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Deciding sowing-window for maize-based cropping system in arid and semiarid environments in Punjab, Pakistan

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Abstract: Crop growth models can be valuable tools for researchers, academia, extension educators, and policy makers/planners for the evaluation of sustainable and long-term husbandry practices. Determining the optimum sowing window, which can be determined using crop growth models, is imperative under changing climate conditions. Thus, the main objectives herein were to 1) assess the performance of the cropping system model-crop environment resource synthesis-maize model for hybrids and sowing dates in the spring and autumn, and 2) determine the optimum sowing window in 15 districts of Punjab, Pakistan. In the spring experiment, 3 hybrids (P-33M15, M-DK6525, and S-NK8441) were planted in the main plots and then on 5 different sowing dates (January 15th, February 5th, February 25th, March 15th, and April 5th), they were planted in the subplots. In the autumn experiment, 3 hybrids (P-30R50, M-DK6714, and S-NK6621) were planted in the main plots and then on 5 different sowing dates (June 15th, July 5th, July 25th, August 15th, and September 5th), they were planted in the subplots. Model calibration and evaluation results were better in the spring and autumn. Performance of the model was good for the grain yield in the autumn (mean percentage difference (MPD): 7.47% to 8.90%) compared to the spring (MPD: 9.42% to 11.72%). Model evaluation was good for the early sowing dates (January 15th and February 5th) (error range: 6.26% to 9.65%) compared to the delayed dates (February 25th to April 5th) (error range: 9.34 to 14.91%). In the autumn, the model showed better performance for the delayed sowing dates (February 25th and August 15th) (error range: 5.22% to 9.43%) compared to the early dates (June 15th and July 5th) (error range: 8.56% to 11.27%). The model simulated good growth, development, grain yield, and yield components in the spring and autumn and of both 2016 and 2017. For the model application simulation of data over the long-term (1980 to 2017), the optimum sowing window in the spring was January 15th to March 5th and for the autumn it was July 23rd to August 27th for the 15 districts in Punjab, Pakistan. Simulation of the sowing dates for the whole year indicated that the spring was better compared to the autumn for obtaining the maximum grain yield. The results of the model were in line with the recommendations of the agricultural extension department for the sowing window for spring and autumn maize. It is therefore suggested that farmers should complete the sowing of spring and autumn maize within the sowing window to attain a higher yield of maize in arid and semiarid areas of Punjab, Pakistan.

Key words: Cropping system model, *Zea mays* L., DSSAT, hybrid, maize, spring, autumn, grain yield

1. Introduction

Maize is an imperative cereal crop around the world, for humans, cattle, and birds. Expanded maize utilization in the industrial sector provides this crop a renowned place in agricultural monetary systems (Fujisao et al., 2018; Sarwar et al., 2021; Khalid et al., 2023). It is the 3rd most important

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food crop in Pakistan and provides raw material for a range of industrial products (Abbas et al., 2017; Qamar et al., 2021; Mubarak et al., 2022). Its share in gross domestic product (GDP) and value-added agriculture (VAA) is 0.6% and 2.9%, respectively. Maize was sown in an area of 1.41 M ha with grain productivity of 7.24 M tons in 2020. A 9% increase in area was observed from 2019 to 2020 due to government subsidy to farmers, the availability of an improved variety of seed, and reduction in the growing area for cotton crops (GOP, 2020). In Pakistan, maize is sown in two seasons, i.e. spring and autumn; however, the average grain productivity is very low, compared to high yielding countries like the USA, Brazil, and India due to high temperatures and an inappropriate sowing window under current climatic conditions.

The growth and developmental stages and phases of maize crops are mostly affected by an increase in both ecological CO_2 concentrations and day and night temperatures due to changing sowing dates (Zhao and Yang, 2018). The increasing thermal trend is a serious threat to spring and autumn maize production; hence, to minimize the negative impact of climate warming, determining the optimum sowing window is imperative in order to obtain the maximum achievable grain yield under changing climatic conditions (Abbas et al., 2019, 2020a; Afzal et al., 2020). A higher temperature during the growing season decreases photosynthetic efficiency and speeds up the growth and senescence of the leaves; thus, using the optimum sowing date can enhance grain yield by providing optimum growing conditions (Bonelli et al., 2016; Caubel et al., 2018; Perondi et al., 2019).

Crop growth simulation models are a very important tool for the assessment of optimum management practices for crops. Crop yield and yield components are simulated with the assistance of crop simulation models (Abbas et al., 2020b; Naz et al., 2022). These models also simulate quantifiable facts regarding key processes related to crop growth and development (Fatima et al., 2020; Raza et al., 2021a, b). Crop simulation models can be helpful in the identification of proper adaptation strategies for attaining maximum sustainable goals (Seidel et al., 2018; Wang et al., 2018; Malik et al., 2019). Crop models have become an essential tool to support scientific research, crop management practices decision as well as economic and policy analysis (Hammad et al., 2013, 2018; Amouzou et al., 2018; Seyoum et al., 2018). Climate uncertainty and the optimum sowing window can be predicted by crop models under changing climatic conditions. Crop modeling has played a vital role in obtaining a better understanding of the performance of crops and yield gaps, better prediction of pest and insect outbreaks, and it is a supportive tool for the improvement in efficiency of crop management comprising proper irrigation management as well as the optimization of sowing dates (Araya et al., 2017; Peng et al., 2018; Adnan et al., 2019). Nowadays, crop growth models are highly advanced and are capable of be employed as multipurpose tools, which are designed for different applications in agriculture (Singh et al., 2017; Ali et al., 2018). Crop models have been employed for various applications in different farming and cropping systems at the global level (Li et al., 2015; Bao et al., 2017). The Decision Support System for Agrotechnology Transfer (DSSAT) is a widespread decision support system for agrotechnology transfer that comprises the crop environment resource synthesis (CERES)-maize model (Jones et al., 2003; Hoogenboom et al., 2021). Maize plant growth and phenological stages and phases can be predicted through the CERES-maize model with day-by-day time steps from sowing to physiological maturity and run on the basis of various plant physiological processes, which illustrate the response of maize crops to soil physiochemical characteristics and aboveground environment circumstances (Corbeels et al., 2016; Adnan et al., 2017). The maize potential grain yield in the model is dependent on photosynthetically active radiation and its interceptions, while the total dry matter yield is reduced daily as a result of suboptimal maximum and minimum air temperatures, soil water shortages, and nutrient deficiencies (Jin et al., 2016; Zheng et al., 2017; Raza et al., 2022).

The optimum sowing window recommendation for maize crops is frequently based on agronomic field trials for only a few years, which are specifically limited to fields and zones (Tsimba et al., 2013; Dobor et al., 2016; Srivastava et al., 2017). Sowing dates based on field experiments cannot be temporally and spatially replicated because the variability of meteorological parameters during growing seasons is very high (Lu et al., 2017; Abdala et al., 2018; Júnior and Sentelhas, 2019). Determining appropriate planting times for maize crops through field experimentations requires repetition of the experiments over an extended period of time so seasonal variations in the meteorological parameters can be observed (Mason et al., 2017; Huang et al., 2018). In addition, the data from one site are not valuable for any other sites due to variations in not only the temperature, solar radiation, and precipitation, but also in the soil properties (Long et al., 2017; Parker et al., 2017). Therefore, decision support tools like DSSAT remain extremely important for the investigation of decisions related to sowing windows and other practices (Dokoohaki et al., 2016; Jing et al., 2017; MacCarthy et al., 2017). In Pakistan, the CERES-maize model was calibrated, evaluated, and applied in only one season, in either the spring or autumn, and only for nitrogen fertilizer management practices, under semiarid conditions (Mubeen et al., 2013 and 2016;

Hammad et al., 2018). Recommendations for the sowing window for spring and autumn maize in Punjab, Pakistan, are normally made on the basis of locally available information. Recommendations for the sowing window are articulated from data obtained from large-scale field trials, carried out all over the region. However, a similar sowing window is suggested for several years and sites, without considering temporal and spatial variations in the weather conditions. Thus, the novelty of the current study is that a calibrated CERES-maize model was used for both the spring and autumn, on different sowing dates, under arid and semiarid conditions, using historical weather data from 1980 to 2017, and the data obtained were evaluated.

Limited scientific research exists about the application of the CERES-maize model in the spring and autumn for management factors like sowing dates and hybrids under arid conditions in Pakistan. Therefore, to fill this gap in the and semiarid, this study was designed with the objectives to 1) assess the performance of the CERES-maize model for hybrids and sowing dates in the spring and autumn under arid conditions and 2) determine the optimum sowing and semiarid in 15 districts of Punjab, Pakistan, for the spring and autumn growing seasons.

2. Materials and methods

2.1. Experimental site and soil

The experiments were conducted in both the spring and autumn of 2016 and 2017 at the Research Area situated at Bahauddin Zakariya University, Multan, Pakistan (30.19°N; 71.47°E; 122 m), which is characterized as having an irrigated arid environmental condition. Miani is the dominating soil series in the research area. According to the United States Department of Agriculture categorization of soils, the Miami soil series is silty, mixed, hyperthermic fluventic haplocambids. Soil physical characteristics such as the soil texture, organic matter, bulk density, soil pH, total N, and available P and K levels in the soil at depths from 0 to 20 cm and 21 to 40 cm were obtained from core samples of soil (Table 1). Soil pH and electrical conductivity values from each of the soil depths (from 0 to 20 cm and 21 to 40 cm) were computed using the data from the core samples of soil using the standard processes (Saxton and Rawls, 2006). Due to its higher evapotranspiration rate, the Multan features were determined as an irrigated arid environment with the highest air temperatures of 35 °C in the spring and 48 °C in the autumn, and an average rainfall of 76 mm in the spring and 145 mm in the autumn.

