). Although the environment is often the limiting factor determining yield, agronomic decisions such as the modification of the planting date and the selection of cultivars are important components that producers can manage [5]. The soybean planting window in Kansas is roughly 3 months, from early April to early July, with a quantifiable reduction in maximum yields of 20 kg/ha/day corresponding to delays in planting [6]. Cultivars in maturity groups III and IV are the most grown throughout central and eastern Kansas, with longer maturity groups V and VI more commonly grown in the southeast region. Previous research has identified some of the impacts of variety selection and planting date on performance [7–9]; however, the resultant recommendations were limited due to a global analysis (not site- or regional-specific) and available field data (e.g., variety trials lacking a range of planting dates and varieties). Thus, a new formal analysis is relevant to guide the process of selecting these key factors.

To provide actionable decisions based on limited field research, the implementation of a crop growth model can help guide the selection of the best scenario for planting date and maturity group for soybeans under changing weather conditions. The selection of the best management practices should not only consider a few experimental years of study, but also the effects of longer trends in weather variation and their influences for optimizing management practices for increasing seed yields. This approach can be explored using the Agricultural Production Systems sIMulator—APSIM [10]. In addition to exploring the effects of the current weather to provide timely outcomes for growers, the effect of future weather conditions is also a relevant research topic to determine the impact on seed yield and guide future research investments. A recent study investigated the relevance of soybean growth models for climate change impact assessments, highlighting the changes in model performance based on the model utilization, assumptions, and approach to evaluate future weather [11]. Different crop growth models highlight the effect of future weather conditions negatively impacting soybean yield by increases in temperature and changes in precipitation patterns [12–14]. Although these predictive models may have limitations, the implementation of these models can assist in targeting key plant traits from a breeding perspective and focus resources on improved management to ameliorate the potential implications regarding soybean seed yield from future weather conditions.

The introduction of modern soybean genotypes requires providing more up-to-date information on the current optimal planting dates and maturity groups across the most prominent soybean producing region in Kansas. The optimal planting times for these modern cultivars under varying soils are not well known for the current weather conditions. Following this rationale, the main aims of this study are to (i) investigate, via utilization of a crop growth model, the best combination for planting time × maturity group within a spatial framework, and (ii) quantify the effect of future weather (30 years) conditions on seed yield relative to the benchmark soybean production (current weather) under different scenarios for planting date × maturity group in the central-eastern region of Kansas, US.

## 2. Materials and Methods

### *2.1. Data Collection*

Soybean seed yield data were gathered from three sources across 13 sites in central and eastern Kansas, United States, from 2014 to 2021 (Figure 1, Supplementary Table S1). The final dataset encompassed a planting window from 6 April to 11 July, four maturity groups (III, IV, V, and VI), plant density from 25 to 38 plant $m^{-2}$, and harvest dates from 8 October to 29 November.

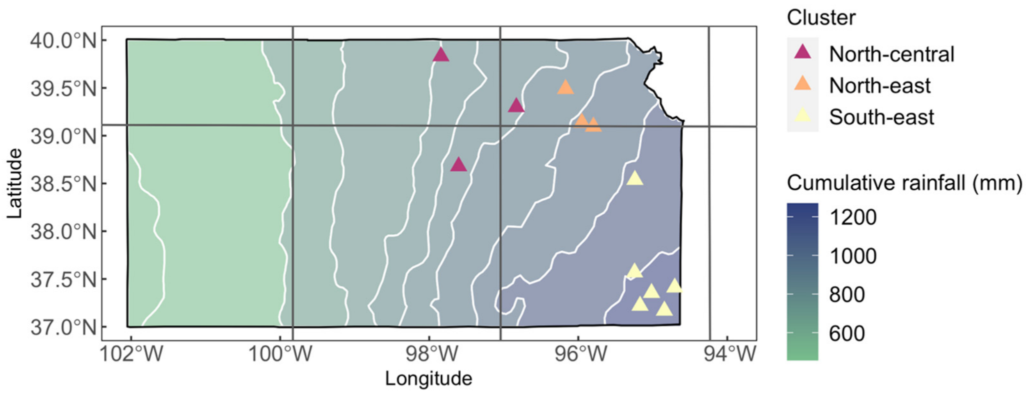


**Figure 1.** Map of Kansas with the three clusters (represented by triangles with distinct colors) for crop seasonal cumulative annual precipitation (mm) and the T42 GCM grid resolution (represented by solid lines) reported by [15].

