Crop Simulation Mediated Assessment of Climate Change Impact on Rice Grown Under Temperate High Altitude Valley of Kashmir

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Abstract

The major parameters that affect climate change pattern include the latitude, ocean currents, wind, air pressure, elevation and relief. These parameters can influence the behaviour of the crops and their performance in time and space. The study was carried out to gain the perspicacity about the prospectus of cultivation of ruling *japonica* rice variety, *K-332* under climate change scenario for next few decades across temperate high altitude ecology (2000-2300m msl) of Kashmir valley located within North-western Himalayas. Grown over a long period of time, *K-332* was released in the year 1972 and is still popular among the farmers. The variety has supported the food security in rice growing hilly and mountainous areas of the region spread across 50,000 ha area. A study was carried out with effect from the year 2000 up till 2019 for 20 years in order to understand the phenology and stability of yield performance of the variety under changing climate scenario using DSSAT CERES crop simulation model (v.4.7). Model simulated traits namely, days to anthesis, days to physiological maturity, tiller number and grain yield marked an agreement with observed data with low mean absolute error, high R^2 (0.85-0.94), high modified index of agreement (0.74-0.85) and modified modelling efficiency varying from 0.47 for the traits. Our observations lead to the projections under climate change scenario and was concluded that the days to flowering and maturity were projected to decrease by 1.96-8.82 % and 2.11-9.86 %, respectively, with increase in air temperature. However, the tiller number and grain yield were predicted to increase by 3.80 and 2.37 % respectively, under RCP 2.6 during 2021-2050 to 19.00 and 8.70 % under RCP 8.5 during 2075-2099. The study revealed the scope of rice cultivation with the same variety in high altitudes with a potential to not only sustain the climate change effect but exploit it for better yield performance due to moderation of low temperature stress and the reversing of the limitations thus far posed by sub-optimal temperatures and short growing period.

Introduction

Climate change, characterized by changes in atmospheric temperature, spatial / temporal distribution of precipitation and unexpected weather events is attributed to global warming. Climate models simulate significant shifts in regional climate characteristics that are likely to be caused due to future increase in temperatures by 1.5-2°C (IPCC 2018). Coupled model inter-comparison project 5 (CMIP5) predicted average global warming of 4.8^{o}C by the year 2080 and an increase of 14% in precipitation relative to 1861–1900 and 1961–1990 baselines, respectively (Rajiv et al. 2012). Due to increase in temperatures and high variability of rainfall distribution, 80 percent decrease in agricultural production is feared by 2080s in India and neighbouring Asian countries (IPCC 2007).

Agriculture continues to be the backbone of rural economy due to its importance in food security and source of employment to 50 percent of the population. India is vulnerable to severe climate change adversities (NIC, 2009) the phenomenon is supposed to pose a direct threat (Birthal et al. 2014). India is second largest producer of rice with the production of 112.76 mt and an area of 43.77 mha (MAFW, 2019). Though, the production trends of rice over last 70 years indicate the overall yield stability, however, it may be disturbed by adversities of changing climate scenario. As per one of the predictions drawn over the last 50 years by Maximilian (2011), rice yield in India would have been in surplus by 5.70 per cent in comparison to the present mark, if no climate change effect existed. However, interestingly, the adverse impact of high temperature and floods associated with climate change will be higher in lowland rice growing areas resulting in yield decrease to the extent of 14.5% (Mohandrass1995), while mid altitude valleys are expected to experience favourable improvements in rice growing conditions with climate change (Castro 2019). The changing climate scenario with a projected increase of 2.0-5.0^{o}C in mean temperature is expected to overcome the constraint of short vegetative period of rice in high altitudes making the conditions more favourable for its cultivation as long as precipitation is not a limiting factor (Shreshtha et al. 2013).

Domesticated *japonica* rice was introduced into northern India followed by hybridization and back-crossing with the *indica* parents. Introduction of *japonica* rice into South Asia through North-Western India and North-Eastern India directly from China/Myanmar aided by traders from Central Asia was demonstrated to be the most probable route using combination of fine spatial modelling and simulation (Silva et al. 2018). The hill zones of North and North Eastern India have 2.3 million ha of rice spread over the states of Jammu and Kashmir, Himachal Pradesh, Manipur, Meghalaya, Assam, Arunachal Pradesh, Uttar Pradesh, and West Bengal. Kashmir region of Jammu and Kashmir represents a typical temperate agro-ecosystem where rice is grown within an altitude of 1500–2300 msl. The temperatures in Kashmir valley during rice-growing season are similar to those of Hokkaido, Japan. Few varieties from Hokkaido, such as *Shen-ei* and *Fujisaka 5* were used as cold-tolerant parents in breeding of local varieties (Hamdani 1979). The breeding programme undertaken in active collaboration with IRRI, Philippines in the year 1965 involved the crossing of local traditional cultivars with exotic *japonica* varieties followed by selection and multi-location testing. The selections among the lines lead to the development of a variety *K-332*, identified and released for higher altitudes of Kashmir in the year 1972. The variety is characterized by early maturity, blast resistance and tolerance to cold stress and has been recommended for high altitudes with an average yield potential of 4.15 t/ ha. Since 1968, several varieties have been released for cultivation but they could not match the popularity and performance of *K-332*. Since its release in 1972, the variety has been dedicated as a check in routine breeding programmes at Kashmir. To achieve an insight into the popularity and performance of the variety and in order to predict its future scope to buttress the load of ever growing population and therefore, sustain the food demand in the mountainous areas of the region, we generated a prediction model of its projected performance under climate change scenario. The hypothesis that the performance of the variety has not changed during the study period or will not negatively change with the projected climate change in future, was tested in the present study.

To workout the impact of climate change on crop performance, it requires the climate to be partitioned into quantifiable factors affecting the crop growth and yield and to assess the crop growth stages at which these factors have maximum or minimum impact. Crop growth and yield simulation model DSSAT CERES v 4.7 studies the impact of climatic factors like daily maximum temperature, minimum temperature, total incoming solar radiation and rainfall on the critical physiological and yield contributing characters of rice to ensure accurate simulation of its yield under diverse agro-climatic conditions on different soils with different crop management strategies. The performance of the model has been extensively validated in predicting physiological, genetic and agronomical behaviour of rice under the integrated effect of climate, soil and biotic factors for assessing the potential impact of climate change on its growth and yield (Diaset al., 2016; Shakeel et al., 2012; Nyangau et al. 2014 and Danladi et al. 2017).

Materials And Methods

Experimental Site

The study was conducted at Mountain Research Centre for Field Crops, SKUAST-Kashmir, Larnoo, Anantnag, J&K (75.331^{o}N, 33.644^{o}E) at an altitude of 2280 msl. The location is characterized by cold temperate conditions with moderate summers and severe winters. The rice crop is grown between April to October with the maximum temperatures falling in the range of 25-30^{o}C. The precipitation follows the even distribution at 75-100 mm per month during active growth phase and then decreases sharply near maturity in September (Figs. 1-6). The soil texture is clay loam to clay with moderate fertility status and slightly acidic pH devoid of any hazardous salt accumulation.

Record of observations

The observations on the variety K-332 were recorded on a uniformly maintained experimental plot of 225 m^2 area for a period of 20 years starting from the year 2000 to 2019. The traits recorded were plant height (cm), days to 50% anthesis, number of tillers per m^2, number of spikelets per panicle, days to physiological maturity and grain yield per plot (q/ha). The observations on yield recorded during the year 2000 were used to calculate the genetic coefficients of the rice variety *K-332* and for subsequent calibration and validation of the CERES model. Validation of the CERES model was carried out with the yearly crop data recorded from 2001 to 2019. Days to flowering was counted from the date of sowing up to anthers dehiscence stage of the terminal spikelets of half of the plant population on plot basis and physiological maturity stage was marked on the day when caryopses of 90 percent of the grains from sampled secondary and tertiary panicles were fully developed in size and were hard, free from greenish tint. The single panicle from the primary tiller was harvested at maturity from thirty plants from random corners of the plot, the number of spikelets was counted and expressed as spikelets per panicle. Height of such thirty plants was recorded from ground level to the tip of the longest leaf and averaged to get the plant height (cm). Grain yield was calculated from the weight of grains harvested from the whole plot and air dried to about 14 percent moisture. Information on texture (clay and silt %), depth, surface albedo, soil organic carbon, fertility factor, and pH was included in soil data sub-module as per the outlined procedure. Soil drainage and hydraulic characteristics were computed through the sub-module (Gijsman et al. 2002, 2007 and Ritchieet al. 1989).