2.2. Meteorological data

On a daily basis, the highest and lowest day and night air temperatures, solar radiation, and rainfall data were acquired from the weather station, which was situated contiguous to the research location in 2016 and 2017. Figure 1 depicts the weather parameters for both 2016 and 2017.

2.3. Experimental design and crop husbandry

The field experiments were conducted with a randomized complete block design and a split plot arrangement in the spring and autumn of 2016 and 2017. In the spring experiment, 3 hybrids (H1: P-33M15, H2: M-DK6525, and H3: S-NK8441) were planted in the main plots and then on 5 different sowing dates (SD1: January 15th, SD2: February 5th, SD3: February 25th, SD4: March 15th, and SD5: April

Table 1. Physical and chemical analysis of the experimental soil.

Soil characteristics	Spring maize		Autumn maize	
	2016	2017	2016	2017
Sand (%)	18	17	16	18
Silt (%)	56	58	55	58
Clay (%)	26	25	29	24
Texture class	Silty loam	Silty loam	Silty loam	Silty loam
Field capacity (cm^3 cm^{-3})	0.29	0.32	0.28	0.35
Permanent wilting point (cm^3 cm^{-3})	0.12	0.14	0.13	0.14
Bulk density (g cm^{-3})	1.35	1.32	1.29	1.32
Soil pH	8.14	8.17	8.07	8.19
Soil electrical conductivity (dS m^{-1})	1.58	1.65	1.49	1.70
Organic matter (%)	0.45	0.41	0.48	0.39
Total soil nitrogen (g kg^{-1})	0.26	0.24	0.23	0.25
Available phosphorus (ppm)	6.82	6.41	6.25	6.39
Available potassium (ppm)	85.28	78.43	89.42	91.24

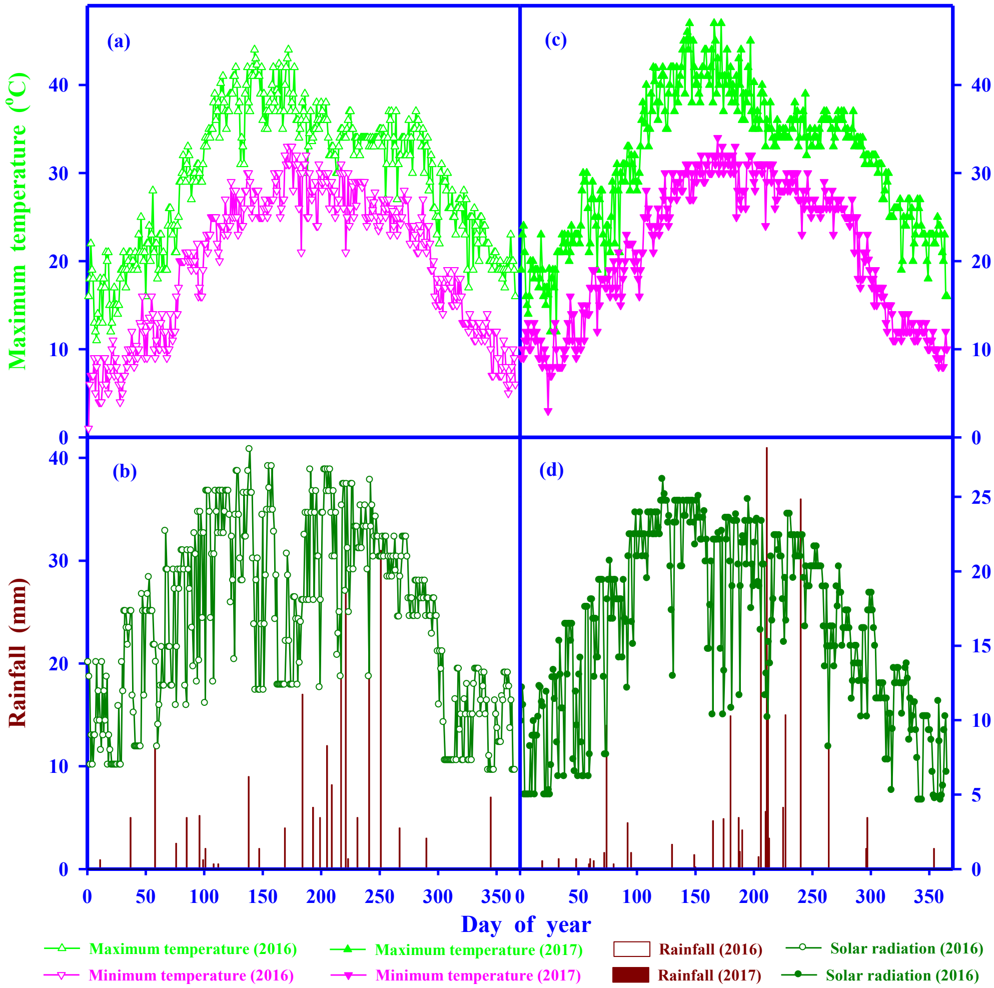

Figure 1. Daily maximum and minimum temperature during 2016 (a) and 2017 (c), solar radiation and rainfall during 2016 (b) and 2017 (d) for spring and fall maize seasons at study site (**Source:** Modified and adopted from Abbas et al., 2020).

5th), they were planted in the subplots. In the autumn experiment, 3 hybrids (H1: P-30R50, H2: M-DK6714, and H3: S-NK6621) were planted in the main plots and then on 5 different sowing dates (SD1: June 15th, SD2: July 5th, SD3: July 25th, SD4: August 15th, and SD5: September 5th), they were planted in the sub plots.

Maize hybrid sowing in the spring and the autumn was done on the same dates in both 2016 and 2017. Husbandry practices other than the experimental treatments were performed based on recommendations by the agriculture department for all of the field trials in both seasons and both years. The seed beds were prepared via ploughing and planking. A row-to-row and plant-to-plant distance was maintained at 75 and 20 cm, respectively. In each trial, a seed rate of 25 kg ha^{-1} was used. Gap-filling was performed in order to maintain plant density. Twelve days after emergence of the seedlings, thinning was carried out to maintain the plant-to-plant distance. Recommended fertilizer at 248, 165, and 115 kg ha^{-1} (N, P, and K, respectively) was applied in each trial. The sources of fertilizer were urea, Di-ammonium phosphate (DAP), and sulphate of potash (SOP). A tube well was used as the source of the irrigation water. Weed management was performed via chemical and mechanical methods at different crop stages. Pesticides and fungicides were applied to control pests and diseases in each experiment.

2.4. Crop measurement data

Ten maize plants were arbitrarily attached a label to obtain the observed day-by-day phenological stage data. The phenological stage data of the maize crops were obtained by counting the number of leaves and leaf collars that emerged on a daily basis from each plot in each experiment. The phenological stages of the tasseling and silking were recorded when 50% of the tasseling and silking had emerged in each subplot, respectively. Maturity at the physiological stage was measured via persistent sampling of the cobs from each plot to assess the blackish layer on the base of individual grains. From each plot, plant samples were cut at ground level in an area measuring 0.35 m^2 at intervals of 12 days. Five to eight destructive samplings were taken between the sowing to harvesting phases and the ultimate samples were taken to determine the grain yield in each treatment. From each harvesting sample, a subsample weight of 15 g fresh leaves was taken and utilized for measurement of the leaf area using leaf area meter in each experiment. The determined leaf area of 12 g of fresh leaves were additionally used for calculating the leaf area (m^{-2}) on the basis of weight, and then the leaf area index of each sub sample was calculated as the leaf area divided by the ground area (Hunt, 2012). The harvest index was calculated as the ratio of seed yield by the biomass yield at the harvesting stage. Then, 25 g of the subsample of every shoot fraction was acquired for measurement of the biological yield, and the samples were dried in an oven at 70 °C for 75 h to obtain the steady dry weight. The number of grains per cob was measured from ten cobs taken from each subplot. The leftover area (2.8 m^2) of every plot of the experiment was used to obtain the ultimate grain yield.

2.5. The DSSAT model

The cropping system model (CSM)-CERES-maize model was employed in the study, which is one of the crop growth simulation modules embedded into DSSAT 4.7.5 software (Hoogenboom et al., 2021). The model was employed for predicting the maize growth and productivity in both the spring and autumn. The model comprises soil physical and chemical features, sowing date information, planting density, row-to-row and plant- to-plant spacing, daily highest and lowest air temperatures, solar radiation levels, relative humidity, rainfall, etc.

Calibration of the model was done with the best performed treatment in the spring and autumn. Sowing of hybrids P-33M15, M-DK6525, and S-NK8441 on February 5th in the spring was used for calibration in 2016. Sowing of hybrids P-30R50, M-DK6714, and S-NK6621 on July 25th in the autumn was used for calibration in 2016. Genetic coefficients of all of the spring and fall maize hybrids were determined using a genetic coefficient calculator. Thus, coefficients P1, P2, P5, G2, G3, and PHINT were used to model the growth and yield simulations for the spring and autumn maize (Table 2).

Evaluation of the model was done for all of the sowing dates (except those used for the model calibration in the 2016 experiments) in the spring and autumn experiments in 2016. After that, the model's performance was also evaluated with data observed in 2017 in the spring and autumn experiments.

Application of the model was done after the calibration and evaluations had been performed. The CERES-maize model was used for the simulations of hybrid P-33M15 (in the spring) and hybrid P-30R50 (in the autumn). The model was used to determine the simulation of the optimum sowing widow for 15 districts in Punjab, Pakistan. The simulations were carried out by employing daily weather data that had been collected over a period of 37 years, from 1980 to 2017. A seasonal strategy program was employed to determine the optimum sowing window in each district. For comparison of the spring and autumn, the model was also applied for all of the sowing dates with a difference of 8 days in 2017. The best performing spring (P-33M15) and autumn (P-30R50) hybrids with recommended standard management practice data were used in the model for simulation purposes.

