Advancing Adaptive Agricultural Strategies: Unraveling Impacts of Climate Change and Soils on Corn Productivity Using APSIM

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A paper from the Proceedings of the
16th International Conference on Precision Agriculture
21-24 July 2024
Manhattan, Kansas, United States

Abstract.
With unprecedented challenges to achieve sustainable crop productivity under climate change and varying soil conditions, adaptive management strategies are required for optimizing cropping systems. Using sensors, cropping systems can be continuously monitored and the data collected by them can be analyzed for making informed adaptive management decisions to enhance productivity and environmental sustainability. But sensors reflect present conditions or provide some history, yet decisions should also consider what is yet to occur. This study leverages the use of the state-of-the-art biophysical model, Agricultural Production System sIMulator (APSIM), which takes the genetics (G), environmental (E), and management (M) data, to predict the growth and yield of corn (Zea Mays L.), a major crop for United States. Using digital twin models, we can project outcomes of different management decisions under varying environmental conditions and soil types and in context of climate change. The key objectives of this research were to elucidate the impacts of varying soil conditions and climate scenarios on corn growth and yield and further identify the best optimum practices (planting date, amount of nitrogen fertilizer, and amount of irrigation) to improve yield and profitability. In doing so, we characterize system resilience by running simulations over 38 years of past weather data for four locations having four different soil types and under two different climate scenarios.

Keywords.
APSIM, Adaptive Management, Biophysical Modeling, Climate Change, Digital Twin, Irrigation Management, Nitrogen Fertilizer Management, Simulation

Introduction

Climate change poses a formidable challenge to global food security as variations in meteorological parameters profoundly impact crop production. These variations in meteorological parameters constitute increases in nocturnal and diurnal warming and irregular rainfall patterns and causes abiotic and biotic stresses (Abendroth, 2021). This issue is particularly critical for corn (*Zea Mays* L.) production in the United States, given its substantial economic importance and its role as a major source of calories and nutrients both for humans and animals. To meet the food demands of growing global population, which is expected to be 9.8 billion by 2050, cereal production, including corn, must increase by approximately 70-100% (Bayu, 2020; Sharma, 2022). This increase in corn production can be achieved by developing genotypes and adaptive farm management strategies that are resilient to new climatic conditions. Adaptive farm management strategies are important because once the seeds with given genetic (G) traits have been sown, the characteristics and response of the seeds are fixed and cannot be changed and new genetic traits cannot be added and their realized performance can be only modulated by changing the management practices in the given environmental (E) conditions This interplay between G, E, and M has been widely studied to design ideotypes for the future (Jamshidi, 2023). Yet, there is a paucity of research focused on recommending adaptive M practices tailored to local conditions and understanding how these M strategies interact with others to impact corn yield.

Therefore, there is a pressing need to reframe the research question related to agricultural production, aiming to enable stakeholders to make informed and adaptive farm management decisions in context of climate change (Thornton, 2014). Some of the management practices that could be changed/adapted in context of climate change are planting date, date(s) and rates of nitrogen (N) fertilizer, and irrigation rules. For example, planting corn early in the season can mitigate the impact of excessive heat in the growing season and can potentially preserve yield. However, planting too early in the season can decrease yield due to frosts (Pathak, 2023). Applying too little N fertilizer reduces yield, while excessive amounts result in diminishing returns as corn N uptake becomes constant, leading to negative ecological and environmental consequences. Additionally, water stress during the critical growth stages of corn production will reduce yield while irrigating more increase incidence of disease and water logging (Pathak, 2023).

Biophysical (process-based) or crop growth models can be used to understand the consequences of the variation in management practices in context of climate change (Baum, 2020). These models are built upon the physiological understanding of plant growth and processes and are represented in non-linear differential equations. Some of the commonly used crop growth modeling platforms include Agriculture Production System sIMulator (APSIM) (McCown, 1996), Decision Support for Agrotechnology Transfer (DSSAT) (Jones, 2003), and World Food Studies (WOFOST) (Van Diepen, 1989). Typically, these models are often used for qualitative understanding of crop response in terms of G, E, and M rather than for their quantitative prediction accuracy. (Pathak, 2023) used APSIM to simulate the growth of corn under different N fertilizer treatments and evaluate the effect of rainfall on corn yield and other environmental factors. Similarly, (Baum, 2020) used APSIM to evaluate how the planting dates of corn might change in Iowa in context of climate change. They simulated the corn production under six climate change scenarios and reported that the optimum planting date will shift by ±5 days with an increase in yield by 10%. Nandan (2021) simulated the corn production under different climate scenarios and found that that reduction in 30% of precipitation could reduce the mean yield by 10% and will require adaptive irrigation strategies to mitigate the loss. However, none of these studies have specifically addressed how the interactions between different management practices might affect corn yield under varying climate change scenarios. Therefore, the primary objective of this research is to examine the influence of distinct management decisions, namely planting dates, N fertilizer application rates, and irrigation protocols, on corn yields within four varied soil types and under two climatic conditions. We will comment on how individual treatments and their interactions impact corn yield.