The Crop model

The DSSAT CERES v 4.7crop model required daily record of observations on total incoming solar radiation (MJ/m^2-day), maximum and minimum air temperature (ºC), rainfall (mm), information on soil parameters (texture, depth, organic carbon, pH and bulk density) and crop management data (planting date, planting density, row spacing, planting depth, crop variety, irrigation and fertilizer practices) as input (Hoogenboom et al. 2019 and Jones et al. 2003). Genetic information about rice crop were defined in rice cultivar file of the software. The simulation model integrated the effects of soil, crop phenotype, weather and management options, and allowed "what if" virtual simulation experiments. The model also provided for evaluation of crop model outputs with experimental data to facilitate comparison of simulated outcomes with observed results.

Model calibration and validation

The DSSAT-CERES v 4.7 rice model was calibrated with average end-of-season data on days to anthesis, days to physiological maturity and grain yield obtained from field experiments carried under optimum crop and soil management in 2000 (Supplementary Table S1). The Genetic coefficients for K-332 rice variety were estimated by running genetic coefficient calculator(GENCALC) module in the DSSAT v 4.7.The GENCALC for K-332 was run with a set of cultivar coefficients available in rice cultivar file after adding the K-332 rice cultivar to the file. The genetic coefficients were increased and decreased through an interactive procedure in the cultivar file, to get a best suitable set of genetic coefficients as per Hunt et al. (1993).

For comparing the impact of projected climate change scenario on phenology and yield of K-332 with that of other four high altitude rice varieties (Koshihikari, Mushk Budji, Kamad and Shalimar Rice 5) at MCRS, Larnoo and five low altitude rice varieties (Jhelum. Shalimar Rice-1, Shalimar Rice-2, Shalimar Rice-3 and Shalimar Rice-4) at MRCFC Khudwani the model was calibrated as per the recommended procedure (Hunt et al. 1993) for each of the nine varieties using the required crop data, recorded during 2019 from experimental plots of these varieties, maintained under optimum management. The simulation performance of the model was validated with crop data for these varieties, obtained during 2020. Subsequently, the temperature in the weather module of the model was increased as per the IPCC climate change projections and effect of every modification on crop performance was simulated and compared with base crop data for the year 2019 (Table 1 and Supplementary Table S2).

Statistical analysis

The observed and model simulated data was subjected to following statistical analysis for elucidating the performance of the simulation.

Coefficient of Determination

$$R^2 = \{\Sigma[(X_i - \bar{X})(Y_i - \bar{Y})] \Big/ \sqrt{[\Sigma(X_i - \bar{X})^2 \ x \ \Sigma(Y_i - \bar{Y})^2 \ ]} \ \}^2$$

Where, X_i**: Observed data; *****Y_i*****: Simulated Data**

R^2 was used as a measure of goodness of fit for the observed and simulated data and ranges from 0-1.

Mean absolute error

$$MAE = \frac{1}{n}\sum |Y_{i-}X_i|$$

MAE takes the units of y - x and is used as measure of accuracy to compare the output of the same variables. MAE >= 0

Modified index of agreement

$$d_1 = 1 - \{\Sigma|Y_i - X_i| \Big/ \Sigma \ |Y_i - \bar{X}| + |X_i - \bar{X}|\}$$

Modified modelling efficiency

$$EF_1 = 1 - \Sigma|Y_{i} - X_i| \,/\, \Sigma|X_{i} - \bar{X}|$$

EF_1 (-∞ to 1.0) is based on sum of absolute values of deviation

Climate change projections

Climate change projections for South Asia made by Intergovernmental Panel on Climate Change (IPCC) using representative concentration pathways (RCPs) under the Coupled Model Inter-comparison Project 5 (CMIP5) were used for the assessment of impact of climate change on rice crop performance (Table 1). The RCPs consider four 21st century pathways of greenhouse gas (GHG) emissions, their atmospheric concentrations, air pollutant emissions and land use. The RCPs rely on Integrated Assessment Models (IAMs) and multiple climate simulation models for making future climate projections. The RCPs include a strict mitigation scenario (RCP2.6), two intermediate scenarios (RCP4.5 and RCP6.0), and one scenario (RCP8.5) with very high GHG emissions. (IPCC, 2014)

Simulation of spikelets per panicle and plant height

The traits plant height and spikelets per panicle were not directly included in the crop model. Therefore, a separate analysis was carried out to estimate the effect of climate change on these two parameters. The simple genotypic correlations between the traits plant height, spikelets per panicle, days to anthesis and number of tillers as against grain yield were mined from the previous studies. Here the data from eleven such studies published in rated journals was used to create a correlation matrix among the four above given traits. Match pair analysis was carried out among the correlation coefficients from all the eleven studies and two arrays from the present study. Only the match pair analysis which involves the comparison with expected and observed values from the present study have been discussed.

Results

Model calibration and Validation

The model simulated rice phenology and yield was in good agreement with the observed values throughout the study period (Table 2 and Fig. 7). The model simulated the days to anthesis (ADAP) and days to physiological maturity (MDAP) perfectly with the difference of 0–2 days between simulated and observed ADAP and 0–4 days between simulated and observed MDAP. The model simulated tiller number and grain yield was in very good agreement with the observed values. The lower mean absolute error (MAE), higher R^2 and higher modified degree of agreement (d_1), obtained between the simulated and observed phenological and yield data indicated that the model was consistently efficient in predicting the growth and yield performance of *K-332*. MAEs of 0.89, R^2 of 0. 85 and d_1 of 0.82 between simulated and observed days to anthesis indicated the accuracy of model in making the prediction. The agreement between the simulated and observed tiller number per m^2 was best among the studied parameters with R^2 of 0. 94 and d_1 of 0.85. Model also predicted the grain yield with good agreement between the simulated and observed values with d_1 of 0.74. The modified modelling efficiency of the simulation ranged from 0.47 for yield to 0.69 for the days to physiological maturity prediction.

Climate change impact on K-332

As compared to the year 2019 days to anthesis in *K-332* was projected to decrease by 1.96% from 2021–2050 under RCP 2.6 with average air temperature increase of 1.70°C and precipitation increase of 1.20 mm. A decrease of 8.82% in days to anthesis from 2070-90 under RCP 8.5 with average air temperature increase of 4.78°C and precipitation increase of 11.3 mm was simulated by the model (Table 3). Days to physiological maturity were simulated to decrease by 2.11% from 2021–2050 under the RCP 2.6 and 8.96 percent from 2021–2050 under the RCP 2.6% (Table 4). The effect of increase in temp and precipitation on number of tillers/ m^2 and grain yield (q/ha) under different RCPs was found to be positive from 2021–2050 under RCP 2.6 to 2070–2099 under RCP 8.5 with respective increase in tillers/ m^2 from 3.80 to 19.00% (Table 5) and grain yield (q/ha) from 2.37 to 8.70 percent (Table 6). For a set of traits used to predict performance of *K-332* under changing climate, the highly significant correlations were detected between observed and simulated data (Supplementary Table S3). The significant P-values were also noted between days to anthesis and days to physiological maturity. Days to maturity and days to physiological maturity showed strong association with grain yield. Both the simulated and observed data explained the observed grain yield in *K-332* with high precision as indicated from confidence interval (Fig. 8).

Match pair analysis was carried out to draw some interpretations on plant height and spikeletes per panicle which were not recorded during the entire 20 year period. The analysis, however, validated a fit between simulated and observed values arising from the correlation matrix. Observed trend of correlations between actual data set and that of the average of eleven correlation studies reported from previous authors fitted the match pair test with high precision (average r = 0.61). From the individual studies, the observed correlations of traits with grain yield showed a perfect match with four out of 11 studies with significant P-values. From the individual studies, the observed trait correlations with grain yield showed perfect match with correlations reported from three (S1, S2 and S11) out of eleven studies with significant P-values. These matches depicted collinearity of r-values in test variety K-332 and supporting literature for both the traits, plant height and spikelets per panicle. Individually, plant height showed significant match pair value with S4 and S9 whereas, spikelets per panicle showed significant match with S7 and S8 (Supplementary Table S4-S6; Fig. 9, Supplementary Fig. S1).