For each site, the current standard planting date was defined as the most frequent planting date (statistical model) of the dataset across years (Supplementary Figure S1). Then, early planting dates were defined as those before the standard planting date, and the late dates are the plantings carried out after this time.

Using the coordinates of each site (Supplementary Table S1), soil data were gathered from USDA-SSURGO (https://www.nrcs.usda.gov/, visited 10 March 2022) up to the 200 cm depth, and the soil parameters were calculated using the function within the APSIM next generation package [16]. Furthermore, long-term weather records (1984–2021) were obtained from Kansas Mesonet (https://mesonet.k-state.edu/weather/historical/, visited: 25 February 2022), using the closest weather station to each site (Supplementary Table S1, maximum distance ~50 km). The variables included maximum and minimum temperatures, precipitation, and solar radiation, in daily time steps. For the Riley and Belleville sites, solar radiation data were retrieved from NASA POWER (https://power.larc.nasa.gov, visited: 1 March 2022). The whole dataset was employed for the spatial clustering (Section 2.2) and the future weather data generation (Section 2.4), and a subset (2011–2021) was employed to represent the current weather data (Section 2.4).

### 2.2. Spatial Clustering

The sites (Supplementary Table S1) were grouped into regions with similar weather, soil, and management characteristics using the spatial fuzzy c-means (FCM) clustering algorithm [17] with the Geocmeans package [18] in R [19]. The variables included (Supplementary Table S2) in this analysis were: (i) management (standard planting date), (ii) main soil characteristics (texture as the percentage of sand, silt, and clay), and (iii) weather (maximum temperature and cumulative rainfall).

Soil texture was included due to its relevance in defining available crop water and its relative invariability in time [20,21]. The maximum temperature variable included for the clustering process was obtained as the daily maximum temperature, averaged by month, considering primarily the months of July, August, and September as a relevant period for yield formation (Supplementary Figure S2). This period includes the crop growth stages of pod formation [22], which are highly sensitive to heat stress [23]. Cumulative rainfall for the soybean growing season (May to October) was calculated based on the observed current growing season in the database. Maximum temperature and cumulative rainfall were selected for inclusion in this analysis due to their impact on yield and their relevance when defining future weather scenarios [15]. Data sources for these variables are listed in Section 2.1.

### 2.3. Model Validation

The Agricultural Production Systems Simulator (APSIM) Next-Generation is a modular modeling system that has been used in many applications, including farming systems design and the assessment of climate forecasting [24]. APSIM generic genotypes for soybeans (Supplementary Table S3, [25]) included in the APSIM-Soybean model [26], https://builds.apsim.info/api/nextgen/docs/Soybean.pdf, visited: 1 September 2022) were used to perform simulations to compare observed grain yields from 66 site-years, testing different planting dates and maturity groups (Supplementary Table S1). Due to the lack of capability of APSIM Next-Generation to represent the early termination of the crop cycle due to frost events, the crop growing season was terminated at the observed harvest day, when this date was available (Supplementary Table S1). Although the lack of crop phenology data provided a limitation, the simulated flowering dates agreed with those expected for the region (Supplementary Figure S3, https://quickstats.nass.usda.gov/, visited: 10 April 2022), denoting the satisfactory performance of the generic cultivars from APSIM [25]. Soil and weather data sources are listed in Supplementary Material.