2.6. Model statistics

The model's performance was analyzed using various model statistics. Calibration and evaluation of the model's analysis, predicted days to anthesis, maturity, maximum LAI, total biomass, and seed production were matched with the field observations (Yang et al., 2014). Different model statistical indices were calculated, such as the error (E), mean percentage difference, and root mean square error according to the method of Yang et al. (2014). The model's performance was assessed by calculating various statistical indices using the equations below:

$$RMSE = \left[\sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}}\right],$$

$$\text{Error (\%)} = \frac{(P-O)}{O} \times 100,$$

$$MPD = \left[\sum_{i=1}^{n}\left\{\frac{|O_i - P_i|}{O_i}\right\} \times 100\right] \Big/ n$$

$$Index\ of\ agreement\ (d) = 1 - \left[\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}\left(\left|\left|P_i'\right| + \left|O_i'\right|\right|\right)^2}\right].$$

Here, n represents to total number of observed values, O_i represents the field observation data values, P_i represents the values predicted by the model, $P_i' = P_i - M$ and $O_i' = O_i - M$ (M represents the mean of the observed variables).

3. Results

3.1. Genetic coefficients

The CERES-maize model required six ecophysiological genetic coefficients for the phenology and yield components and the grain productivity of the spring and

Table 2. Genetic coefficients of the spring and autumn maize hybrids used for the CSM-CERES-maize model. Adopted from Abbas et al. (2023)

Growing season	Hybrid	P1	P2	P5	G2	G3	PHINT
		(°C day^{-1})	(day)	(°C day^{-1})		(mg day^{-1})	(°C day^{-1})
Spring	P-33M15	241.0	0.40	839.0	869.0	9.73	30.0
	M-DK6525	219.0	0.38	812.0	856.0	10.05	35.2
	S-NK8441	203.0	0.39	789.0	832.0	9.97	28.5
Autumn	P-30R50	185.0	0.31	778.0	875.0	7.05	49.0
	M-DK6714	176.0	0.30	762.0	854.0	7.05	47.0
	S-NK6621	168.0	0.28	745.0	812.0	7.00	51.0

P1: Thermal time from seedling emergence to the end of the juvenile phase (expressed in degrees/day, °C/day, above a base temperature of 8 °C), during which the plant was not responsive to changes in the photoperiod. **P2:** Extent to which development (expressed as days) was delayed for each hour increase in the photoperiod above the longest photoperiod at which development proceeded at a maximum rate (which was considered to be 12.5 h). **P5:** Thermal time from silking to physiological maturity (expressed in °C/day above a base temperature of 8 °C). **G2:** Maximum possible number of kernels per plant. **G3:** Kernel filling rate during the linear grain filling stage and under optimum conditions (mg day^{-1}). **PHINT:** Phyllochron interval; the interval in thermal time (°C/day) between successive leaf tip appearances (Hoogenboom et al., 2019).

autumn hybrids (Table 2). Genetic coefficients data for the hybrids did not exist; therefore, genetic coefficients for the hybrids used in model were estimated manually using trial and error until a close match between the observed and predicted phenology, yield components, and seed yield for the spring and autumn hybrids were obtained. Spring hybrid P-33M15 exhibited a greater degree of growth per day for coefficient P1 and P5 compared to the other spring hybrids. Autumn hybrid P-30R50 exhibited a greater degree of growth per day for coefficient P1 and P5 compared to the other autumn hybrids. The spring hybrids exhibited greater P1, P2, P5, G2, and G3 values compared to the autumn hybrids, while the PHINT value was greater for the autumn hybrids in comparison to the spring hybrids.

3.2. Model calibration

Calibration of the CERES-maize model was done using the recorded results of the sowing dates that provided the best performance, on February 5th for the spring hybrids and July 25th for the autumn hybrids, which showed the highest grain yield in 2016. The model exhibited good calibration for the simulation of the time course data of the LAI and biomass for the spring hybrids (Figures 2 and 3) in 2016 and 2017, respectively, and autumn hybrids (Figures 4 and 5) in 2016 and 2017, respectively. The phenology, final biomass, harvest index, and grain yield for the hybrids in the spring and autumn are given in Table 3. The error values between the simulated and observed data for spring hybrid P-33M15 and autumn hybrid P-30R50 were less than those of the others in the spring and autumn. The model overestimated the values of the yield components and grain yield in the calibration process when compared to observed data in both the spring and autumn. The error values ranged from 0% to 1.79% for the anthesis stage, 0% to 0.86% for the maturity stage, 2.40% to 5.49% for the maximum LAI, 4.05% to 9.18% for the grain yield, 2.92% to 5.79% for the total biomass, and 1.10% to 3.20% for the harvest index for the spring hybrids. For the autumn hybrids, the error values ranged from 0% to 2.04% for the anthesis stage, 0% to 1.06% for the maturity stage, 3.23% to 5.68% for the maximum LAI, 3.27% to 7.72% for the grain yield, 2.61% to 5.85% for the total biomass, and 0.65% to 1.76% for the harvest index.

3.3. Model evaluation

3.3.1. Phenology

The performance of the model was assessed using the data observed in 2016 and 2017 to determine its accuracy (Tables S1 and S2). The phenological evaluation of the model was good in both years of the study. The simulated anthesis and physiological maturity were close to the observed phenology data in the spring and autumn. The model overestimated the data compared to the observed data for the spring and autumn in both years. The evaluation of spring hybrid P-33M15 and autumn P-30R50 hybrid was better compared to the other hybrids in both years. In the spring, the mean percentage difference (MPD) ranged from 1.61% to 2.94% in 2016 and 2.19% to 3.59% in 2017 for anthesis, while those for maturity were 0.94% to 1.80% in 2016 and 1.12% to 3.18% in 2017. In the autumn, the MPD ranged from% 1.93 to 2.57% in 2016 and 2.42% to 3.96% in 2017 for anthesis, while those for maturity were 1.59% to 2.25% in 2016 and 2.16% to 3.17% in 2017. The spring and autumn hybrid evaluations were better in 2016 compared to 2017. The average error value was greater at

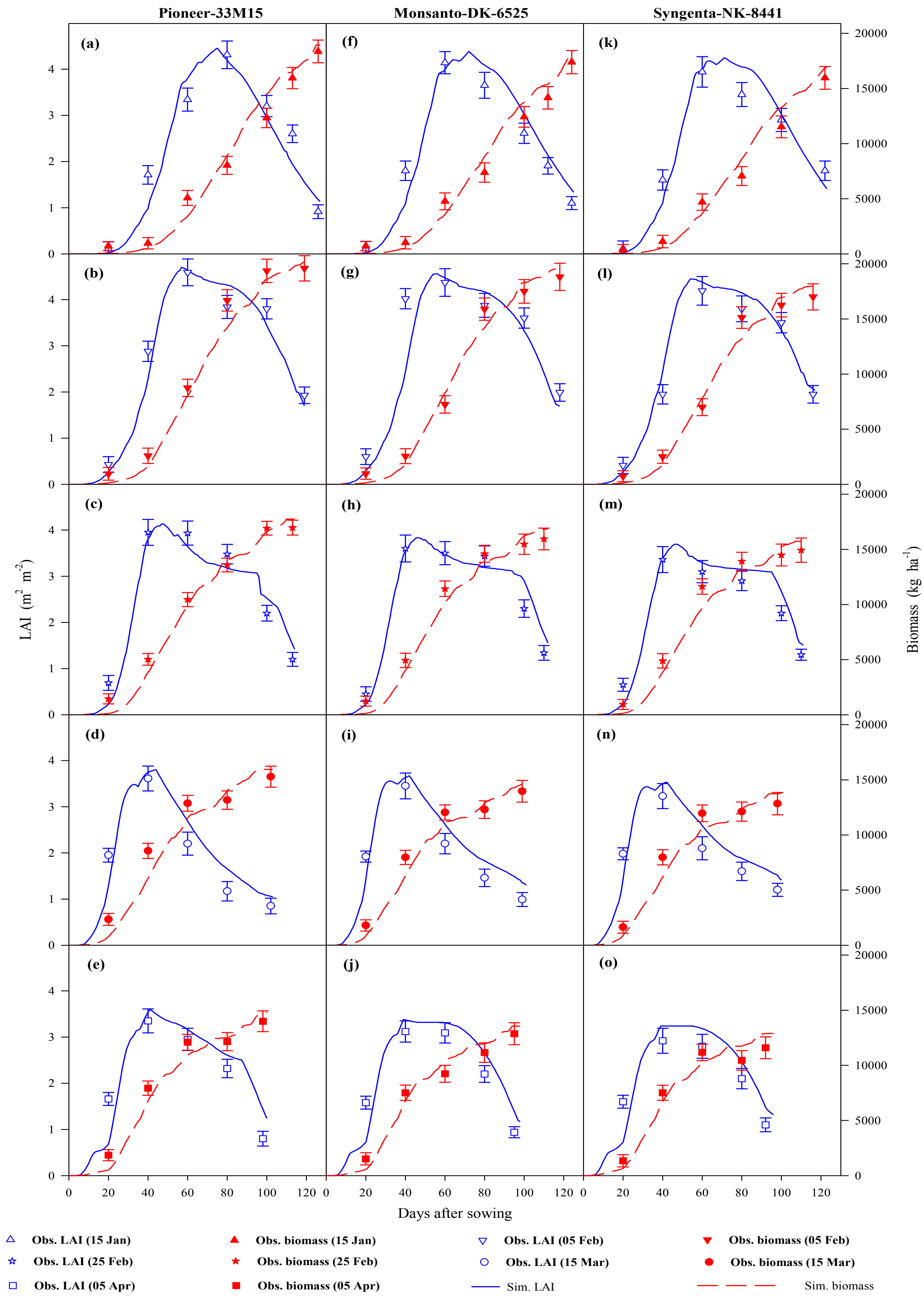

Figure 2. Effect of hybrids and sowing dates on leaf area index and biomass of spring season maize during 2016. (Modified and adopted from Abbas et al. (2023)