Climate change impact on other varieties

The days to anthesis and days to physiological maturity decreased progressively with projected increase in temperature under different RCPs for all the studied rice varieties (Supplementary Fig. S2). Different varieties exhibited variability with respect to the effect of increase in temperature on days to anthesis under different RCP scenarios, with maximum decrease for all varieties in days to anthesis predicted under RCP 8.5 over 2070–2099. The minimum percent decrease in days to anthesis (5.74 %) was predicted for the variety *Jhelum* and maximum (11.42 %) value for variety *Kamad* under RCP 8.5 over 2070–2099, as compared to baseline crop data of year 2019. *K-332* showed 8.82 % decrease in days to anthesis under RCP 8.5 over same period as compared to baseline data of 2019. Days to physiological maturity was predicted to decrease in similar trend as days to anthesis, with minimum decrease under RCP 2.6 over 2021–2050 and maximum under RCP 8.5 over the period 2070–2099. The days to physiological maturity was relatively stable for *Jhelum* over all RCP scenarios with least decrease (6.15%) under RCP 8.5 over the period 2070–2099 and the maximum decrease (9.85 %) in physiological maturity was predicted for *K-332*. In general the percent decrease in days to anthesis and days to physiological maturity was lower for low altitude rice varieties under all the climate change scenarios. Number of tillers/m^2 at maturity increased with increase in temperature as projected under different RCP scenarios, with maximum increase predicted for 2070–2099 under RCP 8.5 (Fig. 8). High altitude rice varieties were predicted to have higher tiller number/m^2 as compared to lower altitude varieties under all climate change scenarios. The minimum increase (4.80%) in number of tillers/ m^2 was predicted for *K-332* and maximum (19.00 %) for *K-332* under RCP over 2070–2099.

Grain yield of high altitude varieties was simulated to increase continuously with increase in temperature from RCP 2.6 for the period 2021–2050 to RCP 8.5 for the period 2070–2099. High altitude varieties will have higher increase in grain yield as compared to low altitude varieties under different RCPs, with maximum increase in their yield expected under RCP 8.5 over 2070–2099. Grain yield of low altitude varieties will increase progressively up to RCP 6.0 over the period 2046–2075 and will decrease thereafter, with maximum decrease under RCP 8.5 over the period 2070–2099. Among the different varieties, the yield of *Jhelum*, a variety adapted to valley plains, will decrease by 9.22 % by the period 2070–2099 under RCP 8.5 as compared to 2019 grain yield, whereas the grain yield of *K-332* will have maximum increase (8.70 %) by 2070–2099 under RCP 8.5.

Discussion

The variation in efficiency of the model in simulations of days to anthesis (0.62), days to physiological maturity (0.73), tiller number/m^2 (0.69) and grain yield (0.47) (Table 2) of the crop under study reflect the need for addition to minimum data required for making the simulation. The agreement between the simulated phenological stages and yield of rice has been reported by Phakamas (2015). The model evaluation results by Saythong et al. (2015) showed strong agreement between simulated and observed days to harvest of rice and acceptable accuracy in grain yield prediction. Ebrahimirad et al. (2018) has also documented the accuracy of DSSAT CERES model in rice grain yield simulation. The model simulation results obtained are further supported by the findings of Ray et al (2018), who found a good agreement between simulated and observed days to anthesis, days to physiological maturity and grain yield of rice.

The positive effect of increase in temp and precipitation on number of tillers and grain yield was noted. Yoshida, et al. (1973) also reported increase in tiller number with increase in temperature, attributing the enhanced leaf age which promotes the tiller bud development and subsequently the tiller number. Partha et al. (2019) reported positive effect of higher temperature on tiller number of rice. Pepijn and Sander (2018) reported an increase of 25 percent in the yield of irrigated rice from East Africa due to more favourable temperatures with climate change. Han et al. (2013) projected a yield increase of rice by 24% in Habrin China under AIB climate change scenario. Mohammad (2019) reported DSSAT-CERES predicted decrease in physiological maturity with increase in temperature under projected climate change. The increased temperature associated with climate change under different RCPs will overcome the low temperature constraints at critical growth stages of rice at higher altitudes. The minimum, maximum and average temperatures at germination, seedling emergence, tillering, panicle initiation, flowering and ripening is lower than optimum temperatures and the projected increase in temperature under different RCPs will optimize the current temperature resulting in yield enhancement. Since the current temperatures are well below the optimum, thus higher the projected increase in temperature higher is the yield simulated by the DSSAT CERES crop model. Further, the decreasing trend of spikelets per panicle of rice at temperatures above the optimum (

30-35^{o}C) like that of grain yield is supported by the findings of Sulaiman et al. (2018), who reported reduced spikelets per panicle under heat stress at booting and vegetative stage (45^{o}C/ 30^{o}C) as compared to control (32^{o}C / 25^{o}C). Similar results have been obtained by Ohe et al. (2007) and Tran et al. (2017). Reduction in plant height of rice at temperatures more than optimum (33^{o}C) have been reported by Krishnan et al. (2011). Sadam et al. (2019) have also reported retarded shoot growth of rice at temperatures more than 35^{o}C.

The low temperature prevalent across high altitudes prolongs the days to anthesis and days to physiological maturity of rice. Increase in temperature as projected under different climate change scenarios, improves the root activity and modulates the physiological activity towards normal resulting in earlier anthesis and physiological maturity. The favourable effect of climate change on number of tillers/ m^2 at harvest and grain yield of high attitude rice varieties is due to the improvement in seedling vigour and decrease in spikelet sterility associated with low temperature. Under the optimum temperatures at low altitude conditions, the effect of temperature increase on phenological and yield traits of rice will not be so pronounced as on higher altitude rice varieties. The gradual yield increase of low altitude rice varieties up to RCP 6.0 and sharp decrease thereafter can be attributed to low panicle weight and shortening of grain filling period. Krishnan et al. (2011) reported similar effect of high temperatures on phenology and yield of rice. The results are in agreement with findings of Dias et al. (2016) who reported decrease in days to physiological maturity and grain yield of rice with increase in temperature above the optimum. Mall et al. (2017) also reported increase and decrease in rice yield under different agro-climatic conditions of India.

In addition to co-efficient of determination (R^2), absolute value based statistical indices, i.e., mean absolute error (MEA), modified index of agreement, d1 and modified modelling efficiency (EF1) were used because these indices are not overly sensitive to major deviations like root mean square error (RMSE), modelling efficiency (EF) and index of agreement (d) (Krause et al.2005 and Willmott et al. 2011). R^2can approach value close to 1.0 (better goodness of fit), even if simulation is an over or underestimation as compared to the observed data (Krause et al. 2005), so further statistical analysis of the data was necessary for ascertaining the efficiency of simulation. As compared to RMSE, MAE to is much efficient in reducing the inflation due the outlier (Willmott et al., 1985). It takes the units of y - x and is used as measure of accuracy to compare the output of the same variables. MAE > = 0 (Yang et al., 2014).The modified index of agreement, d1 (0–1.0), was proposed by Willmott et al. (1985) to overcome the inflated effect of the extreme values in the sum of squares-based index of agreement, d.EF1 (-∞ to 1.0) is based on sum of absolute values of deviation and is less sensitive to extreme values as compared to sum of squares based EF (Legates and McCabe 1999).

Match pair analysis helped us to draw some conclusions about the missing traits in long term data set. The analysis pointed out that plant height and spikelets per panicle are associated with yield and therefore, the predictions based on our model can be applied to these two vital characters which could not be tested directly in our model. As such the spikelets per panicle and plant are simulated to show an increasing trend like that of grain yield under different climate change projections as long as the temperature approaches the optimum range, there after reduction as in grain yield is predicted for these parameters.

Conclusion

A good agreement between the simulated and observed crop parameters with modified degree of agreement ranging from 0.74 for grain yield to 0.85 for tiller number/m^2 indicate that the model can be relied upon for making advance yield estimates of rice. However, variation of modelling efficiency in simulation of the same phenological character and yield trait of the crop during different crop growth seasons suggests requisite additions to minimum data sets needed for crop simulation. Model simulated effect of climate change was in very good agreement with the expected changes in growth and yield of the crop variety, owing to variation in prevailing agro-climatic conditions as a result of projected climate change. Efficient crop simulation models need to be integrated with long range location specific climate projection tools for comprehensive study on crop behaviour in unconventional areas under changing climate scenario, so that timely regional, national and global policy is framed and implemented to help the important crops evade the climate change adversity.