Materials and Methods

Model Description

APSIM is a mechanistic, process-based, open-source simulator that helps to simulate farming systems including crops, soil, and environmental models (Holzworth, 2014). Its popularity has surged due to its modular architecture and user-friendly interface (Brown, 2014). In this research, APSIM next generation (version 2022.6.7044.0) was used along with following modules: maize model, SOILN model, and SOILWAT to simulate the corn production under different weather conditions on the daily time steps (Soufizadeh, 2018; Probert, 1998).

Experimental Setup

In this study, diverse sets of management practices were simulated under different climatic conditions to understand its impact on corn yield. Three different planting dates, namely April 1 (early planting), April 30 (falls under optimum planting window), and May 30 (late planting) were simulated on APSIM. Furthermore, three different amounts of urea-N 142 kg/ha (75% of the common practice), 190 kg/ha (common practice), and 237 kg/ha (125% common practice) were included in the study along with two irrigation rules (zero irrigation and irrigation using 75 percent of plant available water content (PAWC) as trigger point and 100 percent of PAWC as stopping point). The N fertilizer was applied six weeks after planting, typically corresponding to the V4-V6 growth stage. Pioneer P1197 cultivar with a cumulative relative maturity of 111 days was used in this study and was sown at a population of 8 plants per m^2 with 1 bud per plant at a row spacing of 750 mm (about 2.46 ft) and a depth of 50 mm (about 1.97 in). To simulate the potential climate impacts, two global warming scenarios were followed (Filippelli, et al., 2020):

- Mid-century projections: low carbon dioxide emissions (550 ppm), where the base line daily temperature was increased by 2.5 K (2.5 °C) and base line daily rainfall was increased by 6%.
- End-century projections: high carbon dioxide emissions (670 ppm), where the base line daily temperature was increased by 5.5 K (5.5 °C) and base line rainfall was increased by 10%.

Site Description and Agrometeorological Data

The APSIM next generation (version 2022.6.7044.0) was used for running the simulation for four locations, namely Agronomy Center for Research and Education (ACRE) (40˚29’20.9” N, 87˚0’11.7” W), Northeast Purdue Agriculture Center (NEPAC) (41° 6' 51.85'' N, 85° 26' 56.03'' W), Southeast Purdue Agriculture Center (SEPAC) (39° 2' 28.64'' N, 85° 31' 24.24'' W), and Pinney Purdue Agriculture Center (PPAC) (41° 27' 3.61'' N, 86° 56' 28.51'' W). The APSIM next generation facilitates direct download and integration of weather and soil data into the simulation. The weather data required for the experiment simulation was linked with the NASA POWER gridded database (https://power.larc.nasa.gov/data-access-viewer/) and was directly downloaded by the APSIM interface for ACRE farms into APSIM-readable format(.met extension) from 1984 to 2021. The weather data included six weather variables: maximum and minimum temperatures (degrees Celsius), total precipitation (millimeters per day), average incident shortwave radiation (Megajoule per square meter per day), wind speed (meters per second), and specific humidity (grams of water per kilogram of dry air). Additionally, APSIM is linked with ISRIC soil database (https://www.isric.org/), which provides the soil information by location. The data includes soil features from 0 cm to 180 cm depth, encompassing physical properties like soil bulk density, wilting point, field capacity, saturation point, and soil saturated conductivity; chemical properties such as soil pH; and organic properties including organic carbon content and are presented in Appendix table 1 to 4. In this study, both the weather and soil data were directly downloaded and integrated into the simulations, but the weather file remained the same across four locations to evaluate the effect of changing soil properties on yield. For changing the weather files as per climate change, the simple climate controller plugin of APSIM was used to change the temperature, rainfall, and carbon dioxide.