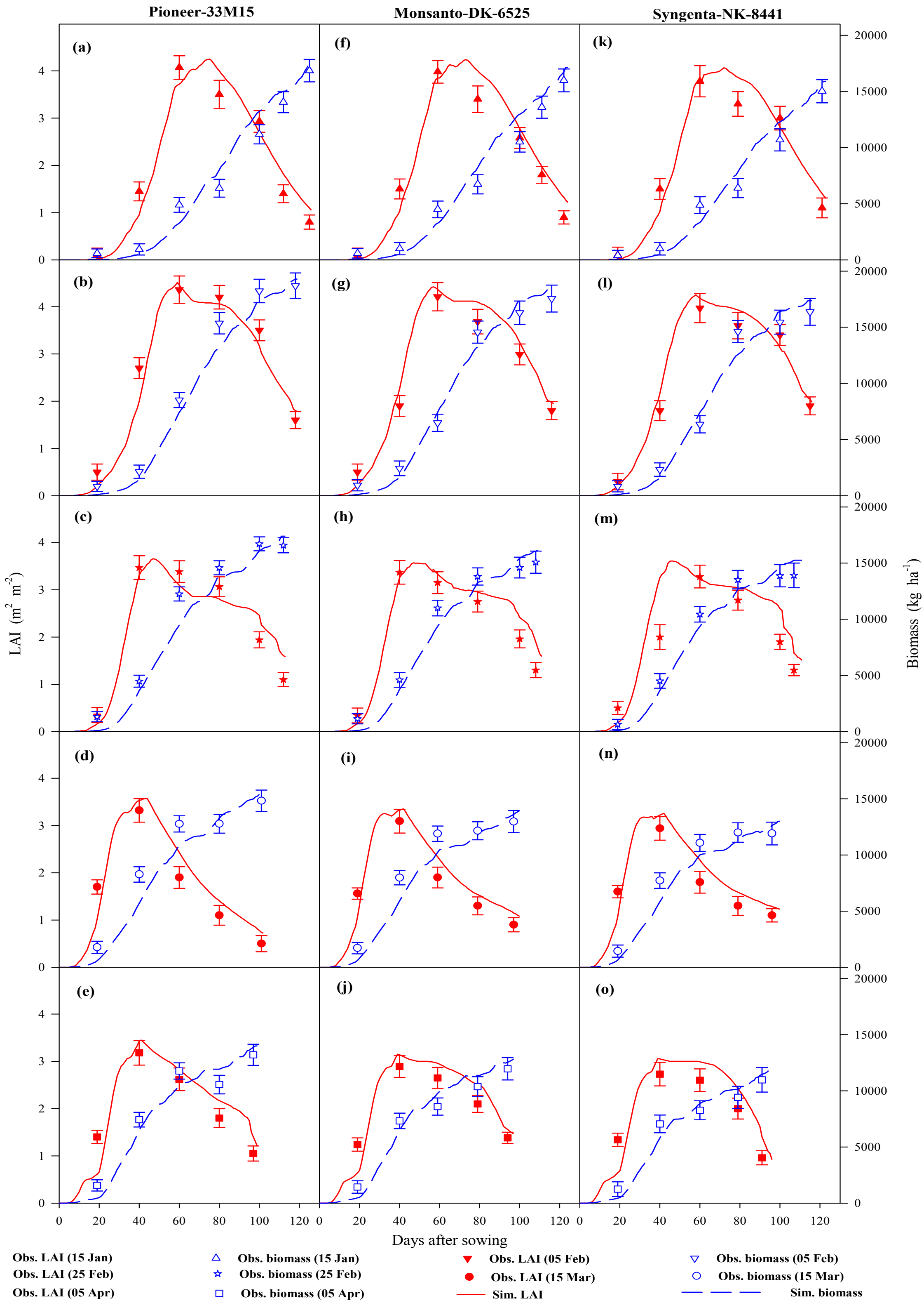

Figure 3. Effect of hybrids and sowing dates on leaf area index and biomass of spring season maize during 2017. (Modified and adopted from Abbas et al. (2023)

Table 3. Summary of the observed and simulated results during model calibration with data recorded on February 2nd, 2016, in the spring and on July 25th, 2016, in the autumn.

Variable	Unit	Spring maize				Autumn maize			
		Hybrid	[a]Sim	[b]Obs	Error (%)	Hybrid	[a]Sim	[b]Obs	Error (%)
Anthesis	Day	P-33M15	58	58	0.00	P-30R50	53	53	0.00
		M-DK6525	57	57	0.00	M-DK6714	50	49	2.04
		S-NK8441	57	56	1.79	S-NK6621	48	48	0.00
Maturity	day	P-33M15	119	119	0.00	P-30R50	102	102	0.00
		M-DK6525	118	118	0.00	M-DK6714	98	97	1.03
		S-NK8441	117	116	0.86	S-NK6621	95	94	1.06
Maximum LAI		P-33M15	4.70	4.59	2.40	P-30R50	5.11	4.95	3.23
		M-DK6525	4.56	4.37	4.35	M-DK6714	4.94	4.71	4.88
		S-NK8441	4.42	4.19	5.49	S-NK6621	4.65	4.40	5.68
Grain yield	kg ha^{-1}	P-33M15	9383	9018	4.05	P-30R50	8450	8182	3.27
		M-DK6525	8876	8377	5.95	M-DK6714	7948	7569	5.01
		S-NK8441	8452	7742	9.18	S-NK6621	7557	7016	7.72
Total Biomass	kg ha^{-1}	P-33M15	19874	19310	2.92	P-30R50	18774	18297	2.61
		M-DK6525	18993	18273	3.94	M-DK6714	17862	17301	3.24
		S-NK8441	17983	16998	5.79	S-NK6621	17285	16329	5.85
Harvest index	%	P-33M15	47.21	46.70	1.10	P-30R50	45.01	44.72	0.65
		M-DK6525	46.73	45.84	1.93	M-DK6714	44.50	43.76	1.69
		S-NK8441	47.00	45.54	3.20	S-NK6621	43.72	42.96	1.76

[a]Sim: Simulated, [b]Obs: observed.

the later sowing dates compared to earlier sowing dates for both the spring and autumn. The error value was lower for the sowing dates in the spring in comparison to the autumn in both years of the study.

3.3.2. Maximum LAI

The time course data of the LAI were good in both years for the spring (Figures 2 and 3) and autumn (Figures 4 and 5) hybrids. In both the spring and autumn, the CERES-maize model was able to predict the maximum LAI in 2016 and 2017 (Tables S3 and S4). The model showed better performance for spring hybrid P-33M15 and autumn hybrid P-30R50 due to a lower error, RMSE, and MPD compared to the other hybrids in both years. When compared to the other hybrids, spring hybrid P-33M15 had the lowest RMSE at 0.19 and 0.21 and MPD at 4.70% and 5.76%, while autumn hybrid P-30R50 had the lowest RMSE at 0.18 and 0.19 and MPD at 5.13% and 5.60% in 2016 and 2017, respectively. The model showed good performance for all of the sowing dates, but was better for the early sowing dates than the late sowing dates for both the spring and autumn. The average error for the sowing dates ranged from 4.03% to 8.95% and 4.55% to 8.66% in 2016, whereas it ranged from 4.86% to 9.77% and 5.06% to 9.25% in 2017 for all of the spring and autumn hybrids, respectively.

3.3.3. Mean grain weight (g)

In both the spring and autumn, the CERES-maize model showed good performance in predicting the mean grain weight in 2016 and 2017 (Tables S3 and S4). The model showed better performance for spring hybrid P-33M15 and autumn hybrid P-30R50 due to the minimum difference between the simulated and observed mean grain weight compared to the other hybrids in both years of the study. When compared to the other hybrids, spring hybrid P-33M15 had the lowest RMSE at 0.016 and 0.017 and MPD at 5.62% and 6.28%, while autumn hybrid P-30R50 had the lowest RMSE at 0.012 and 0.014 and MPD at 4.01% and 4.79% in 2016 and 2017, respectively. The average error for the sowing dates ranged from 4.49% to 9.54% and 3.14% to 6.05% in 2016, whereas it ranged from 5.36% to 9.72% and 3.69% to 7.63% in 2017 for all of the spring and autumn hybrids, respectively. The model showed good performance for all of the sowing dates, but was better for the early sowing dates in the spring and late sowing dates in the autumn.