Declarations

Author Contributions

AS carried out the model validation and analysis of data; NRS, ABS, AH, MS, FAM, NAB and SHW conducted the experimental trials and curated the previous experimental data. NRS, ABS, GHK and AH carried conduct of control experimental trials in the field. Second part of the analysis of data was carried out by ABS. AS, ABS, AH and NRS wrote the manuscript.

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Availability of data and material:

All data generated or analysed during this study are included in this published article and its supplementary information files.

Code availability: No software application or custom code was used

Compliance with Ethical Standards:

- Disclosure of potential conflicts of interest: The authors declare that they have no conflict of interest. Authors share no financial interest.
- Research involving Human Participants and/or Animals: The research did not include any kind of research involving animals
- Informed consent: All authors have been taken consent from before submitting the article in present form

Consent to participate:

All authors have been shown their consent

Consent for publication:

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Tables

Table.1.IPCC (CMIP5) projected change in temperature and precipitation as compared to 1861-1900

Projection	2021-2050		2046-2075		2070-2099	
	Temperature (°C)	Precipitation (mm)	Temperature (°C)	Precipitation (mm)	Temperature (°C)	Precipitation (mm)
RCP 2.6	1.70	1.2	1.92	2.7	1.95	3.5
RCP 4.5	1.85	0.8	2.49	4.3	2.87	7.0
RCP 6.0	1.72	1.6	2.37	3.5	3.27	6.8
RCP 8.5	2.02	2.4	3.31	6.6	4.78	11.3

Table.2. Observed (Ob) vs simulated (Sim) phonological and yield data of rice from 2001-2019

Year	ADAP (Days to anthesis)		MDAP (Days to physiological maturity)		TAM (Tiller number at maturity (number/ m^2)		Yield at harvest maturity (kg/ha)	
	Ob	Sim	Ob	Sim	Ob	Sim	Ob	Sim
2001	100	101	141	140	552	542	5070	4969
2002	96	96	137	138	474	461	6070	5767
2003	97	96	136	136	492	511	6240	6053
2004	99	98	140	141	465	457	5830	5713
2005	99	99	140	139	504	491	5670	6237
2006	96	95	138	138	474	461	5730	6188
2007	96	94	135	135	444	431	5850	6435
2008	98	98	142	143	498	509	6060	6266
2009	99	101	144	140	513	507	5810	6365
2010	105	103	146	145	450	463	4660	5079
2011	93	93	137	137	510	500	6660	7193
2012	95	96	136	136	420	411	5480	5206
2013	98	97	139	139	450	457	5550	5384
2014	103	101	150	147	540	523	2770	2992
2015	96	96	138	138	480	480	6290	6330
2016	94	94	139	136	600	623	5110	5621
2017	96	96	140	140	510	500	4360	4709
2018	99	101	140	139	540	532	4920	5412
2019	102	101	142	142	421	410	5070	5377
	MAE=0.89		MAE=0.89		MAE=11.26		MAE=336.42	
	R^2= 0. **85**		R^2= 0. **86**		R^2= 0. **94**		R^2= 0. **87**	
	EF_1=0.62		EF_1=0.66		EF_1=0.69		EF_1=0.47	
	d_1=0.82		d_1=0.82		d_1=0.85		d_1=0.74	

Table.3. Simulation of climate change impact on days to anthesis

Scenario	2021-2050		2046-2075		2070-2099	
	ADAP	(%) Change	ADAP	(%) Change	ADAP	(%) Change
2019	102		102		102	
RCP 2.6	100	-1.96	99	-2.94	97	-4.90
RCP 4.5	99	-2.94	98	-3.92	96	-5.88
RCP 6.0	97	-4.90	95	-6.86	94	-7.84
RCP 8.5	96	-5.88	94	-7.84	93	-8.82

Table.4. Simulation of climate change impact on days to physiological maturity

Scenario	2021-2050		2046-2075		2070-2099	
	MDAP	(%) Change	MDAP	(%) Change	MDAP	(%) Change
2019	142		142		142	
RCP 2.6	139	-2.11	137	-3.52	134	-5.63
RCP 4.5	137	-3.52	136	-4.23	131	-7.75
RCP 6.0	135	-4.93	133	-6.34	130	-8.45
RCP 8.5	134	-5.63	131	-7.75	128	-9.86

Table.5. Simulation of climate change impact on tiller number at maturity (number/m^2)

Scenario	2021-2050		2046-2075		2070-2099	
	TAM	(%) Change	TAM	(%) Change	TAM	(%) Change
2019	421		421		421	
RCP 2.6	437	+3.80	451	+7.13	482	+14.49
RCP 4.5	456	+8.31	471	+11.88	489	+16.15
RCP 6.0	476	+13.06	483	+14.73	494	+17.34
RCP 8.5	485	+15.20	494	+17.34	501	+19.00

Table.6. Simulation of climate change impact on grain yield at maturity (kg/ha)

Scenario	2021-2050		2046-2075		2070-2099	
	HWAM	(%) Change	HWAM	(%) Change	HWAM	(%) Change
2019	5070		5070		5070	
RCP 2.6	5190	+2.37	5210	+2.76	5290	+4.34
RCP 4.5	5187	+2.31	5230	+3.16	5380	+6.11
RCP 6.0	5193	+2.43	5257	+3.69	5462	+7.73
RCP 8.5	5200	+2.56	5435	+7.20	5511	+8.70