The performance of the model was evaluated for the whole dataset as a first step, and then individually for each region defined in Section 2.2, using root mean square error (RMSE), relative root mean square error (RRMSE), percentage lack of precision (PLP), percentage lack of accuracy (PLA), and Kling–Gupta model efficiency (KGE, Kling et al., 2012). The Metrica package was used for analysis [27] in R (R Core Team, 2021).

*2.4. Developing Scenarios for Yield Stability for the Current and Future Weather*

Future weather data (2022–2052) were generated using long-term weather records (1984–2021) for each site to define the historical seasonality, via the decompose function with the stats package, in R [19]. Future seasonal trends of temperature and precipitation were subtracted from the extensive study done by [15]. Briefly, this study examined the seasonal trends in air temperature and precipitation patterns in a decadal manner as the average monthly output of 21 global climate models under the Special Report on Emissions Scenarios A1B scenario used in the IPCC fourth assessment report (AR4) for six grid cells representing Kansas. These grid cells correspond to the T42 GCM grid resolution (Figure 1). Overall, this approach demonstrated an excellent agreement between the multi-model ensemble mean output and observations for temperature ($r^2$ = 0.99, RMSE = 0.48–1.48 °C), as well as a good agreement for precipitation ($r^2$ between 0.64 and 0.89, RMSE = 322–1144 mm). However, one limitation is the lack of consideration of the effect of the CO2 increment. Each site was treated independently according to where the grid cell was located [15]. One limitation of this approach is the lack of consideration of the effect of the $CO_2$ increment.

The model was set to plant soybean crops on 15 April, 1 May, 15 May, 1 June, 15 June, 1 July, and 15 July in each site from 1984 to 2021, with the current weather and simulated future weather from 2022 to 2052. The model included four maturity groups using the generic genotypes for soybean from the APSIM ([25], Supplementary Table S3; these cultivars can be found in the APSIM platform as: 'Generic_MG3', 'Generic_MG4', 'Generic_MG5', and 'Generic_MG6'). The range of planting dates and the selection of maturity group was based on the observed dataset. The plant density was set as 32 plants $m^{-2}$, and row spacing was set as 0.75 m to evaluate yield and stability across the different combinations of planting date and maturity groups under the current and future weather conditions. Moreover, it is worth mentioning that the simulations were carried out on the same 13 sites used to validate the model.

To interpret and compare the differences between both scenarios, the last decade of the current (2011–2021) and future weather (2042–2052) were fitted with a linear mixed model using the lme4 package [28] in R [19] and then analyzed with ANOVA [19]. For this model, grain yield was a function of maturity group, planting date, cluster, and their interactions, with the site as the random component. Each region was evaluated independently to explore the best combination, as well as the change in every region in both decades. Pairwise comparisons were conducted using the emmeans R package [29], using the Tukey method at a significance level of $\alpha$ = 0.05 in R [19].

## 3. Results

*3.1. Spatial Clustering*

Three clusters were defined within the region of study in Kansas: (i) north-central, (ii) north-eastern, and (iii) south-eastern, named according to their spatial distribution (Figure 1). The clusters differed in their cumulative annual rainfall. These differences were driven by the spatial distribution of each cluster, as Kansas is characterized by a precipitation gradient increasing towards the south-east, but moving from high to low precipitation from east to west.

The south-east cluster showed the latest standard planting date and the greatest seasonal cumulative precipitation (Supplementary Table S1). In contrast, the north-central cluster had the lowest seasonal cumulative precipitation (less than 200 mm less, relative to the south-east cluster). While the standard planting date and accumulated rainfall exhibit notable differences between clusters, the temperature and soil features differed only slightly between clusters (Supplementary Table S1).

### 3.2. Model Validation

The APSIM model simulated soybean seed yield, reflecting an adequate performance (KGE = 0.44) for the whole study region (Table 1). The difference between observed and simulated yields, expressed as RMSE, was 1084 kg ha$^{-1}$, which represented 29% of the observed mean (RRMSE). The model over-predicted yields relative to the observed yields (Figure 2). Overall, the validation model for each maturity group adequately modeled the seed yield dynamics for this study. This result highlights the capability of the generic cultivars to capture the yield variability of the maturity groups.