Statistical evaluations

Simulation results from APSIM were exported into excel (.xlsx) format and subsequently utilized in RStudio for statistical evaluation, namely analysis of variance (ANOVA) to determine the effect of different treatment on corn yield.

Results and Discussions

Effect and interaction of management practices on corn yield under different climate scenarios and soil types

Figure 1 and Table 5 (in appendix) show that planting date, N fertilizer amount, irrigation rules, soil types, and weather scenarios have significant impact on corn yield.

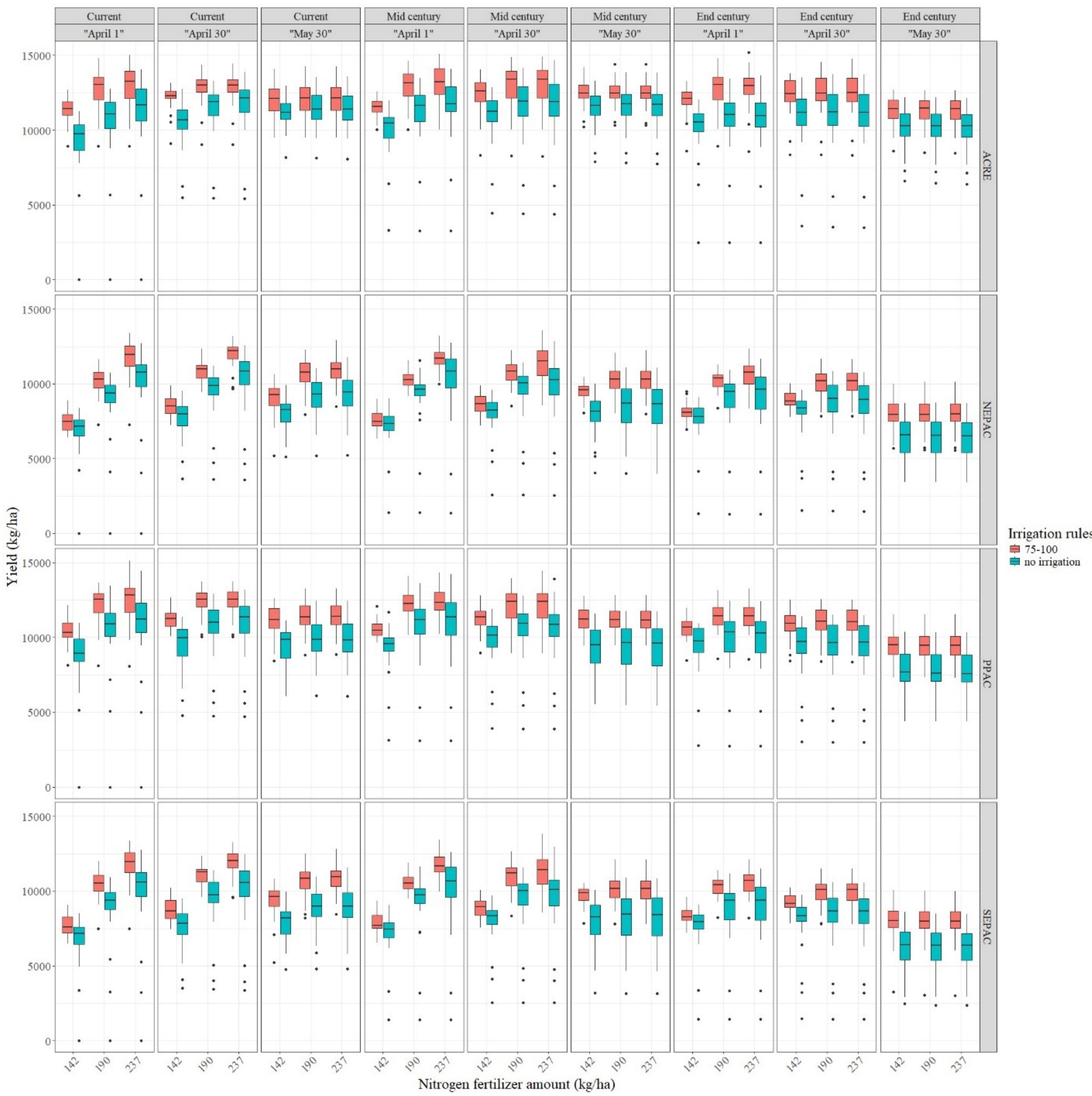

Figure 1: Simulated effect of nitrogen fertilizer, irrigation rules, location (soil type), and weather scenarios on corn yield