Figures

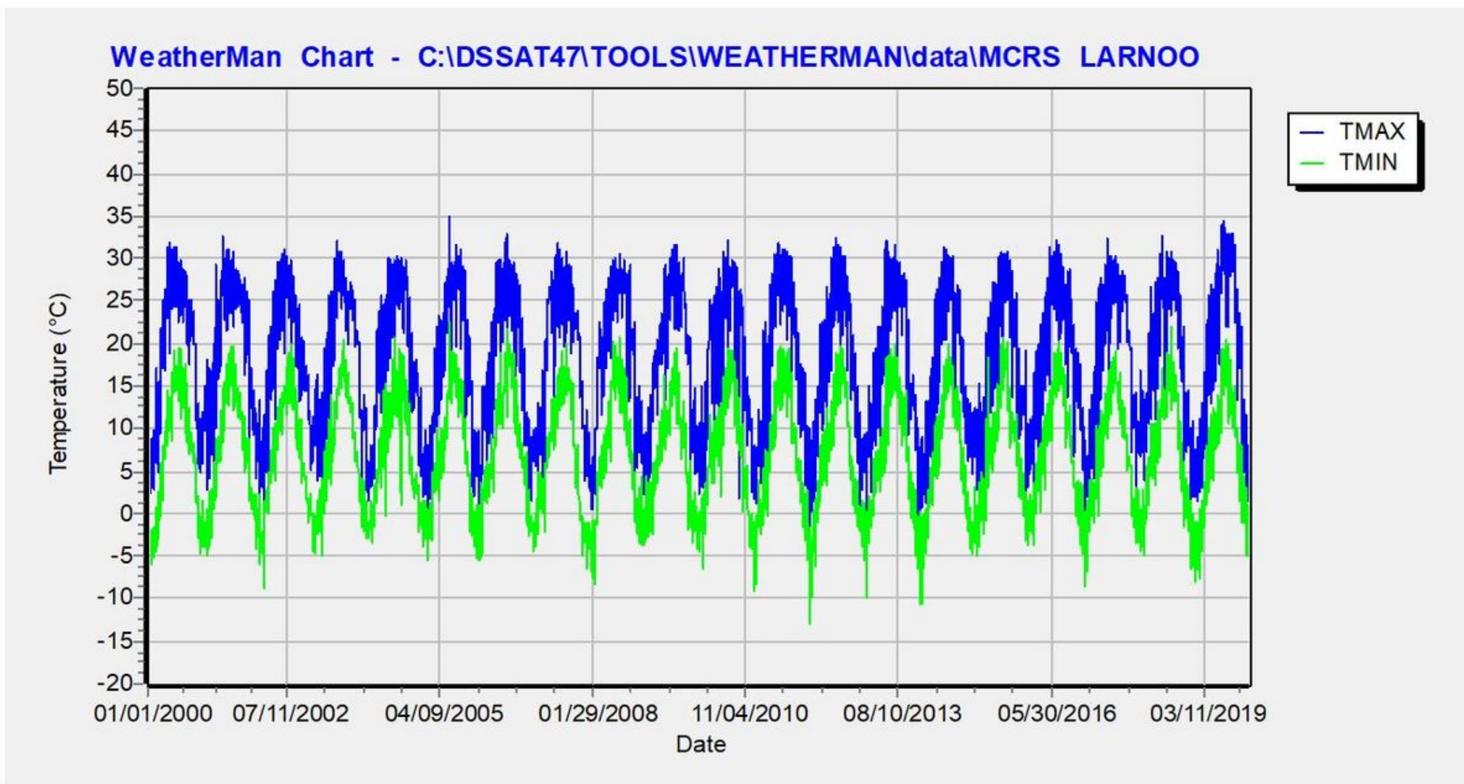

Figure 1

Daily minimum temperature (oC) and daily maximum temperature (oC) recorded at MCRS Larnoo (01-01-2000 to 31-12-2019)

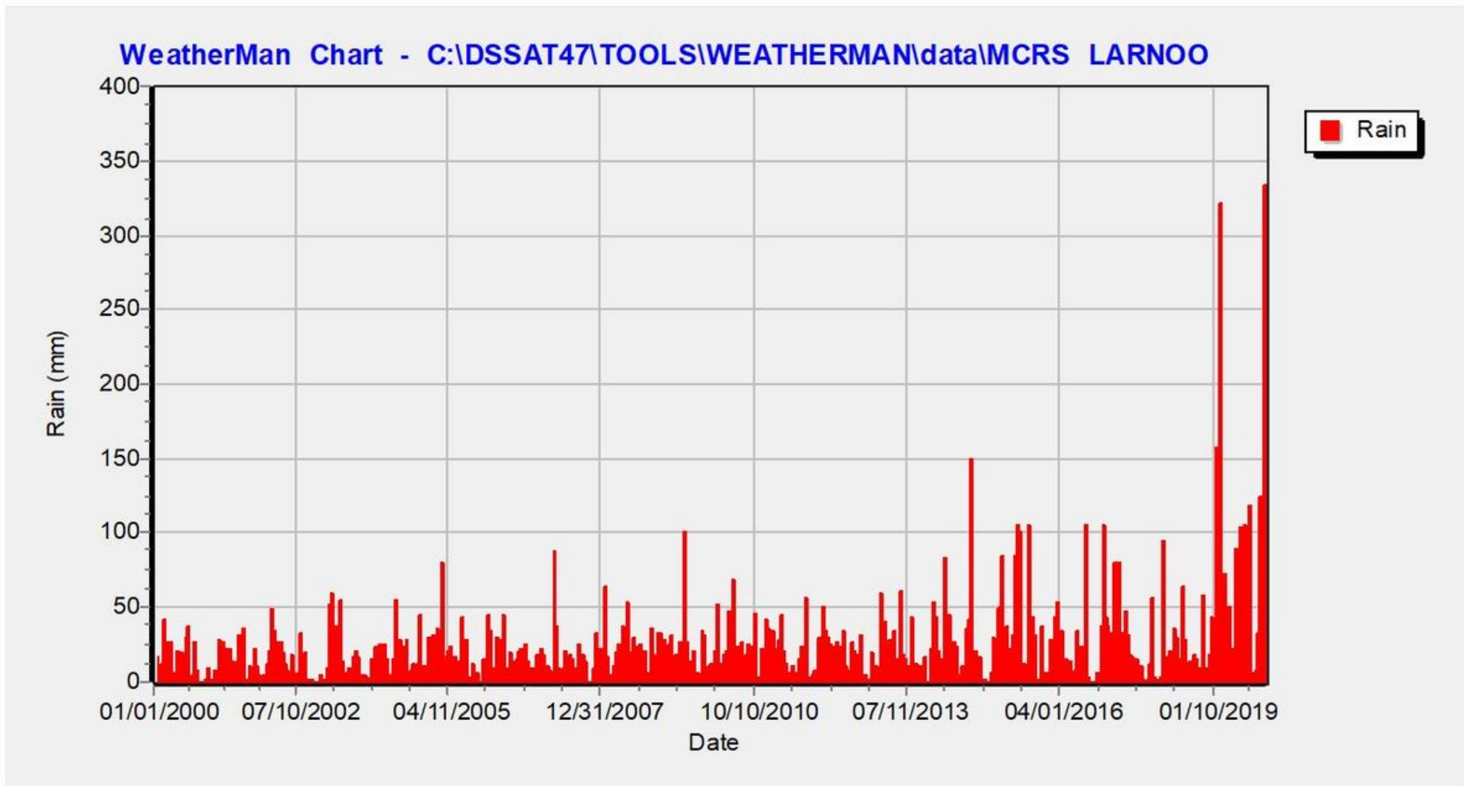

Figure 2

Rainfall / precipitation (mm) recorded at MCRS,Larnoo (01-01-2000 to 31-12-2019)

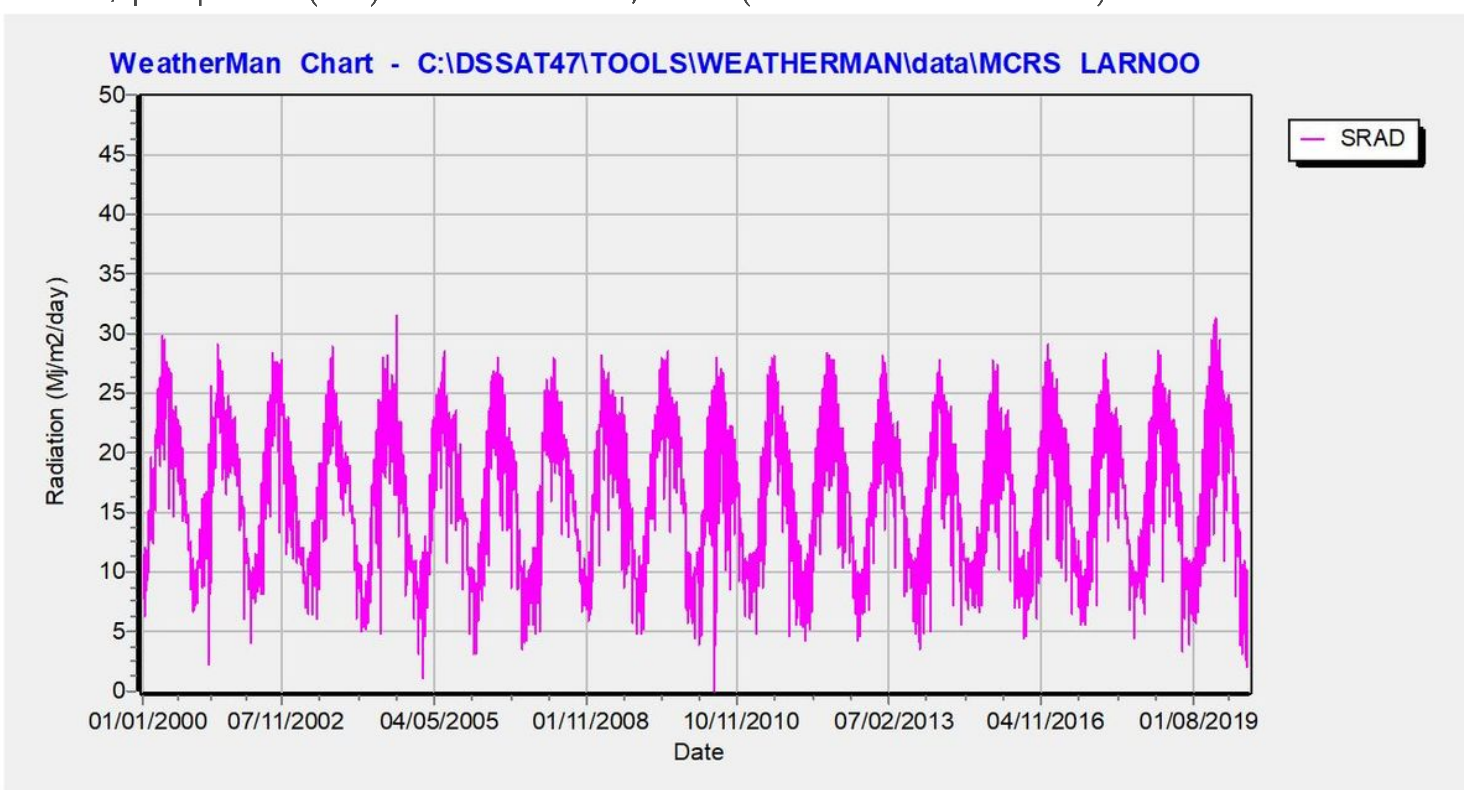

Figure 3

Total incoming solar radiation at MCRS,Larnoo (01-01-2000 to 31-12-2019)