**Table 1.** Measure of agreement between observed and simulated data, for the entire study area. RMSE, root mean square error; RRMSE, relative root mean square error; PLP, percentage lack of precision; PLA, percentage lack of accuracy; KGE, Kling–Gupta model efficiency.

| Metric | Value |
|---|---|
| RMSE | 1084 |
| RRMSE | 0.29 |
| PLP | 68 |
| PLA | 32 |
| KGE | 0.44 |

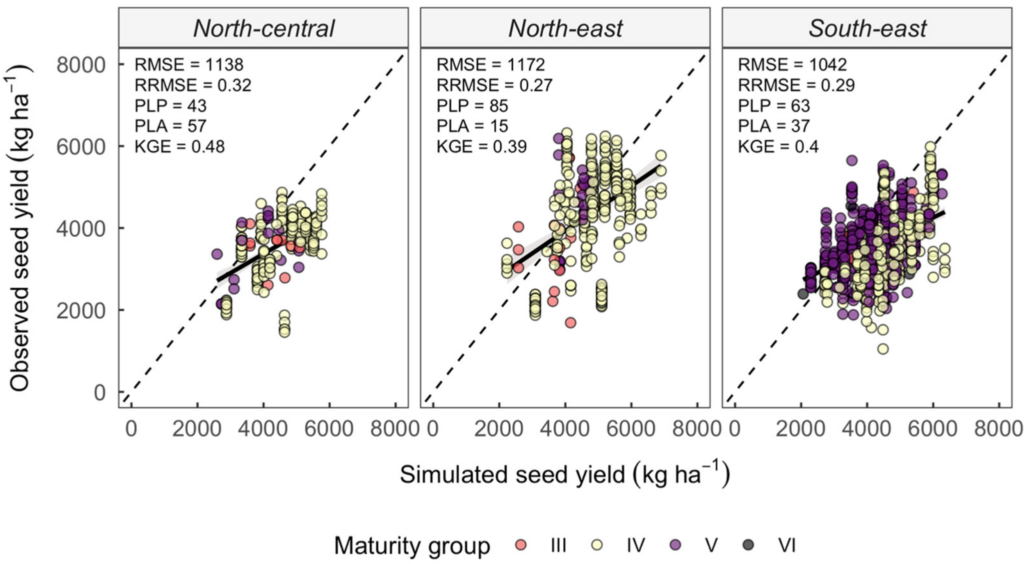


**Figure 2.** Observed versus simulated seed yield for the three clusters (north-central, north-eastern, and south-eastern) with soybean maturity groups III, IV, V, and VI (represented by distinct colors). The dashed line represents the 1:1 line. RMSE, root mean square error; RRMSE, relative root mean square error; PLP, percentage lack of precision; PLA, percentage lack of accuracy; KGE, Kling–Gupta model efficiency.

As a second step, the APSIM model performance was evaluated individually for each cluster (Figure 2). The model simulated more accurately than precisely (Figure 2, PLA < PLP) in the south-eastern and in the north-eastern clusters. In the north-eastern cluster, the soybean seed yield was simulated with an RRMSE of 27%. Meanwhile, in the north-central cluster, the model simulated with more precision than accuracy (PLP = 43 < PLA = 57), and with good efficiency (KGE = 0.48).

### 3.3. Developing Scenarios for Yield Stability for the Current Weather

The simulated seed yield for the current weather varied depending on the cluster. The south-eastern cluster presented the highest yield (mean = 4383 kg ha$^{-1}$), whereas the north-central cluster had the lowest yield (mean = 2774 kg ha$^{-1}$), with all simulations under rainfed conditions. Conversely, the standard deviation did not change among clusters, but varied depending on the planting date. In general, early planting produced higher yields, but less stability, for all the maturity groups within all the clusters (Figure 3).