Planting within the optimum window results in higher yield, while misalignment reduces yield by exposing plants to heat stress or frosts. The results align well with the literature (Van Roekel, 2011), where they reported that corn yield decreases around15 to 30% with the delay in four weeks of planting. Corn yield is highly dependent on the amount of N fertilizer applied, as seen in Figure 1, except for mid-century and end-century late planting (May 30). These findings align with existing literature (Zelenák, 2022), which reported that corn yield increased approximately 5000 kg/ha, with the increase in N fertilizer rates from 0 kg/ha to 150 kg/ha. This increase in yield is because N fertilizer promotes plant growth, increases biomass, and helps plants to reach their genetic yield potential (Soufizadeh, 2018).

In addition to N fertilizer amount, water availability also significantly affects corn yield (p-value < 0.0001). Figure 1 illustrates that the application of irrigation improves the corn yield significantly across all locations and under different climate change scenarios and is also shown in (Pathak 2023). Irrigating reduces corn sensitivity to precipitation, by supplementing soil moisture required at critical growth stages of corn development, particularly during the grain filling stage. From the figure 1, it is clearly evident that why Indiana farmers are now slowly adopting irrigation practices for corn production (Dong, 2023). (Ruis, et al., 2021) found that full irrigation can improve the corn yield by 11% as compared to limited irrigation, where water applied was 5 to 10 cm less than full irrigation. Apart from the management practices, which can be controlled by humans, climate scenarios (weather) and soil properties play crucial roles in determining corn yield. The figure shows that yield varies significantly with change in soil properties and climate scenarios, even with consistent management practices.

From table 5, it is evident that planting date has significant interactions with N fertilizer amount. Early planting enhances N uptake due to cooler soil temperatures and reduced volatilization losses (Liu, 2019). Conversely, higher temperature leads to increased water evaporation from soil, impacting soil moisture levels and consequently N uptake from the soil. Therefore, it can be seen from figure 1, that for all the locations with the climate change the optimal planting date will be early in April to get higher yield. For mid-century and late-century scenarios, planting on May 30 does not significantly increase yield due to the higher temperatures. The warmer days accelerate the vegetation stage, and without side-dress N supplementation until July, N uptake is limited. This interaction between the N and soil moisture is further illustrated by the significant interaction between N fertilizer amount and irrigation rules and are shown with p-value less than 0.0001. Irrigating under extreme heat conditions will supplement the soil moisture and thereby improves N uptake. Soil moisture retention capacity is dependent on soil physical and chemical properties and is also influenced by weather parameters (temperature and rainfall) and in turn also affects N uptake. Therefore, it can be concluded planting date and N fertilizer amounts have significant interactions with soil properties and temperatures.

Conclusion

In this study, we explored how crop growth models, such as APSIM can be used to help make informed farm management decisions at farm-level by simulating the long-term experiment at four locations across Indiana under two climate change scenarios. The simulation study results demonstrates that planting date, irrigation, N fertilizer amount, soil properties, and weather scenarios had significant impact on corn yield (p-value < 0.0001). Furthermore, with the climate change scenarios, the planting date of corn needs to shift ahead, the optimal period for these locations across Indiana will be in early April, irrigation will be required to supplement the soil moisture to help mitigate the higher temperatures, and an N fertilizer increment would not be helpful when delaying the planting beyond optimal window. Based on these results, it can be concluded that the interplay between plants' physiological needs and environmental factors is complex and requires strategic and adaptive planning. Tailoring the farm management guidelines to site-specific conditions by using real-time weather and soil data to improve resilience to climate variability.

Acknowledgments

This work is sponsored by the NSF award number EEC-1941529 and by National Institute of Food and Agriculture, U.S. Department of Agriculture, under the agreement number of 2022-38640-37486 through the North Central Region SARE program under project number GNC23-371.