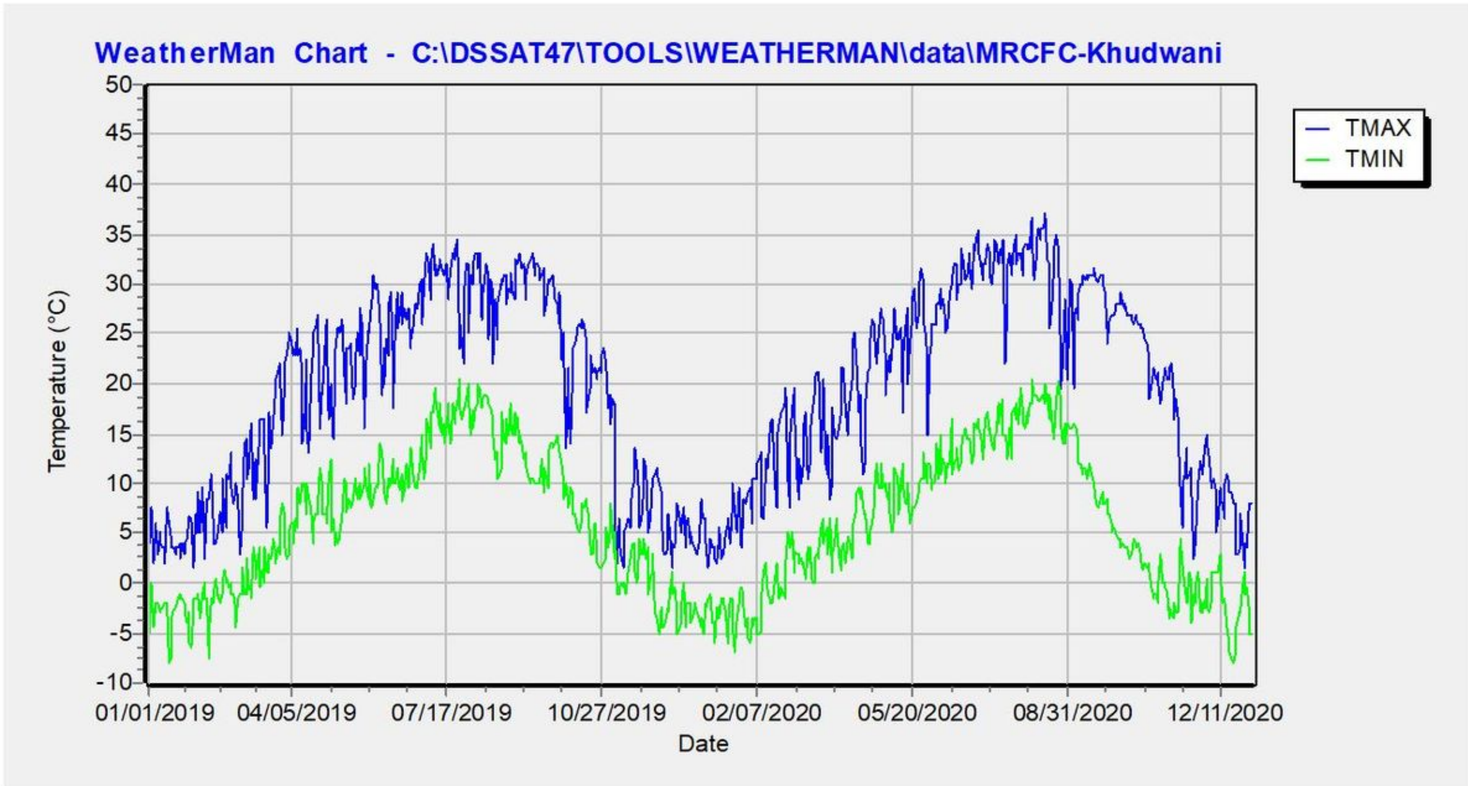

Figure 4

Daily minimum temperature (oC) and daily maximum temperature (oC) recorded at MRCFC, Khudwani (01-01-2019 to 31-12-2020)

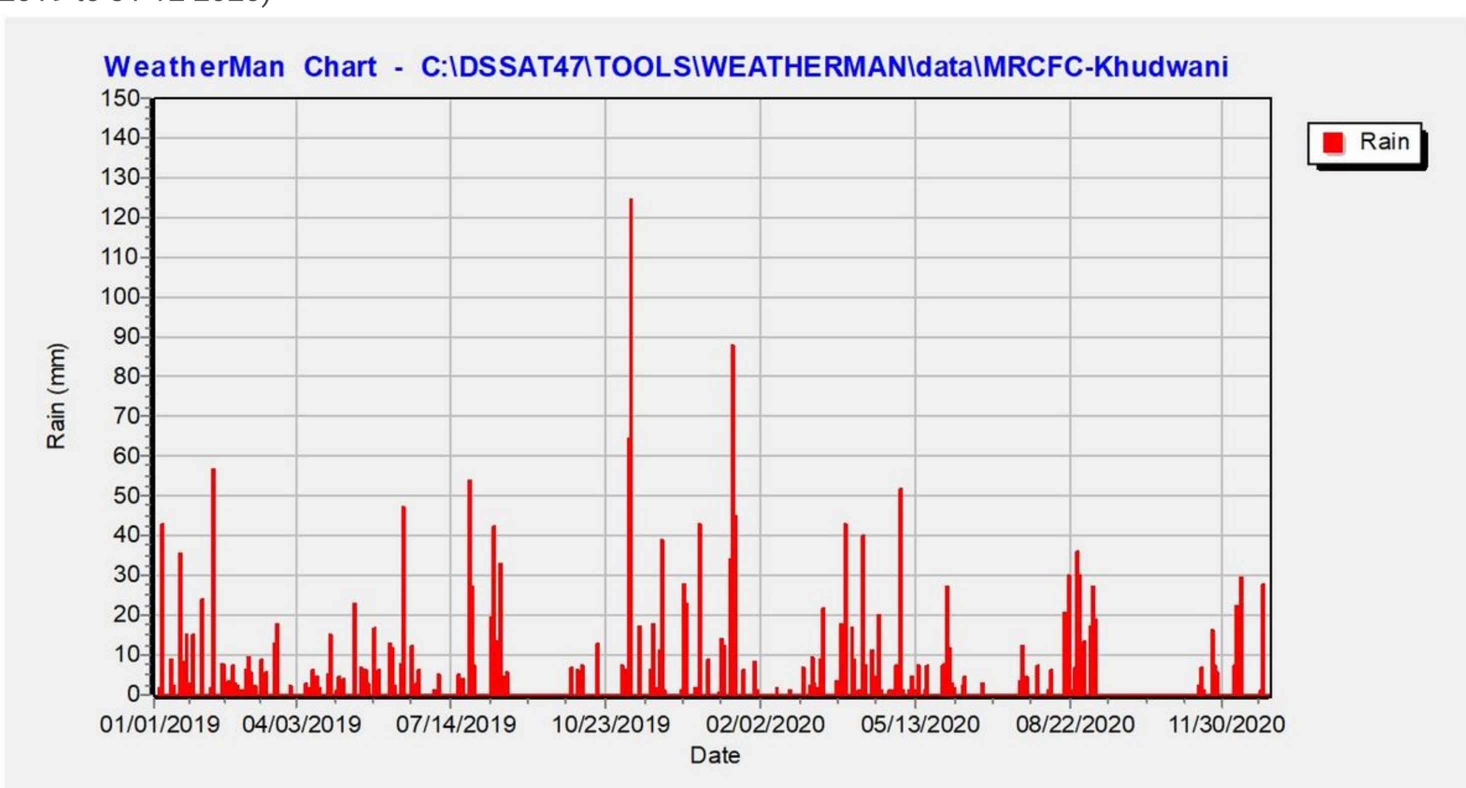

Figure 5

Rainfall / precipitation (mm) recorded at MCFC, Khudwani (01-01-2019 to 31-12-2020)