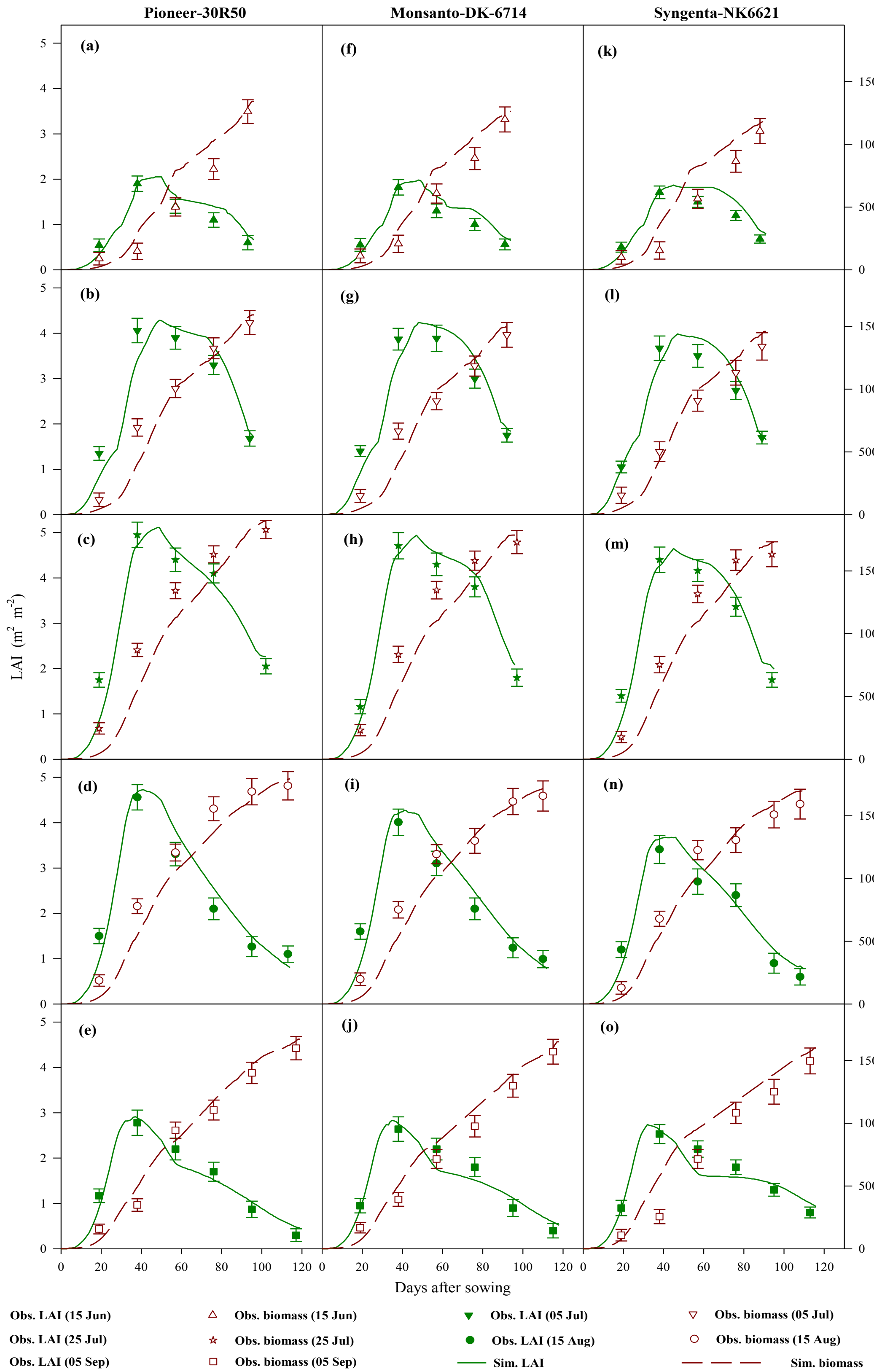

Figure 4. Effect of hybrids and sowing dates on leaf area index and biomass of fall season maize during 2016. (Modified and adopted from Abbas et al. (2023)

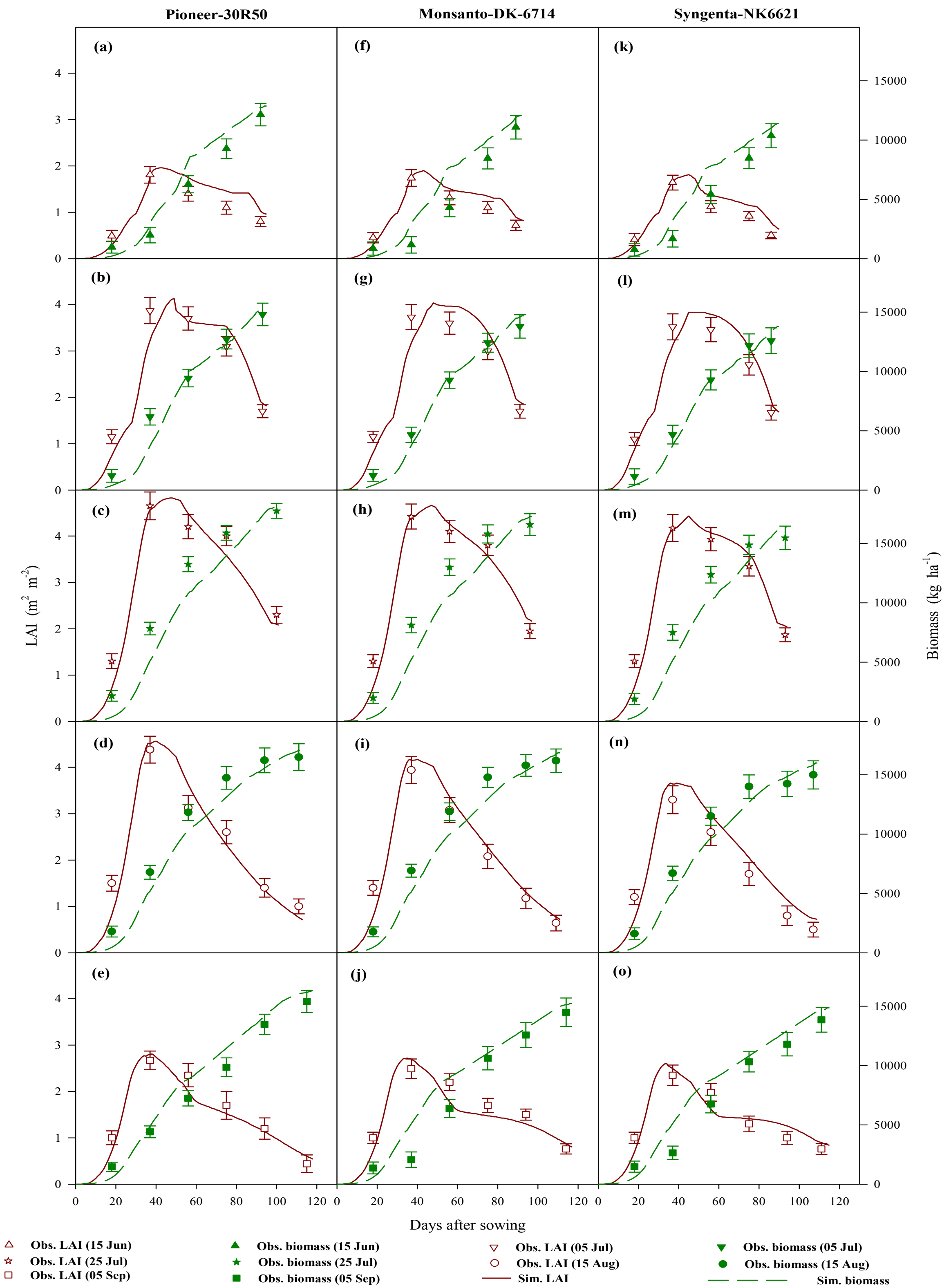

Figure 5. Effect of hybrids and sowing dates on leaf area index and biomass of fall season maize during 2017. (Modified and adopted from Abbas et al. (2023)

3.3.4. Number of grains m^{-2}

In the spring and autumn, the model was able to predict the number of grains m^{-2} in both years of the study (Tables S5 and S6). The model showed good performance for all of the hybrids, but was better for spring hybrid P-33M15 and autumn hybrid P-30R50 in both years. RMSE values of 44.79, 56.65, and 88.40 in 2016 and 57.20, 81.47, and 116.11 in 2017 were obtained for spring hybrids P-33M15, M-DK6525, and S-NK8441, respectively. RMSE values of 33.70, 62.89, and 78.91 in 2016 and 52.68, 70.23, and 69.38 in 2017 were obtained for autumn hybrids P-30R50, M-DK6714, and S-NK6621, respectively. Evaluation of the model was good for all of the sowing dates. It showed good performance for the early sowing dates in the spring and the late sowing dates in the autumn. In 2016 and 2017, the average MPD was 2.66% and 3.69% in the spring and 2.65% and 2.99% in the autumn, respectively, for all of the sowing dates and hybrids.

3.3.5. Grain yield (kg ha^{-1})

The model showed good performance in predicting the grain yield for the spring and autumn in both 2016 and 2017 (Tables S5 and S6). The performance of the maize model was good for spring hybrid P-33M15 and autumn hybrid P-30R50 due to lower error, RMSE, and MPD in comparison with the other hybrids in both 2016 and 2017. When compared to the other hybrids, spring hybrid P-33M15 had the lowest RMSE at 502.98 and 573.50 and MPD at 7.46% and 8.84%, while autumn hybrid P-30R50 had the lowest RMSE at 355.54 and 444.83 and MPD at 5.57% and 7.29% in 2016 and 2017, respectively. The model showed good performance for all of the sowing dates, but was better for the early sowing dates in the spring and the late sowing dates in the autumn. The average error for the sowing dates ranged from 6.26% to 13.36% and 5.22% to 9.34% in 2016, whereas it ranged from 7.95% to 14.91% and 6.17 to 11.27 in 2017 for all of the spring and autumn hybrids, respectively.