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Appendix

Table 1: Soil physical, chemical, and organic properties for farm at ACRE

ACRE (40˚29'20.9" N, 87˚0'11.7" W)												
Depth (cm)	**BD**	**AD**	**LL 15**	**DUL**	**SAT**	**KS**	**LL**	**KL**	**XF (0-1)**	**PAWC**	**pH**	**Carbon**
0-15	1.40	0.12	0.229	0.345	0.442	29.57	0.229	0.08	1	0.116	6.59	4.500
15-30	1.40	0.21	0.229	0.345	0.442	21.70	0.229	0.08	1	0.116	6.59	4.500
30-60	1.49	0.23	0.230	0.346	0.408	15.78	0.230	0.08	1	0.116	7.12	2.250
60-90	1.55	0.18	0.182	0.312	0.385	13.26	0.182	0.08	1	0.130	7.12	1.420
90-120	1.64	0.13	0.125	0.270	0.351	14.46	0.125	0.08	1	0.145	7.23	0.750
120-150	1.80	0.11	0.111	0.254	0.291	20.48	0.111	0.06	0.9	0.143	7.86	0.750
150-180	1.80	0.11	0.111	0.254	0.291	26.13	0.111	0.03	0.5	0.143	7.86	0.750

BD stands for bulk density (g/cc), AD stands for Air dry (mm/mm), LL15 stands for wilting point at 15 bars (mm/mm), SAT stands for saturated water content (mm/mm), DUL stands for drained upper limit (mm/mm), KS stands for saturated soil conductivity (mm/mm), LL stands for lower limit (mm/mm); and PAWC are crop specific parameter and in this case, it's for maize (mm/mm), LL stands for maize lower limit (mm/mm), KL stands for maize water conductivity between soil layers (/day), XF stands for maize extinction coefficient, pH depicts the soil pH, Carbon (total %) is the soil organic matter percentage

Table 2 : Soil physical, chemical, and organic properties for farm at NEPAC

NEPAC (41° 6' 51.85" N, 85° 26' 56.03" W)												
Depth (cm)	**BD**	**AD**	**LL 15**	**DUL**	**SAT**	**KS**	**LL**	**KL**	**XF (0-1)**	**PAWC**	**pH**	**Carbon**
0-15	1.41	0.08	0.235	0.351	0.430	21.70	0.235	0.06	1.000	0.116	6.30	2.733
15-30	1.54	0.08	0.230	0.324	0.390	15.33	0.230	0.06	0.907	0.094	6.30	1.622
30-60	1.59	0.08	0.230	0.313	0.378	10.82	0.232	0.06	0.769	0.081	6.38	1.160
60-90	1.61	0.08	0.228	0.313	0.370	11.14	0.253	0.04	0.717	0.060	6.78	0.977
90-120	1.61	0.07	0.219	0.312	0.371	12.58	0.282	0.02	0.718	0.030	7.13	0.902
120-150	1.61	0.07	0.217	0.312	0.373	13.49	0.299	0.01	0.726	0.013	7.42	0.894
150-180	1.61	0.07	0.214	0.312	0.376	14.72	0.312	0.00	0.736	0.000	7.64	0.885

BD stands for bulk density (g/cc), AD stands for Air dry (mm/mm), LL15 stands for wilting point at 15 bars (mm/mm), SAT stands for saturated water content (mm/mm), DUL stands for drained upper limit (mm/mm), KS stands for saturated soil conductivity (mm/mm), LL stands for lower limit (mm/mm); and PAWC are crop specific parameter and in this case, it's for maize (mm/mm), LL stands for maize lower limit (mm/mm), KL stands for maize water conductivity between soil layers (/day), XF stands for maize extinction coefficient, pH depicts the soil pH, Carbon (total %) is the soil organic matter percentage

Table 3 Soil physical, chemical, and organic properties for farm at SEPAC

SEPAC (39° 2' 28.64" N, 85° 31' 24.24" W)												
Depth (cm)	**BD**	**AD**	**LL 15**	**DUL**	**SAT**	**KS**	**LL**	**KL**	**XF (0-1)**	**PAWC**	**pH**	**Carbon**
0-15	1.42	0.08	0.233	0.365	0.420	38.76	0.233	0.06	1.000	0.132	5.90	2.281
15-30	1.54	0.08	0.230	0.335	0.385	27.37	0.230	0.06	0.876	0.105	5.80	1.041
30-60	1.59	0.08	0.233	0.324	0.375	17.72	0.235	0.06	0.748	0.089	5.70	0.590
60-90	1.64	0.08	0.237	0.316	0.355	14.05	0.264	0.04	0.602	0.052	5.75	0.374
90-120	1.68	0.08	0.228	0.304	0.340	15.87	0.291	0.01	0.516	0.013	5.94	0.295
120-150	1.68	0.07	0.224	0.300	0.340	17.01	0.299	0.00	0.509	0.001	6.02	0.287
150-180	1.69	0.07	0.219	0.294	0.340	18.56	0.294	0.00	0.000	0.000	6.12	0.277