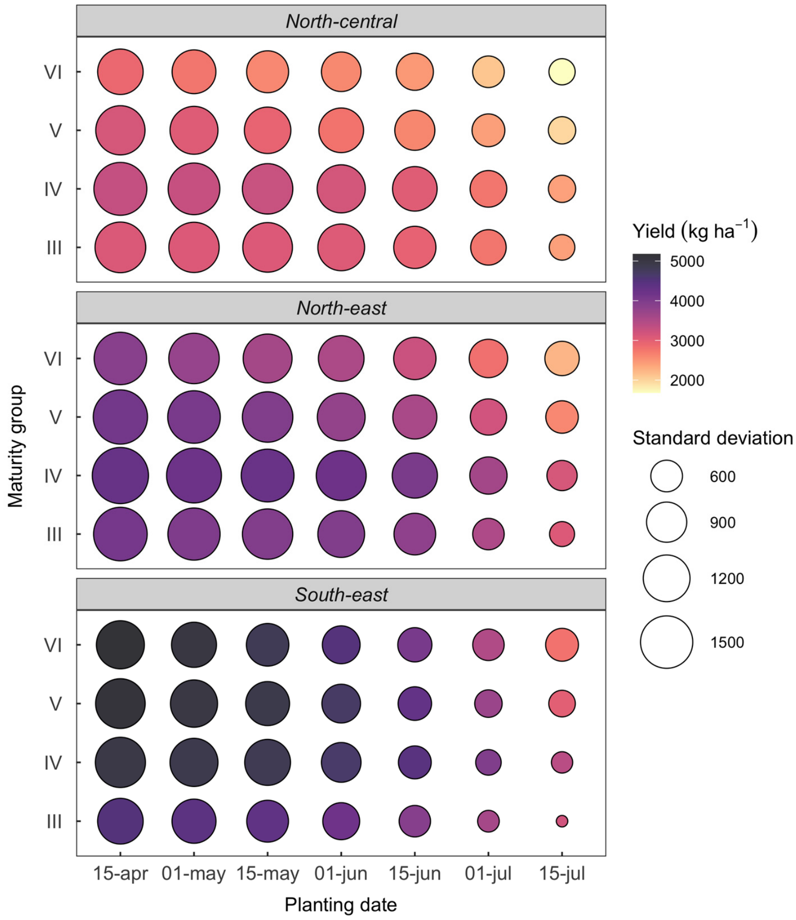


**Figure 3.** Simulated seed yield for the current weather (2011 to 2021), where darker colors represent higher yields, and the size of the bubbles represent the standard deviation across years, within each cluster, for the different combinations of planting dates and maturity groups. Planting dates are referred to as day/month.

The most drastic change in soybean yield due to maturity group and planting date was observed in the south-east (Figure 3). In the south-east, maturity groups IV, V, and VI showed satisfactory results when they were planted from 15 April to 1 June (Figure 3, Supplementary Table S4). These dates maintained similar yields, but increased their stability over the years at the later dates. In the latest planting date (15 July), it was notable that the standard deviation changed depending on the maturity groups, with reduced values for shorter maturity groups.

The north-east presented an intermediate yield (mean = 3662 kg ha$^{-1}$). This cluster did not show a significant difference between the interaction of planting date and maturity group (Supplementary Table S4). In the early dates (15 April to 15 May), seed yield and standard deviation did not vary between maturity groups (Figure 3). Moreover, the yield for maturity group IV did not change until June 15, but the standard deviation of the yield for this variety decreased with late planting times. For the latest planting dates (1 July to 15 July), the yield was greater when the maturity group was shorter, but the stability did not change among maturity groups.

The north-central cluster, as well as north-eastern cluster, did not present a significant difference between the interaction of planting date and maturity group (Supplementary Table S5). Maturity group IV showed the best results, maintaining high yields and reduced variability until 1 June (Figure 3). Similar to the results for the north-central cluster, the north-eastern cluster in the latest planting dates displayed better yields with the shorter maturity group, with less variation in the standard deviation among soybean varieties.