3.3.6. Total biomass (kg ha^{-1})

The model showed good performance in predicting the time course data of the biomass in the spring (Figures 2 and 3) and autumn (Figures 4 and 5). While the model showed good performance for both the spring and autumn experiments, it was better for the autumn hybrids (Tables S7 and S8). The model did well in predicting the RMSE and MPD within acceptable ranges for all of the hybrids, but it was better for spring hybrid P-33M15 and autumn hybrid P-30R50 compared to the other hybrids in both years. For both 2016 and 2017, the RMSE and MPD ranged from 701.85 to 1128.76 (kg ha^{-1}) and from 4.28% to 8.45%, respectively, for spring the hybrids and from 628.25 to 1034.28 (kg ha^{-1}) and from 3.98% to 7.86%, respectively, for the autumn hybrids. The model showed good performance for all of the sowing dates, but was better for the early sowing dates in the spring and the late sowing dates in the autumn. With respect to the sowing dates, the error ranged from 2.92% to 10.14% in the spring and from 2.61% to 9.78% in the autumn.

3.3.7. Harvest index (%)

The model showed good performance in predicting the harvest index in the spring and autumn of both 2016 and 2017 (Tables S7 and S8). The model did well for all of the hybrids, but it was better for spring hybrid P-33M15 and autumn hybrid P-30R50 compared to the other hybrids due to the acceptable range value of the model statistics in both years of study. When compared to the other hybrids, spring hybrid P-33M15 had the lowest RMSE at 1.32 and 1.58 and MPD at 3.05% and 3.79%, while autumn hybrid P-30R50 has the lowest RMSE at 0.64 and 0.88 and MPD at 1.52% and 2.13% in 2016 and 2017, respectively. The average error for the sowing dates ranged from 2.07% to 5.94% and 1.36% to 3.22% in 2016, whereas it ranged from 2.83% to 6.42% and 1.79% to 3.20 in 2017 for all of the spring and autumn hybrids, respectively. The model showed good performance for all of the sowing dates, but was better for the early sowing dates in the spring and late sowing dates in the autumn.

3.4. Model application

The CERES-maize model was used to determine the optimum sowing windows for both the spring and autumn for the 15 districts. Long-term weather data from 1980 to 2017 and soil data were separately used for each district. The seasonal strategy of the CERES-maize model depicted that the seed productivity was affected by the diverse sowing dates in the 15 districts. The best performing spring hybrid, P-33M15, and autumn hybrid, P-30R50, were used to obtain the appropriate sowing windows in each district. Figures 6 and 7 show that the optimum sowing window in the spring ranged from January 15th to March 5th, and for autumn, the appropriate sowing window ranged from July 23rd to August 27th for the 15 districts in Punjab, Pakistan. The maize grain yield was seen to decrease with the very early and very late sowing dates in both the spring and autumn in Punjab, Pakistan (Figures 6–9). Figure 10 shows that at all of the sowing dates during the whole year, the simulated grain yield was higher in the spring compared to the autumn.

4. Discussion

Figure 1 shows that the average maximum and minimum air temperatures in 2016 were less (almost 1.2 to 2.6 °C) in comparison with 2017 for both the spring and autumn and this variation in the temperatures had a significant influence on the phenological stages, phases, growth traits, and ultimately, the production of the maize crops in the spring and autumn. The model showed that the simulated data obtained from the hybrid coefficients

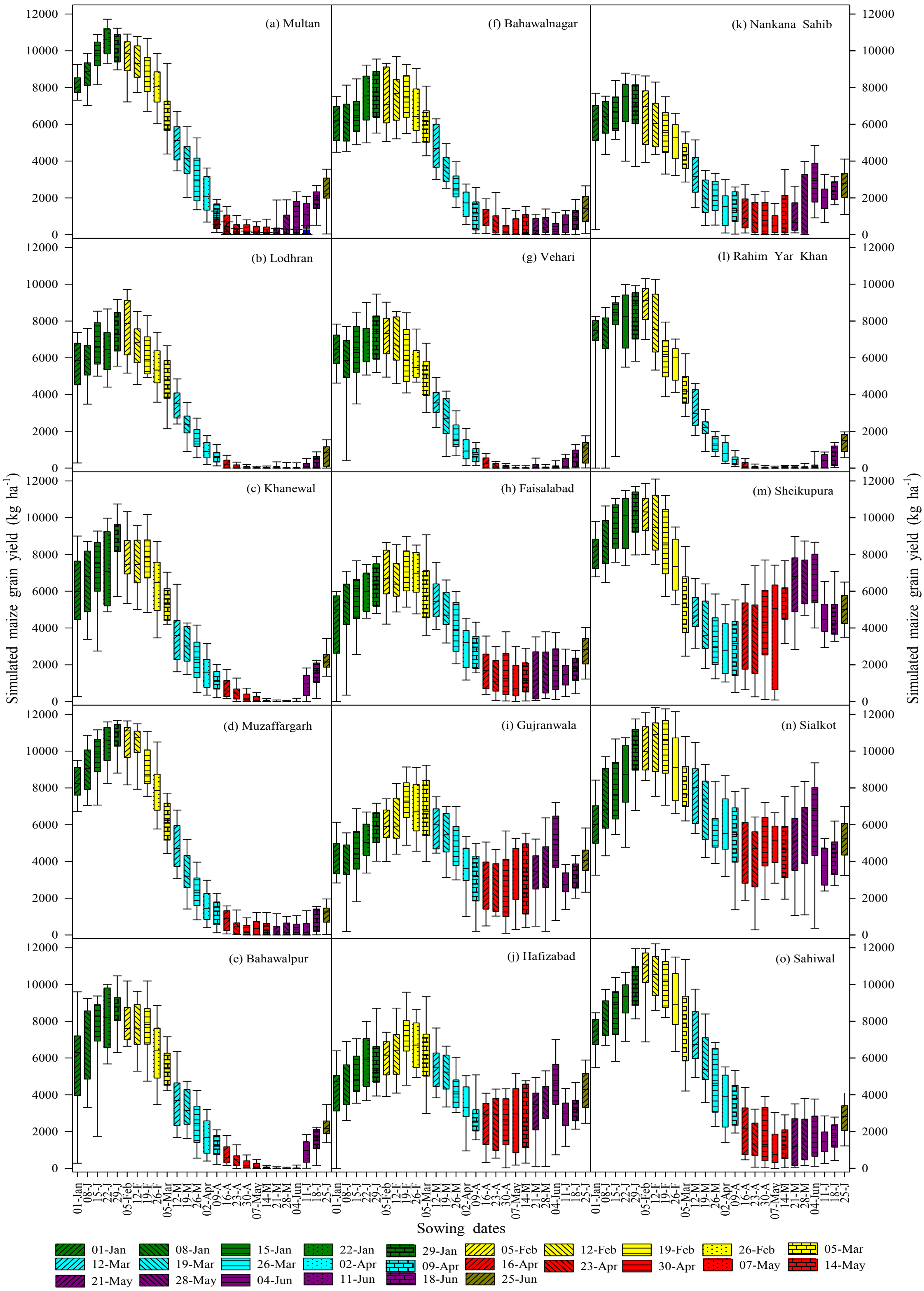

Figure 6. Effect of sowing dates on spring season maize grain yield in 15 districts in Punjab Pakistan (Hybrid-1).

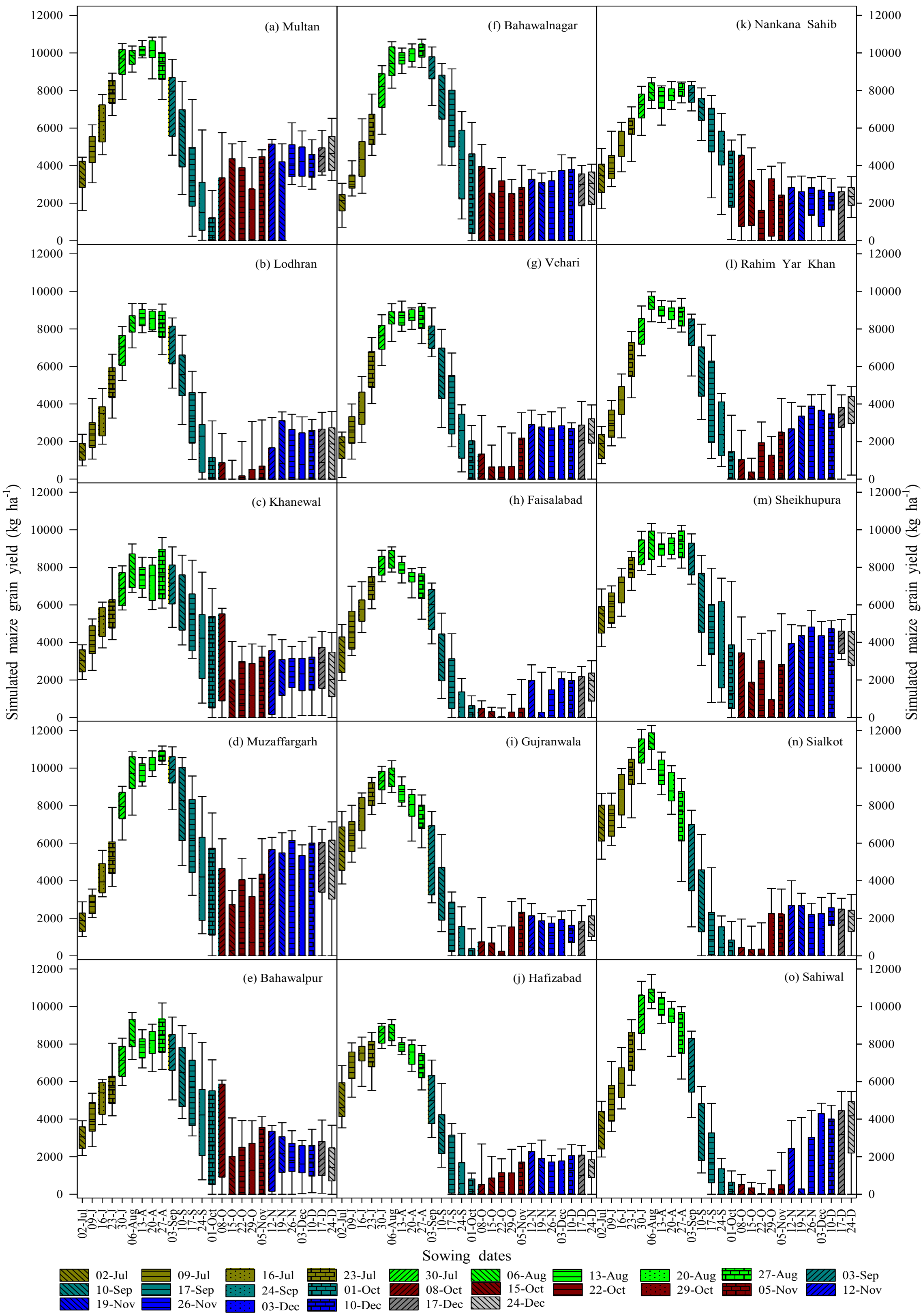

Figure 7. Effect of sowing dates on fall season maize grain yield in 15 districts in Punjab Pakistan (Hybrid-1).