BD stands for bulk density (g/cc), AD stands for Air dry (mm/mm), LL15 stands for wilting point at 15 bars (mm/mm), SAT stands for saturated water content (mm/mm), DUL stands for drained upper limit (mm/mm), KS stands for saturated soil conductivity (mm/mm), LL stands for lower limit (mm/mm); and PAWC are crop specific parameter and in this case, it's for maize (mm/mm), LL stands for maize lower limit (mm/mm), KL stands for maize water conductivity between soil layers (/day), XF stands for maize extinction coefficient, pH depicts the soil pH, Carbon (total %) is the soil organic matter percentage

Table 4 Soil physical, chemical, and organic properties for farm at PPAC

PPAC (41° 27' 3.61" N, 86° 56' 28.51" W)												
Depth (cm)	**BD**	**AD**	**LL 15**	**DUL**	**SAT**	**KS**	**LL**	**KL**	**XF (0-1)**	**PAWC**	**pH**	**Carbon**
0-15	1.36	0.06	0.170	0.286	0.430	77.75	0.170	0.06	1.000	1.360	6.00	3.123
15-30	1.45	0.05	0.160	0.267	0.400	73.37	0.160	0.06	1.000	1.450	5.95	1.979
30-60	1.47	0.05	0.158	0.257	0.395	69.23	0.158	0.06	1.000	1.472	5.93	1.418
60-90	1.51	0.04	0.142	0.232	0.380	73.37	0.160	0.05	1.000	0.072	6.05	0.874
90-120	1.53	0.03	0.118	0.200	0.380	90.4	0.156	0.03	1.000	0.044	6.24	0.607
120-150	1.53	0.03	0.114	0.196	0.380	96.92	0.163	0.02	1.000	0.033	6.32	0.604
150-180	1.53	0.03	0.109	0.190	0.380	105.7	0.171	0.01	1.000	0.019	6.42	0.600

BD stands for bulk density (g/cc), AD stands for Air dry (mm/mm), LL15 stands for wilting point at 15 bars (mm/mm), SAT stands for saturated water content (mm/mm), DUL stands for drained upper limit (mm/mm), KS stands for saturated soil conductivity (mm/mm), LL stands for lower limit (mm/mm); and PAWC are crop specific parameter and in this case, it's for maize (mm/mm), LL stands for maize lower limit (mm/mm), KL stands for maize water conductivity between soil layers (/day), XF stands for maize extinction coefficient, pH depicts the soil pH, Carbon (total %) is the soil organic matter percentage

Table 5 Effect and interaction of different treatments on corn yield

Treatments	p-value
Planting date	<0.0001
Nitrogen	<0.0001
Irrigation rules	<0.0001
Location	<0.0001
Weather scenario	<0.0001
Planting date * Nitrogen	<0.0001
Planting date * Irrigation rules	>0.15

Nitrogen * Irrigation rules	<0.0001
Location * Weather scenario	<0.0001
Planting date * Location	<0.0001
Nitrogen * Location	<0.0001
Irrigation rules * Location	0.001
Planting date * Weather scenario	<0.0001
Nitrogen * Weather scenario	<0.0001
Irrigation rules * Weather scenario	>0.15
Planting date * Nitrogen * Irrigation rules	>0.15
Planting date * Nitrogen * Location	<0.0001
Planting date * Irrigation rules * Location	<0.0001
Nitrogen * Irrigation rules * Location	<0.0001
Planting date * Nitrogen * Weather scenario	<0.0001
Planting date * Irrigation rules * Weather scenario	0.04
Nitrogen * Irrigation rules * Weather scenario	>0.15
Planting date * Location * Weather scenario	0.002
Nitrogen * Location * Weather scenario	0.013
Irrigation rules * Location * Weather scenario	>0.15
Planting date * Nitrogen * Irrigation rules * Location	>0.15
Planting date * Nitrogen * Irrigation rules * Weather scenario	>0.15
Planting date * Nitrogen * Location * Weather scenario	>0.15
Planting date * Irrigation rules * Location * Weather scenario	>0.15
Nitrogen * Irrigation rules * Location * Weather scenario	>0.15
Planting date * Nitrogen * Irrigation rules * Location * Weather scenario	>0.15

It is to be noted that p-value < 0.0001 signifies that the variable had significant effect on response variable. A p-value between 0.0001 and 0.15 suggests that the variables might have significant effect on response variable under certain conditions and number of replications. While the p-value > 0.15 signifies that there is no significant effect of variables on the response variables.