### *3.4. Developing Scenarios for Yield Stability for the Future Weather Conditions*

In general, the analysis predicted that in the next 30 years, seed yield would decrease by 21% (Supplementary Figure S4). The extent of yield reduction varied for the different clusters. The north-central cluster was the least affected by the future weather, presenting the lowest decrease in seed yield (4%), while the south-eastern cluster experienced the largest yield decrease (39%). This result was associated with future weather changes in each cluster (Supplementary Table S6). The south-eastern cluster was the most affected by the future weather scenario, decreasing its cumulative seasonal precipitation by ~26%. Additionally, this cluster presented the highest increase in temperature, especially for the summer season.

In the north-central cluster, maturity groups IV, V, and VI showed a higher decrease in seed yield with early planting dates (Figure 4). In contrast, maturity group III showed a different pattern. For the earlier dates (15 April–1 May), maturity group III showed an increased yield under future weather conditions in comparison with the current weather. Conversely, late planting dates (1–15 July) showed good yield responses with the later maturity groups (V and VI) under the future weather (2042–2052) conditions, presenting a slight increase in yield (Figure 4). Likewise, maturity groups III and IV showed a low yield decrease at the latest planting date (15 July).

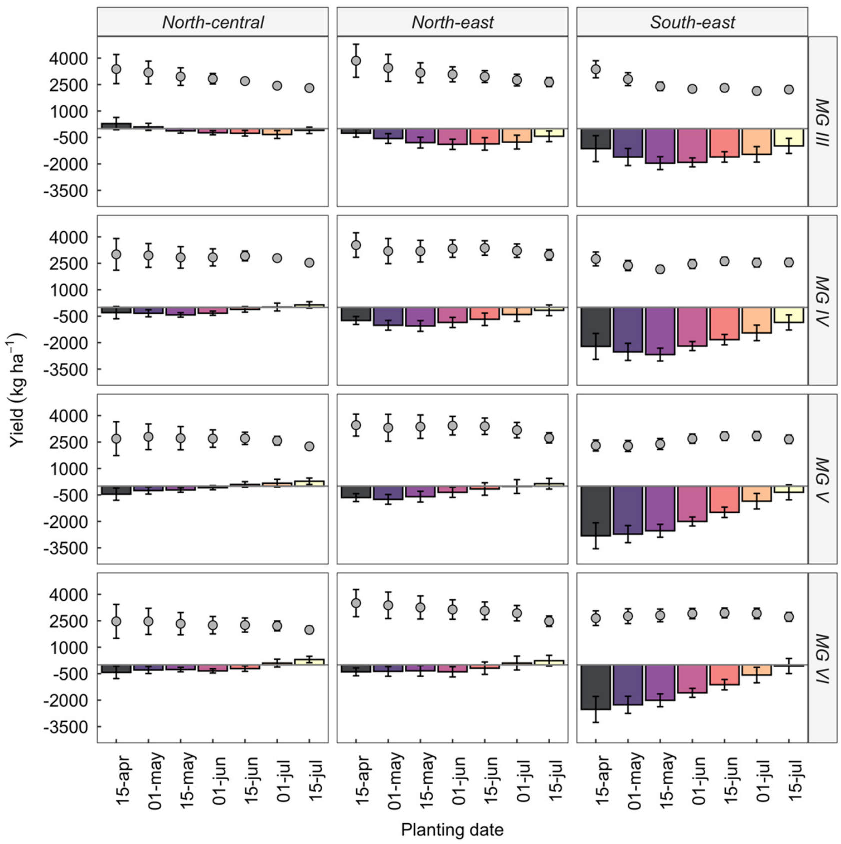


**Figure 4.** Average difference between future and current weather yields (bars show the difference between the year ranges 2042−2052 vs. 2011−2021) and seed yield under future weather scenarios (points show the years 2042 to 2052) for the different combinations of planting dates and maturity groups within the three clusters in Kansas. Vertical lines represent standard deviation of the yield difference across different sites within the clusters (lines over the bars) and across years, and different sites in each cluster (lines over the points). Planting dates are referred to as day/month.