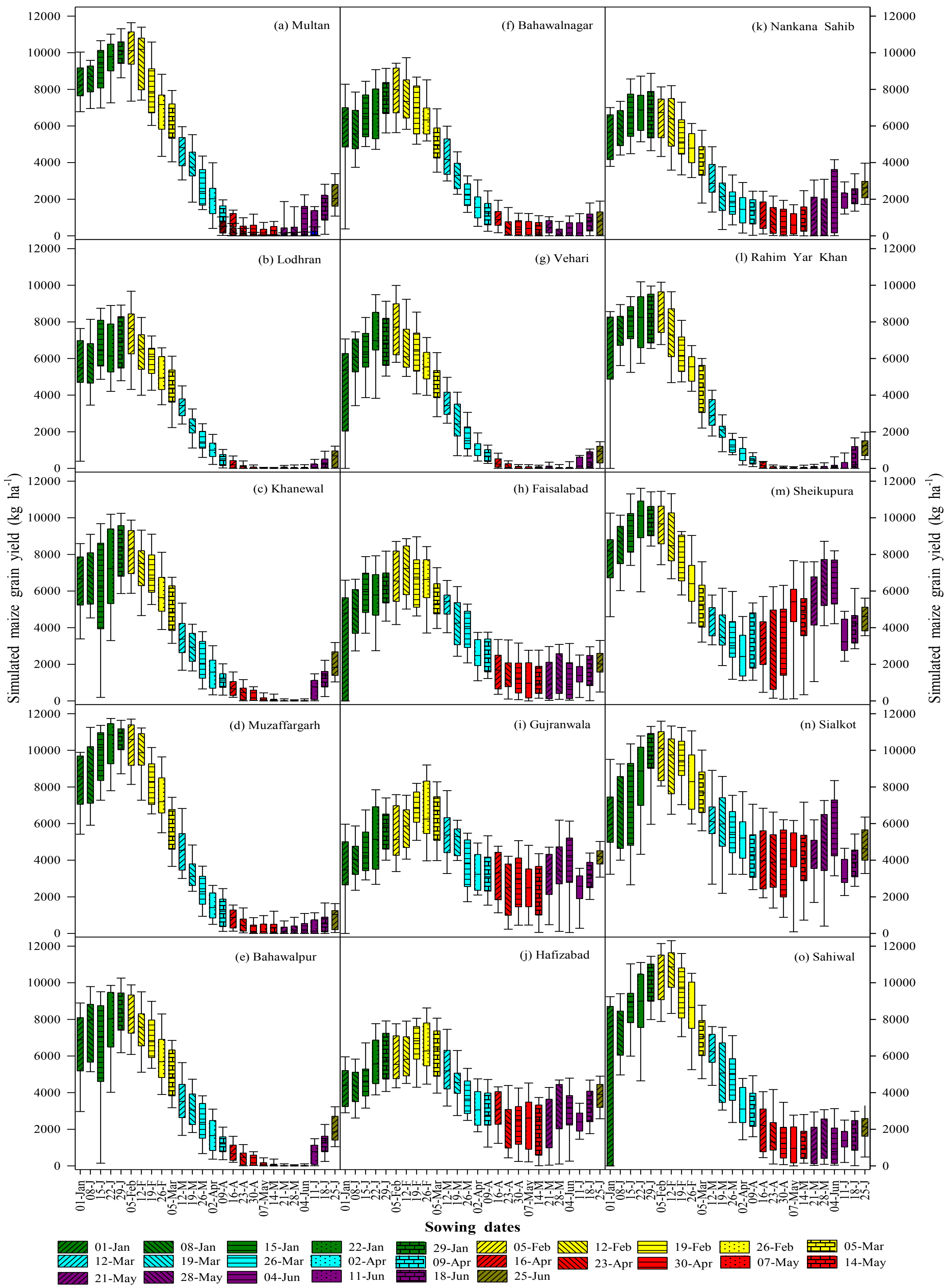

Figure 8. Effect of sowing dates on spring season maize grain yield in 15 districts in Punjab Pakistan (Hybrid-2).

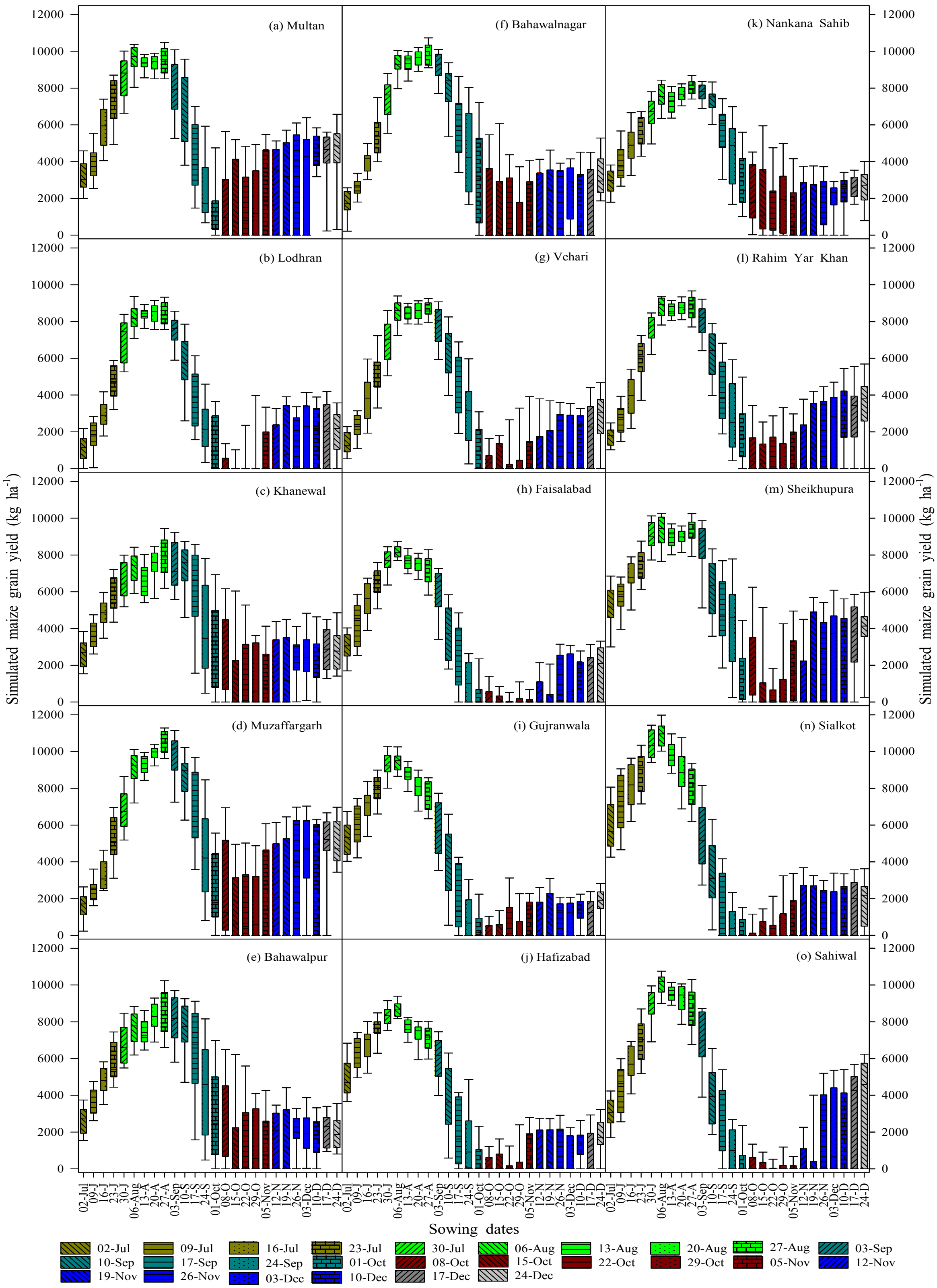

Figure 9. Effect of sowing dates on fall season maize grain yield in 15 districts in Punjab Pakistan 2 (Hybrid-2).