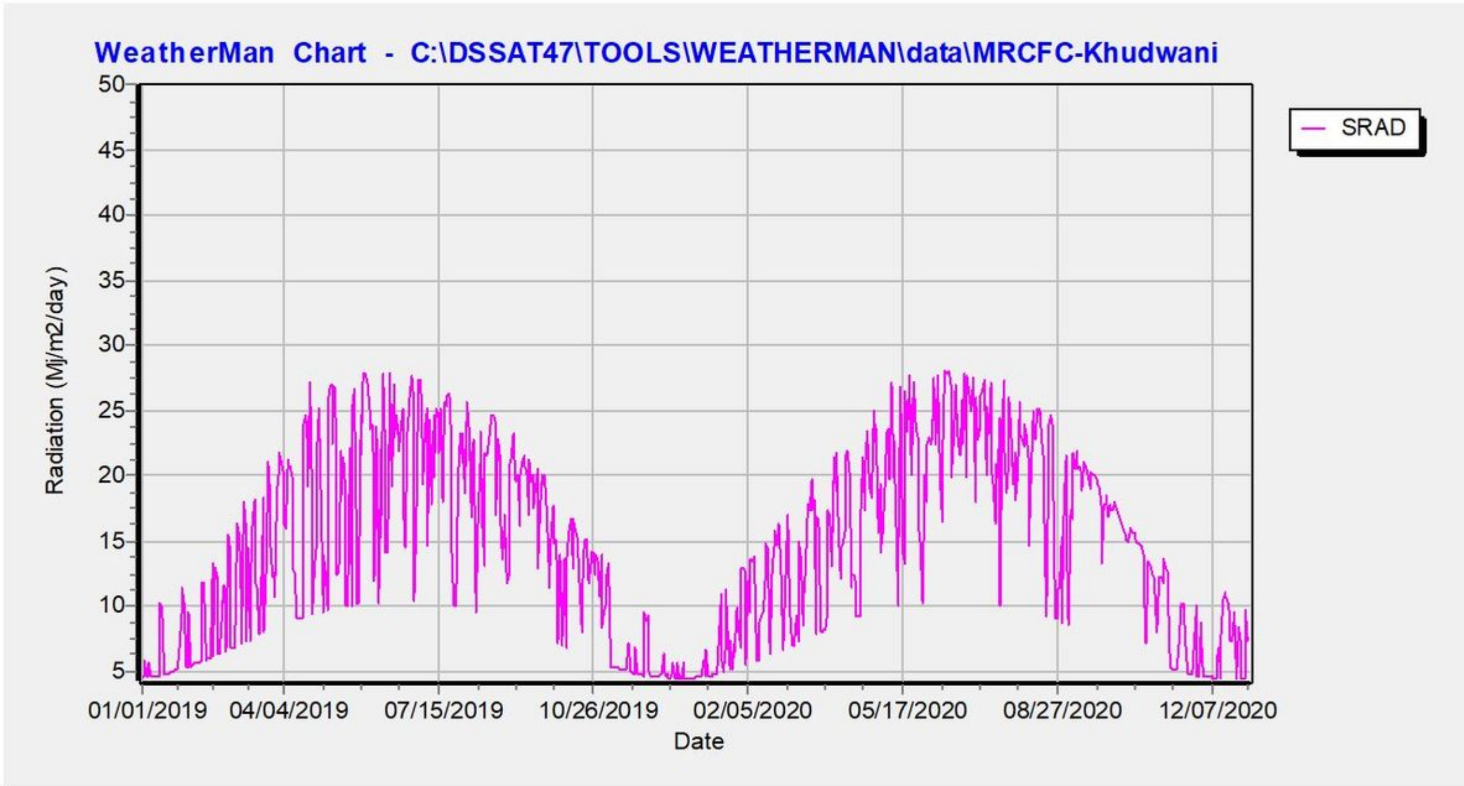

Figure 6

Total incoming solar radiation at MRCFC, Khudwani (01-01-2019 to 31-12-2020)

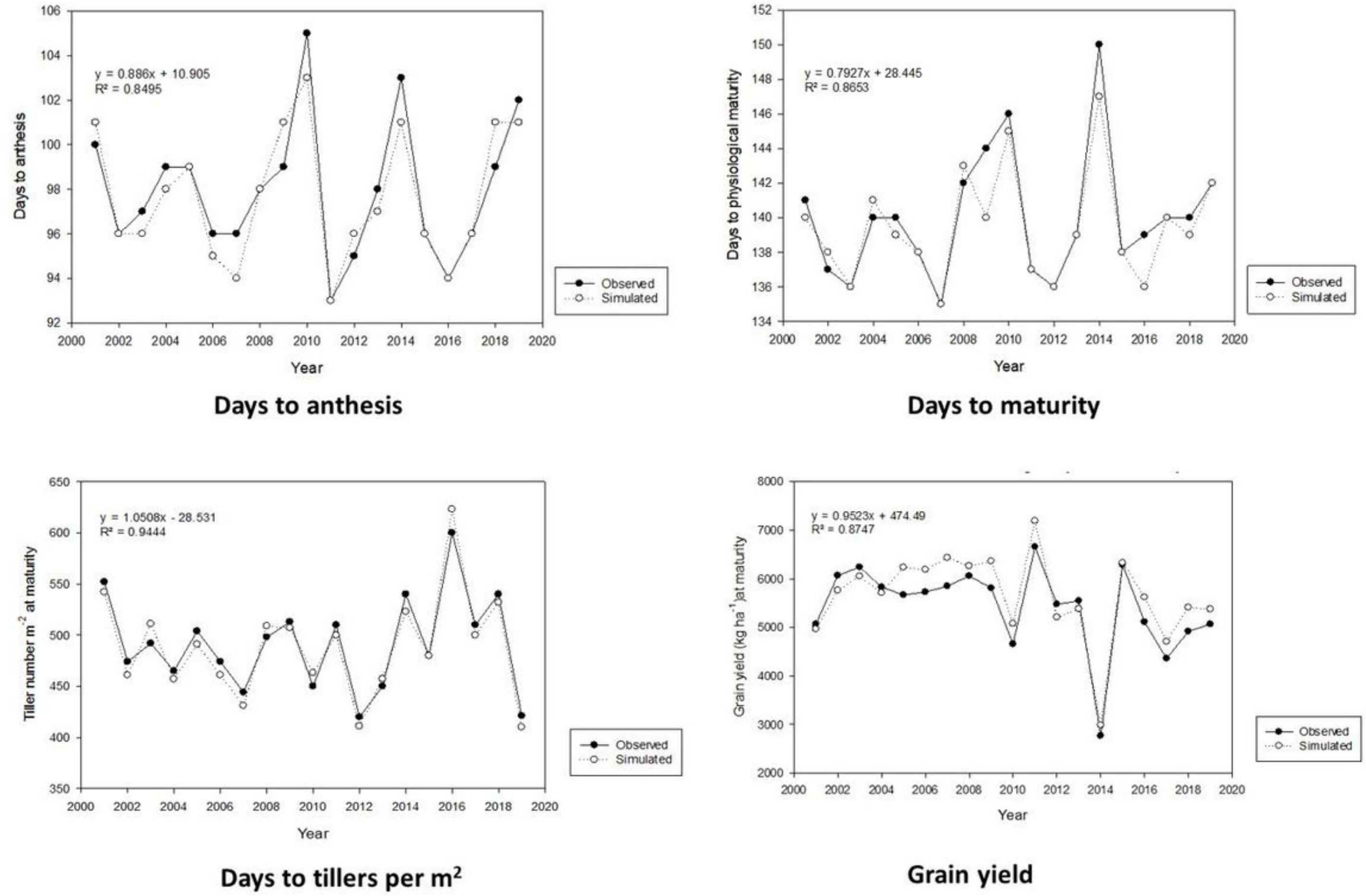

Figure 7

Simulated and observed phenological traits, yield attributes and yield of K-332 (2001-2019)