In the southeast, the most negatively impacted location under future weather scenarios (Figure 4), the early planting dates showed a larger decrease in yield (2235 kg $ha^{-1}$) than late did the later dates (1052 kg $ha^{-1}$). Furthermore, the latest planting date (15 July) demonstrated a smaller yield decrease for all maturity groups. In the case of maturity groups III and IV, intermediate planting dates (15 May, and 1 June) were the most affected.

In general terms, early planting dates maximized seed yield in the northern clusters, even with the impact of future weather. However, late planting dates (15 June to 1 July) increased in importance for yield maximization in the south-eastern cluster (Supplementary Table S7), without changing the superiority in yield of the later maturity groups.

## 4. Discussion

This study provides a quantification of the optimum planting date by soybean maturity group combinations under current and future weather conditions in the western border of the main US soybean producing region [30]. Even though there is a wide range of plausible planting dates in the central southern area of Kansas [6], an extensive and formal study of management optimization has not been previously reported for this region. This situation leads farmers to determine management strategies with uncertainty, not only on how to maximize yields, but also to consider its stability (yield variation) over time. Lastly, although the future weather for this region has been described [15], the overall impact on yield and crop management adaptation practices has not been formally assessed.

Several studies in the literature suggested that early planting dates may produce higher yields in the Midwest [5,31,32], and Southern regions of the United States [5,7,33]. Comparable results were shown in this research for the three clusters within Kansas. Additionally, [7] reported a decline in yield of 13–36% for late planting dates in the Southern region of the US (United States), similar to the simulated yield decreases observed in this study (24–30%). Furthermore, when focusing on the maturity by planting date interaction, [8] described a decrease from 7% (for maturity group, MG III) to 18% (for MG V) in the US Mid-Southern region when the planting dates were late. Similarly, this study revealed a larger impact on yield across the explored genotypes (from 25 % for MG III, to 44% for MG VI), highlighting the conclusion that maximizing yields is only possible if the selection of variety and planting dates are tailored to regional environmental factors [33]. Usually, late planting shifted the reproductive stage into a less favorable environment with shorter days [34–36], and early planting increased the risk of crop failure due to late spring frosts [32,37]. As reported in this current study, early planting dates maximized yields, but penalized stability, whereas late planting dates penalized yield, but resulted in higher stability [6,38].

Not surprisingly, the effect of future weather conditions was reflected in a reduction in soybean yields (ranging from 4 to 39%), pointing out the potential variation under different environmental conditions. Furthermore, previous studies suggested that water deficit is one of the main causes of the yield gap [39,40]. Likewise, our study reflected comparable reductions in yield with less seasonal precipitation. Several studies have already documented reductions in soybean yield and its stability under future weather conditions [12,40–43], ranging from 19 to 82%. However, those past investigations focused on quantifying yield reductions, without providing any adaptation strategies [44]. In this context, crop management arises as an important mechanism to mitigate the impact of climate change on yield [39,45–47]. Among the management options, the selection of planting date [43,45,48,49] and maturity group [46,47] are crucial factors that can be managed by producers. According to [47,49], delaying the planting date could mitigate the yield penalty under future predicted weather conditions, as reported for Brazil and China, respectively. Similarly, in central-east Kansas, results showed that for future scenarios, long maturity groups (IV, V, and VI) with late planting dates provide smaller yield reductions relative to early planting dates. To obtain maximum yields under future weather conditions, early planting dates remain the best choice for farmers. Nonetheless, for the southeast cluster, long maturity groups can help to express their compensation capability [49] relative to the short duration of the growing season due to the late planting dates.