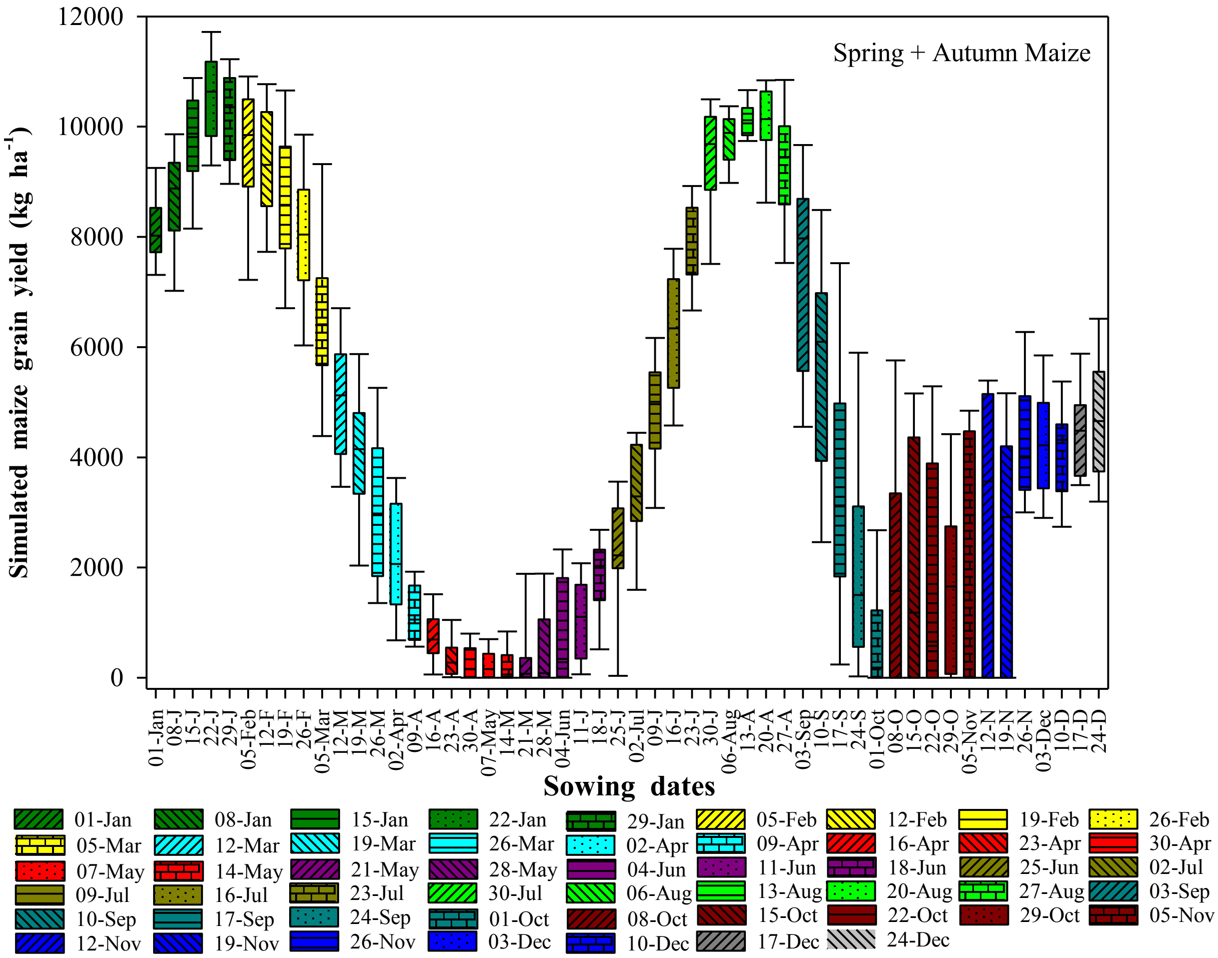

Figure 10. Simulated maize grain yield as affected by sowing dates during spring and autumn seasons.

for the spring and autumn hybrids could be adequate for determining the proper crop management practices in an arid environment for both spring and autumn maize. The anthesis and physiological maturity date were determined through the genetic coefficients of P1 and P5 in the genotype file in the CSM-CERES-maize model, and precise simulation of the phenological stages was obtained due to the close agreements between the field recorded and model predicted number of days to tasseling and physiological maturity in the calibration and evaluation in both seasons. Accurate simulation of the spring and autumn maize phenology was the most imperative stage in the calibration of the model. When phenological stages are precisely calibrated, it is expected that the model will be capable to determine the variations in the genetics of all of the hybrids that influence the leaf area development, grains m^{-2}, mean grain weight, biomass production, and grain yield of maize (Saddique et al., 2019; Sarwar et al., 2021; Khalid et al., 2023). Further research is needed to reduce the amount of mandatory data necessary to determine the coefficients of spring and autumn maize hybrids, especially to decrease the destructive sampling numbers and make it practical under spring and autumn growing conditions (Seidel et al., 2018; Malik et al., 2019; Mubarak et al., 2022). To determine whether the calibration of the CERES-maize model was sufficiently sensitive in capturing the differences among the various spring and autumn hybrids, the coefficients of each hybrid were evaluated (Table 2). The high variations between the hybrids were indicated for the coefficients of phenology. The CERES-maize model was quite capable of simulating the maize phenological stages in both growing seasons (Hammad et al., 2018; Seyoum et al., 2018). The model showed good performance for the maximum LAI, mean grain weight, grains m^{-2}, total biomass, grain productivity, and harvest index in both seasons. The model showed good performance for all of the studied parameters, but overestimated the data as a result of having less sensitivity to temperature. The model-predicted values for the maximum LAI throughout the crop cycles were usually in agreement with field recorded values due to the careful and accurate calibration of the model (Basso et al., 2016; Adnan et al., 2017; Raza et al., 2022).

The CERES-maize model performed well in both the spring and autumn, but it was better in the autumn compared to the spring due to the statistical indice values. This may have been because the model can be more sensitive to weather variables, particularly temperatures and rainfall, in the autumn compared to the spring (Shelia et al., 2018). In the autumn, the average temperature during the phenological phases, and particularly during the anthesis to maturity (grain filling particularly) phase, was greater compared to the spring, so the model showed poorer performance for the spring compared to the autumn (Yakoub et al., 2017). The model showed a greater ability toward adaptation in the autumn compared to the spring in an arid environment. In the spring, the model showed good performance for the early sowing dates (January 15th, February 5th) compared to the delayed sowing dates (February 25th, April 5th), while in the autumn, the model showed good performance for the delayed sowing dates (February 25th, August 15th) compared to the early sowing dates (June 15th, July 5th) in both 2016 and 2017. This may have been due to the model's response to the weather parameters being different due to differences in variability. The model showed good performance for both the spring and autumn hybrids in both 2016 and 2017. With respect to the season, the model showed better performance for the autumn hybrids compared to the spring hybrids due to responding differently to the weather data (Dzotsi et al., 2003; Abbas et al., 2017).

During the calibration and evaluation processes of the DSSAT model, close agreement between the observed and simulated data for the spring and autumn hybrids means that the model could be employed successfully for evaluating the performance of spring and autumn hybrids in Punjab, Pakistan. The results of the simulations showed in low error, MPD, and RMSE for both seasons for the tested variables, signifying that the effectiveness and heftiness of the maize model was reasonably sufficient and the model could be employed in an arid environment for study. Grain production is influenced by intercepted radiation by the crop canopy, radiation-use efficiency, and harvest index. Grain yield simulation in crop growth modeling is the most significant variable for improving crop management (Wolf et al., 2015; Dokoohaki et al., 2016).

Application of the CERES-maize model to determine the optimum sowing windows for the 15 districts suggested sowing dates of February 15th to March 15th in the spring, and July 15th to August 15th in the autumn, for maize in Punjab, Pakistan. Each district has different agroecological and soil conditions. A finding from this study showed that there were variations that exist between various districts with respect to the appropriate sowing date window. Sowing date recommendations for spring and autumn maize in Punjab, Pakistan, are generally based on local information. Recommendation of the sowing date by researchers is also made from extensive field experiments carried out across the districts. Generally, a similar sowing window is suggested for several years as well as various districts with no consideration of the temporal and spatial variations (Li et al., 2015; Bao et al., 2017; Adnan et al., 2019). The farming community also takes a risk when sowing spring and autumn maize with the first onset of rainfall due to the uncertainty of weather conditions in Punjab, Pakistan. Thus, the sowing regulations in the area include a sowing window of approximately 25 days, with roughly projected optimum sowing dates. The optimum sowing windows were different for the different districts due to the variability of climatic conditions, because the grain yield of spring and autumn maize is affected by variations in meteorological parameters such as temperatures, solar radiation, and rainfall (Singh et al., 2017; Ali et al., 2018).

5. Conclusion

The CERES-maize model performed well in the calibration and evaluation for anthesis, maturity dates, maximum LAI, grains m^{-2}, mean grain weight, biomass, grain yield, and harvest index for the different hybrids and sowing dates in the spring and autumn. The time course data of the LAI and biomass yield were rationally well predicted by the model for the spring and autumn sowing dates. When the model was applied after calibration and evaluation, it was able to predict the sowing dates for both seasons, as January 15th to March 5th for the spring and July 23rd to August 27th for the autumn for maize in Punjab, Pakistan. Findings from the study depicted that variations exist between different districts with respect to the optimum sowing date in both seasons. The results of the research support the potential for employing the CERES-maize model for determination of the best crop management plans for higher maize productivity in the spring and autumn under the arid conditions of Punjab, Pakistan. The results showed that the model's simulations were in accordance with the findings of the extension wing regarding the sowing date recommendations for spring and autumn maize. Therefore, it is recommended that maize growers in arid and semiarid areas of Punjab, Pakistan sow spring and autumn maize during these optimum sowing windows to attain higher maize yields.

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