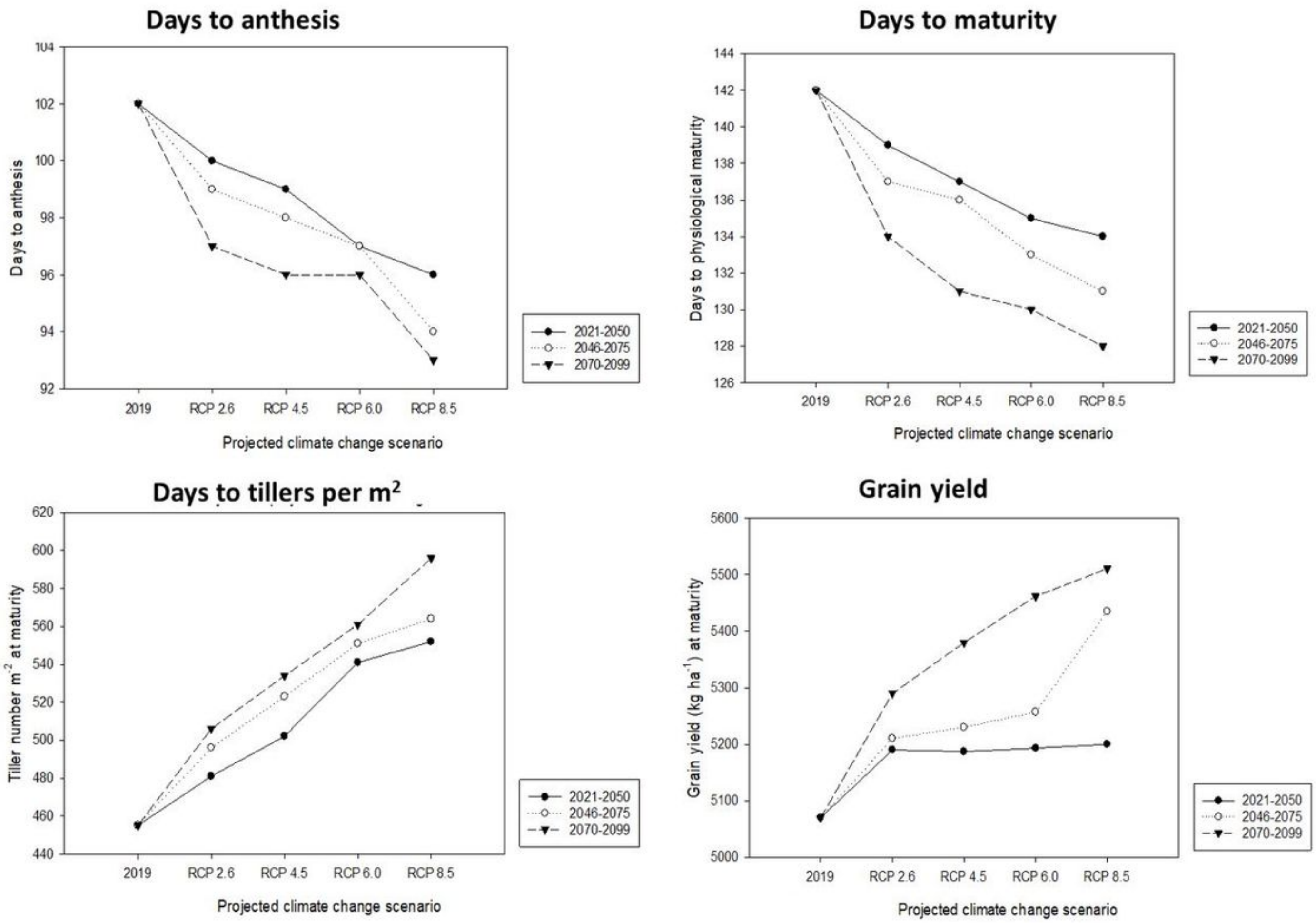

Figure 8

Simulated phenological traits, yield attributes and yield of K-332 under changing climate scenario

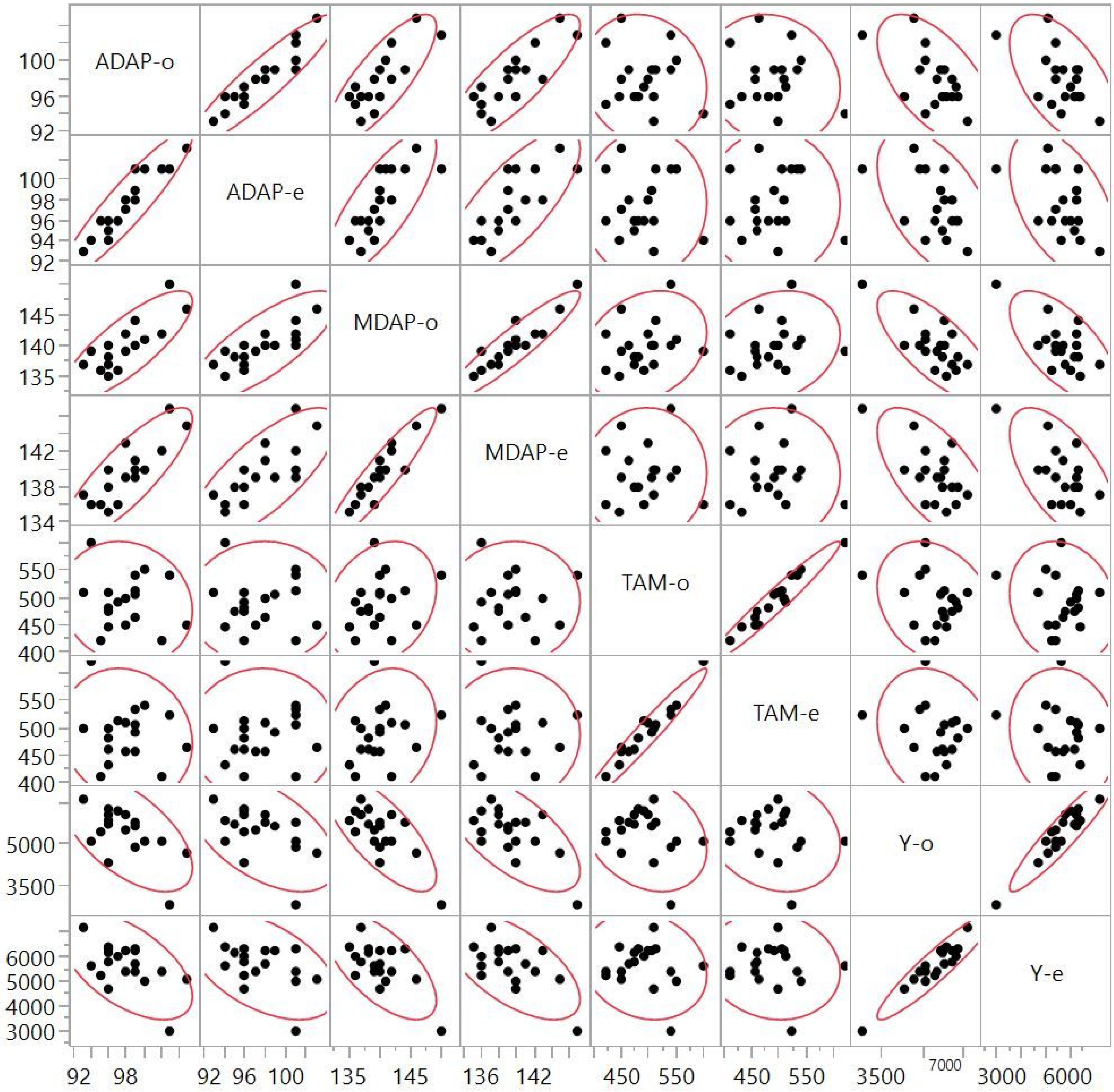

Figure 9

Scatterplot depicting the pairwise correlations among the traits used in simulation study

Supplementary Files

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- SupplementaryTablesS16.pdf