Some limitations in this study were: (i) a limited observed dataset on crop phenology for improved model calibration [50,51], (ii) a lack of observed soil data, necessitating data generation via the average of a large scale, not related to a specific zone [52], and (iii) a lack of relevant geographical representation (more environments). Overall, this modeling approach captures the aim of this study correctly and provides a starting point related to improving the planting date × maturity group management in this region as a way to mitigate future weather conditions. Future research could enhance the quality of this information by providing observed data with phenology to assemble a correct model calibration and validation [50,51], thus improving its accuracy in predicting events. Nevertheless, the capability of the generic cultivar available in APSIM to capture the yield variability of the maturity groups was remarkable. However, future research studies should focus on collecting a dataset with greater spatial distribution and high-resolution soil mapping, which are critical to attain more suitable "site-specific" recommendations regarding the planting date with maturity group across this region.

## 5. Conclusions

This study highlights the potential benefits for farmers when selecting the optimal combinations of planting dates by maturity groups for soybean yield. The most relevant outcomes of this study under current weather conditions are: (i) farmers can maximize soybean yield by planting in April to early May, and (ii) farmers can achieve more yield stability (less variation) over time when planting late, but with a clear yield penalty for maximum yields. For the future weather: (iii) yield reductions should be expected, but the selection of the right maturity group × planting date could be used as a mitigation practice, and (iv) later maturity groups (IV, V, and VI) can result in a smaller yield reduction for late compared to early planting dates.

**Supplementary Materials:** The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su15021081/s1, Figure S1: Distribution of planting dates in the 13 sites of the dataset from 2014 to 2021; Figure S2: Interval where setting pods occurs in the state of Kansas according to NASS-USDA (https://quickstats.nass.usda.gov/results/20E59F49-96CD-3192-AEF5-6B5B63E28C43, visited 11 December 2022); Figure S3: Comparison of days of the year where anthesis occurs between the simulated data and data obtained from the National Agricultural Statistics Service (https://quickstats.nass.usda.gov/results/21B7C2DA-A180-3470-A7F4-383E92588748, visited 11 December 2022); Figure S4: Simulated seed yield (kg ha$^{-1}$) across the 30 years of study within the three clusters in Kansas (North-central, North-east, and South-east); Table S1: Data sources. KSU performance test; Table S2: Standard planting date, soil characteristics, and weather variables used to create the clusters; Table S3: Parameters included in the generic genotypes used from APSIM Next generation; Table S4: Soybean seed yield (kg ha$^{-1}$) for the different planting dates × maturity groups combination in the South-east cluster. Values within different letters are significantly different at $p < 0.05$; Table S5: ANOVA (Type III Wald chi square tests) of the current weather (2012–2021) for the three clusters within Kansas; Table S6: Climate change in the future (2043–2052) compared to the current weather (2012–2021) in the three clusters in Kansas; Table S7: Soybean seed yield (kg ha$^{-1}$) for the different planting dates × maturity groups combination within the three clusters in Kansas. Values within different letters are significantly different at $p < 0.05$.

**Author Contributions:** Conceptualization, E.v.V., A.J.P.C. and I.A.C.; methodology, E.v.V. and A.J.P.C. software, E.v.V. and A.J.P.C.; validation, E.v.V. and A.J.P.C.; formal analysis, E.v.V. and A.J.P.C.; investigation, E.v.V., A.J.P.C. and I.A.C.; resources, I.A.C., E.A., G.S., S.D. and J.L.; data curation, E.v.V. writing—original draft preparation, E.v.V., A.J.P.C. and I.A.C.; writing—review and editing, E.v.V., A.J.P.C., E.A., G.S., S.D., J.L. and I.A.C.; visualization, E.v.V.; supervision, I.A.C.; project administration, I.A.C.; funding acquisition, I.A.C. All authors have read and agreed to the published version of the manuscript.

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**Data Availability Statement:** Data will be available on request.

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